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Launch at GLOBAL FINTECH FEST

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September 2023

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SPECIAL ISSUE ON INNOVATIONS AND TECHNOLOGY IN FINTECH (ITFT-2023)

ENHANCING CREDIT CARD FRAUD DETECTION IN FINANCIAL TRANSACTIONS THROUGH IMPROVED RANDOM FOREST ALGORITHM

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Abstract

Credit card Fraud detection is a critical task in various industries, including finance and e-commerce, where identifying fraudulent activities can help prevent financial losses and protect users. It begins by combining two datasets containing fraudulent and non-fraudulent transactions to create a comprehensive dataset for analysis. Data is preprocessed by removing unnecessary features, calculating distance metrics, and generating new variables to capture temporal patterns and transaction history. Multicollinearity issues are addressed through feature selection. Improved Random Forest (RF) algorithm is used to improve fraud detection. The experimental results indicate that the improved Random Forest algorithm achieves commendable accuracy in fraud detection. The proposed model achieves 99.87% training accuracy and 99.41% testing accuracy. The Model's performance is evaluated by measuring precision, recall, F1-score and support. Our research emphasizes the importance of considering improved algorithms to achieve better results. The findings provide valuable insights for organizations aiming to enhance their fraud detection capabilities and make informed decisions to protect their systems and users.

Keywords:

Credit Card, Fraud detection, Random Forest, Classification, Accuracy, Precision, Recall, and F1 Score

1. INTRODUCTION

Fraud detection is an important task in various industries, especially in the financial sector. The ability to identify fraudulent activities can help prevent financial losses and maintain the integrity of transactions. In this research, we explore the application of machine learning techniques for fraud detection using a dataset containing transaction information.

With increase in credit card usage, fraudulent activities have become a significant concern for card holders. Among inner card fraud and external card fraud, the latter is accountable for the majority of credit card frauds [1]. Through many means fraudulent activities continue to happen. It's quite interesting that card owners are affected the least compared to merchant, because the former have limitations than the later [2]. Credit card fraud may be attempted online or offline. Through virtual mode, illegal fraud activities happen without the knowledge of users. User information such as card number, account number and other details are stolen to perform fraudulent activities [3].

A lot of studies have been conducted on credit card fraud detection. One such research uses machine learning techniques to develop an effective model that can accurately identify fraudulent transactions in credit card data. Various machine learning algorithms, such as Support Vector Machines (SVM), are employed to classify transactions as legitimate or fraudulent based on historical data. In the study on credit card fraud detection using machine learning, various algorithms were employed, including logistic regression, decision trees, and support vector machines [4]. Machine learning approaches analyses behavioral patterns of credit card transactions and enhances security in the financial industry [5]. Next advancement in technology: Neural Networks (NN), which is inspired by human brain. Artificial neural networks are a solution for detecting credit card fraud. They are capable of learning complex patterns and relationships from large datasets, making them suitable for fraud detection tasks. It explains that neural networks simulate the human learning process and consist of artificial neurons organized in layers [6]-[7]. With advancements in research, machine learning models and artificial neural networks are combined to tackle this problem [8]. Some researchers use variants of Machine learning algorithms for fraud detection [9]. Deep learning is a subset of machine learning. It is widely used in many applications including fraud detection [10]. Unlike machine learning algorithms, feature selection is automated in deep learning [11]-[12].

The objective of the study is to develop a system for credit card fraud detection. Section 2 explores the existing work done by various researchers. Section 3 presents the implementation of proposed system and detailed technical explanation of proposed improved Random Forest machine learning algorithm. Section 4 elaborates the results and discussion section with enough visualization. Section 5 concludes the paper with futuristic work.

2. LITERATURE REVIEW

The authors highlight the increasing incidence of credit card fraud and the need for effective detection mechanisms. They propose the random forest algorithm as a potential solution due to its ability to handle large datasets and deal with the imbalanced nature of fraud detection datasets. The research suggests that the random forest algorithm can be a valuable tool in credit card fraud detection and provides insights into the application of this algorithm and its potential to enhance the security of credit card transactions by accurately identifying fraudulent activities [3].

The models were trained and evaluated on a large dataset of credit card transactions. The results demonstrated the effectiveness of machine learning in detecting fraudulent activities, achieving high accuracy rates ranging from 90% to 95%. The study aims to improve the security and integrity of credit card transactions by leveraging the power of machine learning for fraud detection. The study highlights the potential of machine learning techniques in enhancing fraud detection systems and improving overall security in financial industry [4].

The paper presents a behavior-based approach for credit card fraud detection using Support Vector Machines (SVM). By analyzing the behavioral patterns of credit card transactions, SVM models are trained to identify fraudulent activities. The results demonstrate the effectiveness of the proposed method, achieving high accuracy rates of over 95%. The study highlights the potential of behavior-based approaches and SVMs in detecting credit card fraud, contributing to enhanced security in the financial industry [5]. Stolen or Lost Cards, Counterfeit Cards, Card-Not-Present (CNP) Fraud, Identity Theft, Skimming, Account Takeover, Phishing and Social Engineering, Friendly Fraud are the fraud techniques addressed by the authors. NN makes use of patterns to authorize transactions. Back Propagation is used for training purpose. Genetic Algorithm and Neural Network (GANN) combination is discussed as an innovative ideology for fraud detection [6].

The authors describe the experimental setup for credit card fraud detection using neural networks. Research utilizes perceptron model, a basic type of artificial neural network, and the multilayer perceptron, which is a more complex model capable of delivering outputs with more than two classes. The dataset used for training and testing consists of transaction details of 20000 active credit card holders over the past six months. The authors explain how they categorized transactions as fraudulent or legitimate based on various factors such as spending areas, number of transactions, average monthly balance, and total purchase amount. They utilize Neuroph, a lightweight Java Neural Network Framework, to develop and train the neural network [7]. Preprocessing techniques, such as feature selection and correlation analysis, are applied to the dataset. Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), RF and Artificial neural network (ANN) are utilized. Two approaches are used to address class imbalance: resampling the dataset and applying class weights to the classifiers. From their experiment, RF outperforms with more than 96% accuracy [8].

The study focuses on supervised learning techniques and compares the performance of Decision Tree, Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor (KNN) algorithms for credit card fraud detection. Study confirms that SVM outperform DT, KNN and RF. [9]. Authors propose the use of a deep learning model based on an auto-encoder (AE) and a restricted Boltzmann machine (RBM) to detect anomalies in normal transaction patterns. The implementation of the AE and RBM models is done using the TensorFlow library [10].

3. PROPOSED WORKFLOW

The proposed system creates an enhanced mechanism for credit card fraud detection in finance transactions. This section provides an in-depth explanation of the proposed system.

3.1 DATA ACQUISITION

The data is acquired from public dataset, Kaggle. The dataset contains two folders for training and testing. https://www.kaggle.com/datasets/kartik2112/fraud-detection.

3.2 PREPROCESSING

Preprocessing improves accuracy by eliminating noise and potential distractions from unnecessary data. In the data preprocessing step, four columns were removed from the dataset. These columns include 'Unnamed: 0', 'trans_num', 'first', 'last', 'street', and 'city'. The removal of these columns was deemed necessary either due to their redundant nature or because they contained sensitive or irrelevant information for the analysis or modeling task. This preprocessing step helps streamline the dataset for further improving accuracy and efficiency of fraud detection model.

3.3 MODEL ARCHITECTURE

The proposed architecture is depicted in Fig.1.

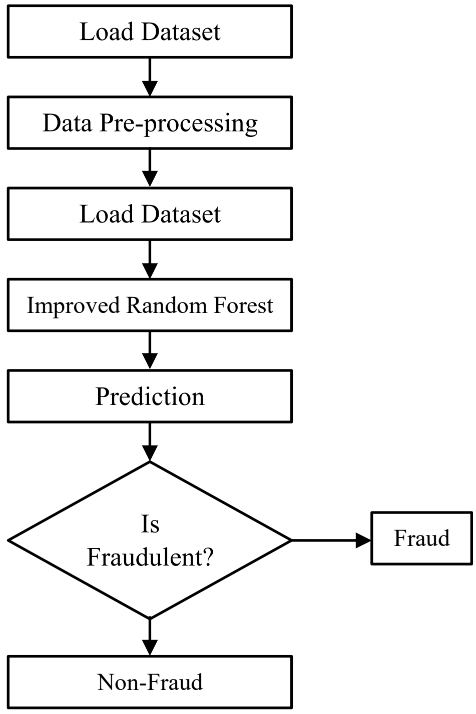

Fig.1. Proposed workflow

3.3.1 Proposed Random Forest Model:

We propose an improved RF model to identify fraud detection and the steps are explained below.

Step 1: Load the dataset.

Step 2: Preprocess the dataset by dropping irrelevant columns, calculating distance between locations, calculating sum of transactions in past 30 days.

Step 3: Data is split into train and test set.

Step 4: Model is trained and evaluated by improved RF classifier.

Step 5: Model makes predictions on test dataset.

Step 6: Accuracy score of the model is calculated.

3.4 CLASSIFICATION

It involves classifying data into different classes. This research involves binary classification, where the improved RF model is trained on a dataset, which is later used to predict the class. Dataset is divided into train and test set in 80:20 ratios.

Step 1: Data is split into test and train dataset.

Step 2: The model is trained by improved RF classifier.

Step 3: Data is trained on training data using ‘fit’ method.

Step 4: Model is predicted using ‘predict’ method.

Step 5: Accuracy of classification is predicted using 'accuracy_score' method.

3.5 IMPROVED RANDOM FOREST CLASSIFICATION ALGORITHM

RF algorithm has the ability to handle complex and high-dimensional data. Multiple decision trees are constructed using random subsets of features and samples. Each tree is trained to classify transactions as fraudulent or non-fraudulent based on the input features. During the prediction phase, each tree in the RF model independently classifies a new transaction as either fraudulent or non-fraudulent. The final classification is determined by aggregating the results from all the trees through voting or averaging.

$$RF(x) = \Sigma(T_i(x)) / N \quad (1)$$

where, $RF(x)$ represents the final prediction for a given input transaction x, $T_i(x)$ represents the prediction of the i_{th} decision tree in the random forest for transaction x and N represents the total number of decision trees in the random forest.

3.6 IMPROVED RANDOM FOREST

The Random Forest classifier in this code is created with optimized parameters, including n_estimators, max_features, max_depth, min_samples_split, and min_samples_leaf.

Feature selection is performed in this code to identify and select the most important features from the dataset, allowing the model to focus on the most informative attributes and improve its overall performance.

Out-of-bag error provides an estimate of the model's performance on unseen data. It enables the assessment of generalization ability and detection of overfitting or underfitting issues without the need for a separate validation set.

Cross-validation is performed to obtain a more reliable estimate of the model's performance by assessing its stability and generalization across different subsets of the training data. It leads to a more robust evaluation of the model's effectiveness in fraud detection.

4. RESULTS AND DISCUSSION

The proposed system utilized Intel(R) Core(TM) i3-5005U CPU with 4GB of RAM and a 64-bit processor. The software environments are Anaconda 1.9.0 and Python 3.9.7.

The correlation coefficient measures the strength and direction of linear relationship between two variables. A positive value indicates positive correlation and negative value indicates negative correlation. Correlation matrix is a square matrix that shows the pair wise correlations between variables in a dataset. The Fig.2 displays correlation matrix as heatmap, providing visual summary of correlations, with annotation values.

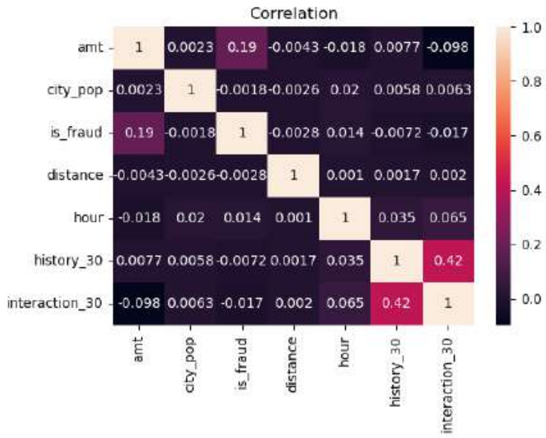

Fig.1. Correlation matrix

Confusion matrix evaluates the model's performance by comparing actual target values with the predicted values. Evaluation metrics like precision, recall, support, and F1-score to assess the efficiency of the classification system. Confusion matrix estimates are explained in Table.1.

Table.1. Key terms in Confusion matrix

Outcome	Explanation
TP	Correctly predicted positive values
TN	Correctly predicted negative values
FP	Incorrectly predicted as positive values
FN	Incorrectly predicted as negative values

The Eq.(2)-Eq.(4) show formula for precision, recall and F1.

$$\text{Recall} = TP/(TP+FN) \quad (2)$$

$$\text{Precision} = TP/(TP+FP) \quad (3)$$

$$\text{f1-score} = 2*((\text{precision}*\text{recall})/(\text{precision}+\text{recall})) \quad (4)$$

The Fig.3 and Fig.4 depicts the confusion matrix for Random Forest and improved Random Forest algorithm.

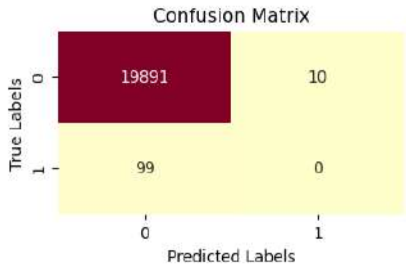

Fig.2. Confusion matrix - Random Forest algorithm

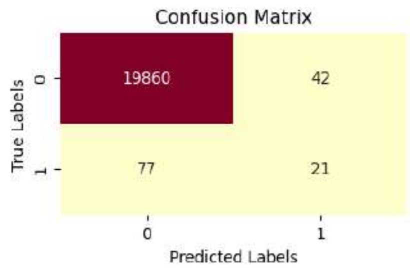

Fig.3. Confusion matrix – Improved RF algorithm

The Fig.5 represents ROC AUC curve for proposed model.

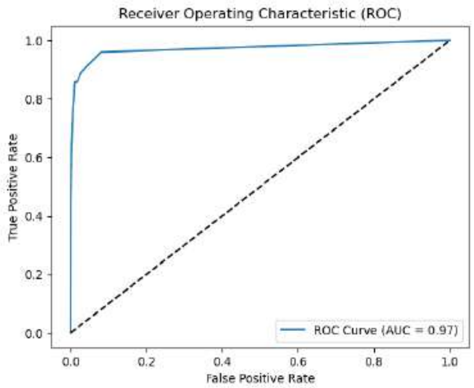

Fig.4. ROC-AUC curve of improved RF model

The Table.2 shows classification report for the proposed model. Precision, recall, F1-score and support are the parameters considered.

Table.2. Classification report

	Precision	Recall	f1-score	Support
0	1.00	1.00	1.00	19902
1	0.70	0.60	0.65	98
Accuracy			0.995	20000
Macro avg	0.85	0.80	0.65	20000
Weighted avg	0.99	0.995	0.99	20000

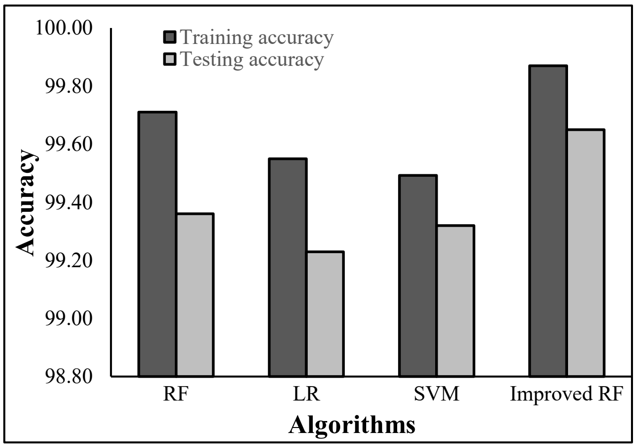

Fig.6. Accuracy of proposed method with other methods

The proposed method is tested against RF, LR and SVM. Experimental results indicate that improved RF outperforms other three classifiers in terms of training and testing accuracy. The Fig.6 depicts the accuracy of proposed method with other machine learning algorithms.

Aburbeian et al. [13] developed a similar system and the comparative results are summarized as follows.

- An accuracy of 98% for predicting transactions, with Class 0 (non-fraud transactions): Precision: 100%, Recall: 96%, F1-score: 98% and Class 1 (fraud transactions): Precision: 96%, Recall: 100%, F1-score: 98%. Results clearly indicate that the model performed exceptionally well for both classes, with minimal false positives and false negatives.
- The results of the proposed system are compared with [13], where our classifier gained overall accuracy of 99.87% for training and 99.41% for testing. An accuracy of 100% for predicting transactions, with Class 0 (non-fraud transactions): Precision: 100%, Recall: 96%, F1-score: 98% and Class 1 (fraud transactions): Precision: 70%, Recall: 60%, F1-score: 65%.
- The results clearly indicate that the proposed model performed exceptionally well for class 0, with minimal false positives and false negatives and slightly lower accuracy of 98.47% for Class 1, which needs to be improved further.

5. CONCLUSION

Early detection of fraudulent transactions allows timely action to be taken at an early stage which minimizes potential financial losses. Analyzing patterns and trends in fraudulent transactions can provide valuable insights into emerging fraud techniques and vulnerabilities. This information can be used to improve fraud prevention strategies and stay ahead of evolving fraud threats. Fraud detection is an ongoing process that requires constant adaptation and improvement to stay effective in the face of ever-evolving fraud techniques. The proposed system achieves 99.41% testing accuracy and 99.87% training accuracy. The limitations in this study are fraud detection done solely on previous month transaction. Combining historical data with additional features and more advanced fraud detection techniques, such as anomaly detection or network analysis, can enhance the overall fraud detection capability and the same will be futuristic work. Future studies will be conducted with cutting edge technologies like Convolutional Neural Network and Deep learning technologies.

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INCREASING COMPETITION BETWEEN BANKS AND MOBILE MONEY COMPANIES: COMPETITORS OR ALLIES?

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Abstract
This paper investigates the increasing competition between traditional banks and mobile money service providers. Although mobile money service is a well-researched area in the literature, the competition between mobile money operators and banks has yet to receive much attention. This paper contributes to a better understanding of the competition between banks and mobile money service providers through a qualitative study framed within Porter's competitive advantage theory. This study applied purposeful sampling of experts in mobile money service provision, Fintech and Banks operating in Ghana. The banks saw mobile money at inception as unattractive, and therefore no pressure on the banks to support this type of innovation. Over time, it has evolved into a critical digital payment service, forcing the banks to launch their mobile money service, Ghana Pay. This study highlights three elements of Porter's theory and provides evidence that banks led mobile money service is not expected to increase competitive pressure on existing mobile money service providers; it is an uphill task because the incumbents benefit from network externalities effects. The data from this research shows that for many years it was challenging for the banks in Ghana to collaborate and deploy common platforms; therefore, the introduction of Ghana Pay is significant since it is the first-time banks as competitors are collaborating to deal with existential threat to their business.

Keywords:
Mobile Money, Ghana, Banks, Digital Finance, Competition

1. INTRODUCTION

Fintech firms are now in direct competition with banks, challenging banks in many ways while at the same time bringing digital disruption to the financial sector with mobile money wallet as one of the most profound examples [1]-[3]. Money service has spurned a wide range of services including credit, micro insurance, micro pension, savings, digital payments, utility bill payments, cash transfer to dispersed populations during humanitarian crises, bulk cash disbursements, merchant payments, peer to peer transactions, and international remittances [4]-[5]. Mobile money service is now a mainstay of Ghanaian economy representing 82% of GDP in terms of transactions meaning majority of payments run through this service, making Ghana one of the fastest growing mobile money markets in Africa [6].

Mobile money services have now established themselves as a tool to enable cashless or cash lite society while contributing to reducing the number of financial excluded population. Mobile Money was launched mobile service in Ghana in 2009, over time the mobile money service has seen significant growth and development with over 50.2 million registered mobile money accounts generating over 87.7 billion cedis as at April 2022 [7] . Until recently players in Ghana's money mobile industry were Mobile Network Operators (MNO) namely MTN Ghana, Vodafone and AirtelTigo, Fintech player known as Zeepay and Bank led product known as GCB G-Money. A major change occurred in the mobile money ecosystem when banks in Ghana form a consortium known as Ghana Pay to offer money in direct competition to existing providers.

Although there are a number of studies on mobile money its relationship with the banking sector in Ghana such as [8], [9] there is relatively low research on the competition between banks and mobile money service providers. The objective of this paper is to understand the dynamics of the competitive forces between Ghana Pay offered by banks and traditional mobile money service providers. Based on this objective, this paper sets out to answer the following a key research two related questions: What are the differences in Banks and Mobile Network Operators mobile money services? and What are the main drivers of competition in mobile money service space? This paper is organised as follows, the next section describes the methodology followed by results, the paper discusses its findings, outlines its conclusion and discussions.

2. LITERATURE REVIEW

In many Sub-Saharan African countries, there is growing evidence that mobile money is enabling a wide spectrum of socioeconomic benefits, financial developments and general well-being of a country [10]. Mobile money can be described as an innovative tool which enable users to conduct a number of financial transactions including sending and receiving remittances, cash-in (deposit of cash and electronic equivalent of cash), cash out (withdrawal of cash), savings, payments of utility bills, purchase of goods and services, consumption of other financial products such as pensions, loans, insurance, stock among others [11].

Mobile money works as a financial wallet typically linked to a user's phone effectively serving as a bank account on mobile phone for the underserved and underbanked population. Mobile money has significantly reduced the barrier to the consumption of financial services, making it a cost-efficient financial inclusion solution [12]-[14]. Mobile money is now the biggest rival to commercial banking since it offers security, convenience, affordable access to financial services, greater choice and wider network than banks [15]. Since its inception, mobile money service providers have enjoyed a near monopoly in the offering mobile money service, this changed when Bank of Ghana licensed Fintech to offer similar mobile money service and on January 30th, 2020, G-Money (mobile money service) launched by GCB Bank [16].

A major milestone took place on June 15th 2022, when the banks in Ghana through their industry association Ghana Association of Banks, under the aegis of The Ghana Interbank Payment and Settlement Systems Limited (GhIPSS) a wholly owned subsidiary of the Bank of Ghana launched Ghana Pay [17]. This new development does not come as a surprise as noted by [18]-[19] banks in Africa have long ignored mobile money's target market that is financial excluded persons in favour of higher-income customers who are able to consume banks more lucrative traditional products, however, these traditional banks have woken from their slumber and are now rushing to capture a share of mobile money market. Money mobile was launched in Ghana in July 2009 by MTN, an MNO in conjunction with nine banks namely Merchant Bank, Stanbic, UBA, Zenith Bank, CAL Bank, Ecobank, Fidelity Bank, GT Bank and Intercontinental Bank.

At inception mobile money regulations was a gray area, so the Central Bank of Ghana, relied on branchless banking licensing regulations which mandates mobile money service to partner with at least 3 banks in the delivery of mobile money services. Bank at inception of mobile money service were not interested in this partnership, due to their strategy not to pursue mass market customers but to focus on high worth individuals and large account holders. Secondly, the regulatory framework led to prematurely forced collaboration between the banks and mobile money service provider without any room for any of these two parties offering a robust leadership, since any investment by any of the commercial banks in strengthening mobile money service infrastructure will lead to a free-rider problem since this investment will be benefits its competitors that is other banks [20].

According to [8] bank clients make use of money service through integration of the accounts enabling them to move between mobile money wallets and their bank accounts. For example, instead of visiting a bank branch to make a bank deposit, a user can transfer funds from their mobile money wallet to a connected bank account and vice versa. Also, most banks in Ghana offer mobile money service through the online banking, SMS banking or banking mobile app, which means bank customers can undertake mobile money services similar to what a typical mobile money wallet account can do through these platforms, the only exception is that they cannot receive money from third party mobile money wallet to their bank account.

2.1 MOBILE MONEY SERVICE DELIVERY THROUGH PARTNERSHIPS

In their study which examines the effects of mobile money revenue allocation [21] reveals that mobile money services may provide benefits to participating banks. Authors [22] noted that banks and mobile money providers on their own may not have all the diverse resources to operate mobile money services exclusively, mobile money providers may have the mechanism for rapid development, branding, marketing and distribution, systems and analytics management. On the other hand, banks have experience and capacity to manage depositor's funds, banking license and long history of managing money. Given this background, mobile money provider and bank partnership becomes a critical success factor.

In agreeing with the notion that mobile money services are better deployed through partnership between banks and mobile money service providers [20], [23] argue that partnership between banks and mobile money service providers is now the most common relationship mechanism in delivering mobile money service, driven by the need to deliver mobile money in cost effective and profitable manner. Furthermore, regulatory requirements sometimes mandate the need for mobile money service providers to partner with banks in mobile money service delivery.

The drivers for partnerships arrangements between banks and mobile money service providers are competitive forces, revenue generation and distribution. The banks are interested in how to increase mobile money float that is mobile money funds held at banks, and possibly recruit underbanked clients to be bank account owners. Whereas the mobile money service providers are motivated to partner with the banks based on the need for a banking license which is a regulatory requirement. Also, mobile money service providers by going into partnership with the banks, are able to offer financial products such as savings, loans as a value-added service for mobile money client thereby increasing revenues. [24] points out that, banks and mobile money service providers have now developed a symbiotic value chain, with mobile money service provider reselling financial services from banks such as a saving product. Sometimes not very common, these mobile service providers are able to provide financial services independent of the banks if regulations permit. In actualisation of these partnership, the banks and mobile money service providers either utilises an operational management or co-management partnership model [20].

Banks started relationship with MNO as partners in delivery of mobile money through serving as custodian of mobile money float, over time some banks started developing alternatives or creating their mobile money service, leading to coopetition or co-opetition (portmanteau of cooperation and competition). For example, mobile money account holders are able to withdraw funds from Bank's ATM under co-opetition model. In assessing the relationship between coopetition and first mover advantage [25] points out that the coopetition intensity decreases the propensity of achieving a radical innovation and first mover advantage in contrast propensity to imitate increases in context of an increased coopetition intensity.

In describing the nature of the relationship between banks and mobile money services, [9] pointed out mobile money is complementary to the strategic goals of banks. On the other hand, [26] pointed out that although commercial banks have started experiencing the impact of mobile money services on their long term financial and operational sustainability of banks in Kenya, their study concluded that mobile money services have a negative insignificant impact on the sustainability of banks. An author [27] suggested that mobile money has forward and backward linkage with bank's performance in Nigeria. [28] indicated that there is fierce competition between mobile money operators and banks with significant threats for survival of banks including potential reduction of banks profit base.

2.2 THEORETICAL BASIS

According to [15] the effects of network externalities on competition in the mobile money industry is well documented, this means consumers are incentivised to join firms with a larger network since the consumers are able to increase their utility and benefits from the said firm. Though competition is possible through introductory pricing or price wars this may result in efficiency losses. The network externalities make it extremely difficult for other mobile phone operators, Fintech or banks to compete with dominant mobile money operator. The downside of network externalities could mean there in no incentives for the dominant to reduce prices or offer better deals or innovate since they have a larger consumer base. [29] suggest that while network externalities may contribute to mass adoption of mobile money in one situation, another country's institutional and industrial context may not lead to the achievement of similar adoption rates.

In the literature, competitive advantage is described as a set of attributes that enable an organisation to outperform its competitors. The two dominant competitive advantage theories are the Market-Based View (MBV) and the Resource-Based View (RBV). One of the best-known theories under The Market-Based View (MBV) is Porter's five forces model which is derived from Structure-Conduct-Performance (SCP) framework [30]. Porter's Theory of Competitive advantage focuses on competitive responses in a given business context, which is responsible for how various firms react in the face of competition. The Porter's theory highlighted five key elements, namely competition among existing competitors, bargaining power of the buyers, threats of product substitution in the market space, the bargaining power of suppliers and barrier of entry to entry of new players [31]. New digital technologies can create competitive advantages for firms manifesting in three ways, it can change industry structure while altering the rules of competition, second it creates new pathway companies' new ways to outperform their rivals and lastly it can create a new business [32]

In the case of mobile money technological innovations, mobile money services providers are now able to outperform traditional banks especially in increasing accessibility of financial services to a mass market. Competitive advantage can be seen in three areas namely cost advantage; ability to produce and market product or service as a rate lower than competition, second the ability to provide product or service features which is considered valuable by customers and third niche advantage where a firm is able to serve a segment of the market better than its competitors. [33] noted that competitive advantage therefore offers a new way of understanding how a firm operates by disaggregating a firm activity that represents the key building blocks of competitive advantage.

The power of competitive advantage is not only through the identification of core activities, but also how these activities relate to each other and elements in a value chain. In this sense competitive advantage offers a tool to capture the complexity of competition through unpacking value chain analysis to construct underlying activities which makes a firm perform better than its competitors. In the case of mobile money service providers, their competitive advantage over banks is convenience, that is the customers' ability to consume financial services anywhere and anytime. To identify and analyses competitive forces, we apply Porter's five forces: A company working in an industry with low number of competitors coupled with low rivalry among competitors, strong barriers to new entrants into the industry, large pool of suppliers, low bargaining power of customers and low threats of substitutes products and services is able to boost profits and maintain a competitive advantage over the market [34]

Porter's 5 forces are not without criticism, it ignored effect of complements on the industry, a firm's agility holds more value than market dominance especially a firm's ability to be fast, fluid and flexible is paramount in fast technological driven market space. Another critique of Porter's model is that it explains how a firm can get competitive advantage and it is very weak on how to maintain it [30], [35], [36]. It is imperative to note the boundaries between industries are becoming blurred, making it difficult to put them in distinct baskets, however, Porter's five forces is very useful in evaluating a firm's place within an industry and how it can strategies in the evolving long-term plans [37].

First mover connotes a situation where an industry player derives significant advantage as the first actor to provide a service leading to a significant market share which can ultimately led to abnormal profitability [38]. An author [39] suggested that the persistence of first mover advantage performance can negatively be impacted by industry dynamics that is market growth and technological discontinuity. [40] posits that first mover can be difficult to achieve and if an organization can gain first mover advantage it is a function of two conditions that is the pace at which technology linked to a product is evolving and the rate at which the market for the said product is expanding. Furthermore, authors [41]-[43] argue that first mover (leader) can be costly since the firm needs to start product or service development from scratch, pay a lot of development, setup and learning costs. However, the follower (the second mover) in relatively terms incurs a smaller upfront entry cost in comparison to the leader. At the end of the day, a firm must balance the benefits of waiting at the opportunity cost of forgoing current period's profit versus going in as a leader and enjoying current period's profit.

This study relies on three elements of Porter's competition advantage theory that is barrier to entry of new players, competition among existing competitors in the market, and threats from substitute products in the market combined with first mover advantage as its theoretical underpinning. These theories are important for this study because it help elucidate how Ghana banks through their mobile money service Ghana Pay compete with traditional mobile money services.

3. METHODOLOGY

This paper utilised a qualitative approach to provide the mechanism for an-in-depth understanding of a phenomenon, especially in situation where information is not readily available. Qualitative approach is appropriate for understanding complex, nuanced situations with multiple interpretation, though it does not provide definitive answers to such complex questions, it can help provide better understanding and a springboard for further research [44], [45]. This study applied purposeful sampling based on experts who are knowledgeable and experienced in mobile money and banking sector from a population of MNOs, Fintech and Banks operating in Ghana.

3.1 DATA COLLECTION AND ANALYSIS

The summary of interview respondents is listed in the Table.1. An interview guide was developed to collect data, which was recorded, transcribed and all the interviews were done though online means.

The interview guide was based on Pyramid Model which starts with research purpose interfacing central research question linked to literature leading to theoretical questions thereafter culminating in specific interview questions [46].

The Data collected from the interviews were process through six-step processes to develop themes; familiarisation, coding generation of themes, reviewing themes, defining and naming these and final analysis [47]. As noted by [44] coding is the first process in data analysis of interviews where transcripts from interviews are converted into usable data through systematic process of identification of themes, concept and connections with each other. Thereafter, themes were generated from the data using MAXQDA software. Interviews data were supplemented with secondary data mainly industry reports, laws and policies.

Table.1. Summary of Interview Respondents

Code	Description
FT 01	Mobile money technology solution provider
FT 02	Expert with experience in Banking, Fintech and mobile money company
FT 03	National digital payments integrator and facilitator of mobile money services
FT 04	Fintech focusing on payments
FT 05	Mobile phone company providing mobile money service
FT 06	Fintech experience with experience working with mobile money company
FT 07	Banking Expert
FT 08	Fintech expert working with banks on digital micro loans
FT 09	Banking Expert
FT 10	Banking Expert

Source: authors' own constructs (2022)

4. FINDINGS

4.1 CONFIGURATION OF MOBILE MONEY SERVICE

The Fig.1 below explains the configuration of mobile money services and related parties. The process starts with onboarding mobile money customers using ID and physical address, which leads to creating a mobile money wallet. The actors in the mobile money ecosystem are Users, mobile money agents, Banks, mobile money service providers, and regulators situated within the context of Porter's competitive factors: substitute competition, first-mover advantage, barriers to entry and existing rivalry. The results of this study indicate that banks have a bilateral agreement with mobile money service providers, and the banks hold funds on mobile money users' wallets as a float. The float serves as liquidity for the banks since they can monetize it. Banks, as the custodian of mobile money funds, hold this fund like any other bank account. This regulatory arrangement ensure mobile money funds are protected under Ghana's deposit insurance system based on The Ghana Deposit Protection Act, 2016 (Act 931), as amended which established the Ghana Deposit Protection Scheme [48]. Mobile money providers cannot intermediate the funds on clients' mobile money wallets leaving this function in the hands of the bank partners. Based on the terms of partnership agreements, periodically the bank and mobile money providers will undertake reconciliation of balances of the escrow account and value of mobile money wallets transactions [49].

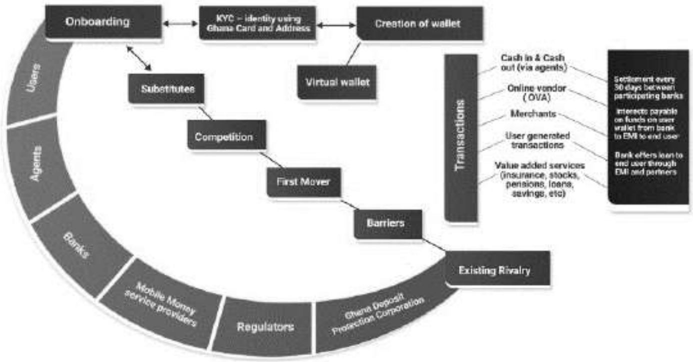

Fig.1. Configuration of Mobile Money Service (Source: Authors own construct (2022))

In describing how the mobile money and the banks are relationship are structured, a respondent noted, "Periodically, the banks must settle with each other and mobile money providers therefore the role of banks is central to Mobile money. Banks do not get paid for participating in the money service, however, the float that run through the banking system based on mobile money transactions, they are able to monetize this float through utilising it for loans or other financial services provisions" (FT05 personal communication, July 8, 2022)

Funds on mobile money wallets are treated as an interest-bearing account by the custodian banks. First, the bank pays the mobile money service provider, an annual interest of 4% on float that is mobile money users funds held at these banks. This interest is paid monthly. Second, the mobile money service provider, upon receipt of this 4% interest from the bank distribute 90% of this interest to the user on quarterly basis and the mobile money provider keeps 10%. Third, according to the regulation of mobile money services by the regulator, Bank of Ghana, when a bank holding mobile money users' funds, exceed 25% of the banks net worth, they are expected to invest this excess float in Government of Ghana 21-day treasury bill. The returns on this excess float investment are shared in the ratio 10% to the bank, 15% to mobile money service provider and 75% to the users.

4.2 BARRIERS TO ENTRY

The data from this study reveals that there are a number of barriers influencing the entry of new entities into mobile money service provision. In terms of regulatory barriers to entry, an applicant for a mobile money license (Dedicated Electronic Money Issuer) need to put up an integrity capital of 20 million Ghana cedis (1,818,181 USD) which can be a barrier for some entities. Second, provision of mobile money service requires a lot of up-front capital, therefore, lack of financial resources can also be stated as a major barrier to entry. In assessing technical barriers to the entry of mobile money services, a respondent noted:

"The platform itself is not complicated you have basically a server that posts all the wallets of mobile money and processes all the requests and it's integrated to channels like Unstructured Supplementary Service Data (USSD) like apps web browser so it's not a differentiator since it the conventional infrastructure that is used for mobile money service provision platforms" (FT 01 Personal Conversation 14th July 2022).

Therefore, from a technology point of view, it takes me less than 48 hours to set up an infrastructure for mobile money service based on a Unstructured Supplementary Service Data USSD or an short message service centre (SMSC) backbone. However, a technical barrier may arise when it comes to integration into a MNO to drive the service, thus this it becomes a more or less a more a commercial barrier rather than a technical barrier. Another respondent noted,

"I wouldn't say there's no significant barrier to entry because i don't regard technology as the biggest differentiator distribution is the biggest differentiator so anybody can do mobile money, but you have to be distributed" (FT 02 Personal Conversation 8th July 2022).

In this direction, the need to establish a distribution platform is a key barrier to entry for banks interested in offering mobile money services, since this distribution platform cannot be built overnight. Another respondent provided a counter view on distribution:

"Agent's network which is the primary distribution mechanism for mobile money service provision is no longer a barrier, since agents cannot be exclusive to a particular provider, regulations prevent exclusive agents. Co-branding is key in terms of agents serving multiple providers. However, mobile phone companies which establish these agents' network with deep historical ties with them, have a first mover advantage therefore this could be a barrier" (FT 10 Personal Conversation 10th August 2022)

Also, traditional mobile money relied on the need for a mobile phone number, which was under the exclusive control of mobile phone companies, today this is no longer a barrier since a new entry into mobile money service provision can have access to these mobile numbers. That said, banks do not have a detailed database of mobile phone users and their transaction history making this a key barrier to entry. Lastly, existing mobile money services providers are able to be innovative while the banks are not nimble enough negatively impact their capacity to compete.

4.3 THREAT OF SUBSTITUTES

In terms of a substitutes for mobile money, one respondent noted,

"I don't know of any immediate substitute as things are happening cryptocurrency, digital currencies are being discussed, non-fungible token (NFT)is in the works. I don't know where it all lands, but these are some possible substitutes for mobile money. (FT 02 Personal conversation 8th July 2022).

Some respondents noted that cash is a key substitute to mobile money services, especially in an environment where cash is a predominant means of payments. Due to the imposition of electronic levy (e-levy) in Ghana on mobile money, more users are now turning to cash instead of using mobile money. According to a respondent.

"The e-levy has rolled back almost a decade of hard work is promoting digital payments especially mobile money, so i think the society have now turn back to the use of cash which is very unfortunate" (Personal Conversation FT 08 9th July 2022). Respondents suggested Central Bank Digital Currency (CBDC) known as eCedi to be issued by Bank of Ghana, blockchain type applications and cryptocurrency as a possible substitute for mobile money services.

4.4 EXISTING RIVALRY

The results of this research indicated that banks have been in direct and indirect competition with mobile money services since the inception of mobile money. The rivalry is manifested in terms of pricing and convenience with mobile money service providers performing better than banks on both counts. The second level of rivalship is loan provision, traditional loan provision has been the preserve of banks, however, mobile money service providers are now operating in this area. A respondent suggested:

"Micro loans offered by mobile money services providers are based on data analytics derived from mobile phone users' activities, i mean there's modeling there's uh cleaning and sorting of data there's credit scoring and then you are able to properly use these credit scores to then make a credit decision which the banks do not have" (FT 08, personal conversation 9th July 2022)

Some respondents opined that the banks could compete in mobile money loan space by offering loans to Small and Micro Enterprise (SMEs). Lastly interest rates offered on bank loans and savings are also a source of rivalry between banks and mobile money service providers.

4.5 FIRST MOVER ADVANTAGE

The data from this study points to the fact that mobile money service providers have gained a first mover advantage over the banks through established partnership with last mile mobile money distribution agency network. The current dominance of mobile money service providers is based on the control of this distribution mechanism. Respondent said, "so if look at the reserve requirements of a bank like Stanbic nine billion in comparison to MTN mobile money service provider transactions of 10 billion then you see this first mover advantage at work" (FT 02, personal conversation 8th July 2022). Another respondent in summarising first mover advantage for mobile money service providers:

"The mobile phone companies who started the mobile money services have superior advantage that it would take a monumental investment to try to crash and it makes no sense for the bank of to try to compete with them, it will be better for these banks to actually go the route rather of an enabler that is experiential products built on mobile money service." (FT 01, personal conversation 14th July 2022)

4.6 COMPETITION IN THE MARKET SPACE AND THE IMPACT OF COMPETITION

In assessing competition between Ghana Pay and traditional mobile money service, one respondent noted:

"Ghana pay it would never be as popular as traditional mobile money and the point is that even if banks invest a lot of money into Ghana pay to make it rival mobile money it would be still money being washed down the drain because now i think it has come rather late in the day that is my worry i say is that it's Ghana pay 10 years behind time this is what the bank should have come together 10 years ago" (FT 08, personal conversation, 9th July 2022).

The mobile money service industry in Ghana at inception had difficulties, it took two years for pioneer, MTN Ghana to find a bank partner. So, after a decade of mobile money service which has now grown to trillion Ghana Cedis (97,087,378,000 USD) business, it may be too late for the banks to compete. Banks have over time invested in significant legacy technology systems meaning they are slow to response to uptake of modern technology such as mobile money services. It is important to stressed that, Ghana Pay introduction means there is going to be competition among banks, for Ghana Pay mobile money customers, though this is a common platform, with each individual bank, must acquire their own mobile money customers.

The data from this research shows that for many years it was very difficult for the banks in Ghana to collaborate and introduce common platforms, therefore the introduction of Ghana Pay is significant since it is the first-time banks as competitors are collaborating to deploy this service due to existential threat to their business. In term of how-to Ghana Pay should interact with traditional mobile money service, a respondent opinionated that the relationship should be more of more cooperation than competition, where the competition is at the level of experiential delivery of services rather than competition across board.

According to a respondent, the launch of Ghana Pay is a competitive response aimed at expanding the scope of mobile money services to value additions such as payments, savings, insurance, pension thereby evolving the service from cash-in and cash-out services to a fully-fledged digital payments tool. Lastly the banks have the muscle, financial strength, long history of holding people’s money in trust thereby strengthening their competitor advantage.

5. DISCUSSION

The findings of this study, shows six key characteristics that shape the relationship between the traditional mobile money service providers and banks : the configuration of mobile money service demands a high level of partnerships between the two primary actors, barriers to entry to mobile service is dominated by commercial, regulatory and technical barriers, there is currently no threat of substitutes for mobile money services, predominance of high level of existing rivalry, first entrants are enjoying first mover advantage and there is now intensive competition in the mobile money market space.

This study highlights the fact that three elements of Porter’s competition advantage theory that is barrier to entry of new players, competition among existing competitors in the market explains developments in mobile money market. [33]. However, the study results show there is no threats from substitute products in the market for mobile money services, explaining why mobile money is enjoying a significant first mover advantage while maintaining a unique competitive over traditional brick and mortar service. Banks are now struggling to develop their version of mobile money service in order to compete, however, it is an uphill task for the banks to compete effectively in the mobile money service market since the mobile money industry is benefiting from the effects of network externalities on competition [15].

It must be noted that that the next level of competition will come from cryptocurrency of a sort or Central Bank Digital Currency in case of Ghana known as eCedi, therefore both banks and mobile money service providers must work towards evolving cryptocurrency solutions or work towards the use of blockchain in their service delivery. Banks by entering into mobile money service sector are aiming to remove traditional money mobile money service providers as a middleman in order to directly serve clients. This development does have significant partnership and competition implications, the bank are still big and important actors in payments ecosystem, however, mobile money has significantly eroded their monopoly as financial intermediator since mobile services are equally performing this role. Competition between banks and mobile money service providers is going to accelerate, however, given how mobile money services is structured around the need for partnership among stakeholders, there is going to be more coopetition than competition.

6. CONCLUSION

This paper aims to understand the dynamics of the competitive forces between Ghana Pay offered by banks and traditional mobile money service providers. This paper sets out to find the differences between Banks' and Mobile Network Operators' mobile money services and the main drivers of competition in the mobile money service space. According to the results of this study, mobile money was launched as a critical vehicle for domestic remittances at inception. At the launch of mobile money, the banks saw mobile money as unattractive, and there was no pressure on the banks to support this innovation. Over time it has evolved into a critical digital payment service and a dominant payment mechanism in the economy, making it a key competitor to the banks. This background compelled the bank to launch its mobile money service to compete. The results indicated that there are no substitutes for mobile money, and there is fierce competition between banks and mobile money service providers. At the same time, the two parties are in partnership leading to a coopetition situation. The traditional mobile money service providers are enjoying first mover advantage, with banks trying to play catch up by launching their mobile money service. The evidence from this research shows that banks-led mobile money services will not increase competitive pressure in the mobile money service ecosystem.

7. LIMITATIONS AND FUTURE RESEARCH

Although this study contributed to the theory and provided insights, it has some limitations. The small size of respondents is a key limitation of this research; future research could expand the pool of respondents beyond experts to include consumers and other stakeholders. Further research could explore how a higher degree of competition driven by the entry of banks into the mobile money ecosystem can promote greater access to financial services, thereby improving financial inclusion. Also, there is the need to empirically evaluate how heightened competition could contribute to cost efficiencies which can be passed on to consumers in terms of lower prices.

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PRICE PROGNOSTICATION OF CURRENCY WITH DEEP LEARNING

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Abstract

In this modern era of technology, the more secured ways are needed to deal with financial investments or transactions. Cryptocurrency can be named as one of the solutions for this concern. Cryptocurrency is a digital payment system that doesn't rely on banks to verify transactions. A digital payment system called cryptocurrency doesn't rely on banks to validate transactions. Anyone can send and receive funds using this method. Payments made using cryptocurrencies only exist as digital records in an online database that detail specific transactions. This new sort of investment is providing vast areas for research to the researchers. By predicting its price this can be as more efficient asset for investment. Much research is going on in this area. This paper proposes two different recurrent neural network (RNN) algorithms to predict prices of cryptocurrency namely Bit coin and they are Long short-term memory (LSTM) and Gated Recurrent Unit (GRU). the measures being used in this paper to assess the accuracy of the used algorithms are mean squared error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), are also used to assess different prediction algorithms. Comparisons are carried out on the basis of three datasets training, testing, and validation. The loss and evaluation functions are based on the mean squared error. The model performs better the lower the value. Based on findings the GRU model outperforms the LSTM algorithm in terms of accuracy and reliability in predicting cryptocurrency prices, but both algorithms produce excellent outcomes.

Keywords:
Cryptocurrency, Bitcoin, LSTM, GRU, RNN

1. INTRODUCTION

Virtual currencies are a kind of cryptocurrency that, despite its limitations, is a remarkable technical achievement in the field of digital marketing. Virtual currencies will continue to exist, but they will never be able to entirely replace fiat or traditional currencies. Satoshi Nakamoto proposed a system that transformed the current system on October 31, 2008, with the invention of Block-chain technology and the first digital currency Bitcoin. Blockchain technology applications go further in the peer-to-peer system of payment. A blockchain is on a really basic level a scattered information of records or open record everything thought of or modernized occasions that are dead and shared among sharing parties.

The real advantage of this system is to be decentralized and fully secure of whole environment which only allows that the new blocks append. The blockchain applications ranges are at the head of many blockchain and cryptocurrencies.

Cryptocurrency is a string of encrypted data used to represent a unit of money. A peer-to-peer network called a block chain, which also functions as a secure record of transactions, such as buying, selling, and transferring, oversees and manages it [1].

The best cryptocurrency forecast uses a variety of technical indicators, including Bollinger bands, fib retracement, moving averages, etc. When joining the market and executing the appropriate actions, they execute three basic functions: prediction, confirmation, and creating alerts for investors and traders [1].

The main benefit of this system is its decentralized nature and complete environmental security, which only permits the appending of new blocks. Many blockchain and cryptocurrencies are led by the blockchain applications categories.

Bitcoin is a peer-to-peer cryptocurrency in which no third entity regulates or controls any transactions. It is not feasible for a third party to intrude between consumers. The market price is extremely volatile and operates 24 hours a day, seven days a week. Bitcoin's market capitalization rises and falls.

Deep learning algorithms have yet to be widely employed to forecast cryptocurrency market values. We investigate applications of deep learning to forecast the cryptocurrency market value, knowing that deep learning models have evolved into state-of-the-art neural network design that enhances prediction accuracy in a variety of domains, including time series.

The proposed system is based on prior research on cryptocurrency price prediction, as well as deep learning models for predicting time series. The primary difficulty with cryptocurrency exchange rates is their fast pace of price volatility. Because of the high price volatility, various precautions should be followed in order to properly anticipate the price of cryptocurrency. Understanding forecasting activities is essential for forecasting bitcoin prices as well as building trust and acceptance globally. The economic function of Bitcoin and global interactions on different market techniques can be influenced by a variety of factors, including a nation's political system, public relations strategy, and market policy. To get a greater insight into the issues of crypto-vulnerability, currency risk detection, mitigation, regulation, and acceptance, future researchers should come up with the range of approaches. Prediction of bit coin prices benefits the investors by giving opportunity to them to make decisions on their investments. To maximize profits and reduce risk, traders and investors are interested in making accurate bitcoin price predictions.

This section presents overview of cryptocurrencies whereas the remaining part of paper is designed as section 2 states the challenges faced in price prediction of cryptocurrency, section 3 presents the Methodology used to in the proposed study followed by section 4 description of the data set used in the study and section 5 gives the result analysis followed by conclusion.

2. CHALLENGES

Regardless of the opportunities in cryptocurrency, cryptocurrency still faces many challenges that need to be faced. Curious and new investors have taken prudent measures to invest massively or not due to risks and challenges associated with trading and investing in cryptocurrencies. Future studies should devise a variety of strategies in order to gain a deeper understanding of the problems related to cryptocurrency vulnerability, risk identification, mitigation, regulation, and acceptability. Research that shows the downsides and upsides of altcoins, a digital currency that competes with bitcoin, is necessary for government actors. Furthermore, a comprehensive mapping of this spread will help business actors, among others, better recognize and manage impending volatility concerns as well as make wise policy decisions in this rapidly evolving area. A model to examine the antecedents in various situations using more sophisticated statistical modelling techniques, such as structural equation modelling or partial least squares, is also urgently needed.

2.1 PROBLEM STATEMENT

To develop a model that will enable us to anticipate the price of the cryptocurrency being used (in this example, Bitcoin), with a low error rate and high precision and accuracy. Although the model is unable to foretell our future, it can point to broad trends and the general way that prices are likely to move.

2.2 OBJECTIVES

The main objectives of this study are:

- To transform cryptocurrency into a publicly traded good with predictable price.
- To employ a machine learning technique to anticipate the direction of the price of a cryptocurrency.
- Do digital currencies like Bitcoins have the potential to displace US dollars and other conventional currencies as the principal form of transaction with weekly price prediction? Our goal is to find a solution to this question.
- To create an automated application that uses machine learning to forecast an upsurge in cryptocurrency prices relative to various time series.
- To guarantee lower risk and higher returns for investors.

3. METHODOLOGY

In this study, we used historical bitcoin prices to train two different models for two different types of price prediction in order to accomplish the goals of this work. The suggested technique analyses two alternative deep learning-based prediction models to estimate daily cryptocurrency prices by the model itself identifying and assessing important variables. We can identify which model is much more accurate for the future fulfilment of our aim after using both models for cryptocurrency prediction as well as selecting appropriate parameters to get a higher performance. The block diagram for proposed model is depicted in Fig.1.

The research offers deep learning methods associated with Recurrent Neural Networks (RNN) such as Long Short – Term Memory (LSTM) and Gated Recurrent Unit (GRU), which are the most recent and efficient algorithms for cryptocurrency price predictions. Since Bitcoin is the most widely used cryptocurrency, the issue of price volatility must be addressed quickly.

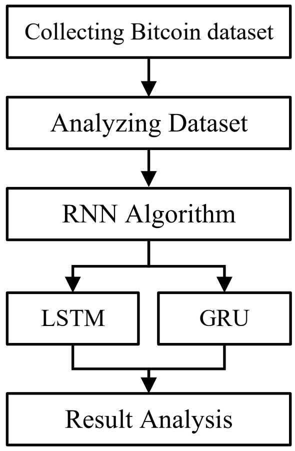

Fig.1. Block diagram for proposed model

3.1 MACHINE LEARNING ALGORITHM

3.1.1 RNN:

An artificial neural network that employs sequential data or time series data is called a recurrent neural network (RNN) [3]. Because they use data from earlier inputs to affect the present input and output, they are distinguished by their "memory". Recurrent neural networks' outputs are dependent on the previous parts in the sequence, unlike typical deep neural networks, which presume that inputs and outputs are independent of one another. This approach looks appropriate for the proposed study.

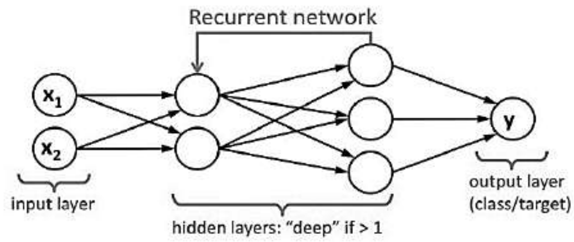

Fig.2. Recurrent Neural Networks [3]

3.1.2 LSTM:

The LSTM is a Recurrent Neural Networks (RNN) style architecture with gates that govern the flow of information between cells. A cell, an input gate, an output gate, and a forget gate make up a typical LSTM unit. The three gates control how information enters and leaves the cell, and the cell stores values across arbitrary time intervals. The input and forget gate structures can modify information traveling along the cell state, with the ultimate output being a filtered version of the cell state based on inputs [2].

A Gated Recurrent Unit (GRU) is a Recurrent Neural Network (RNN) architecture type. GRU can process sequential data such as time series, natural language, and speech. The main difference between a GRU and other RNN architectures, such as the Long Short-Term Memory (LSTM) network, is how the network handles information flow through time. The Gated Recurrent Unit (GRU) cell is the basic building block of a GRU network. It comprises three main components: an update gate, a reset gate, and a candidate hidden state.

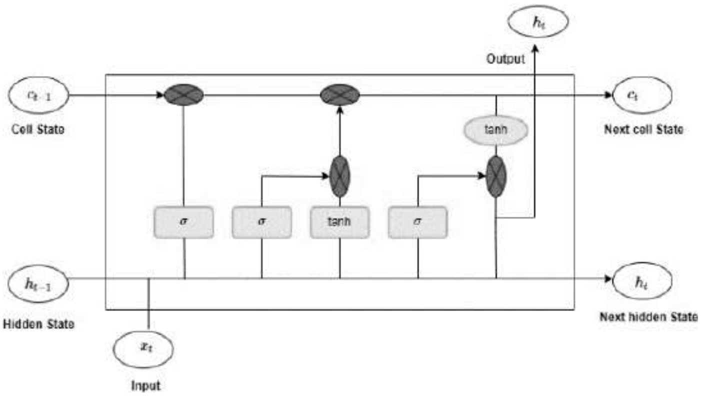

Fig.3. Long Short-Term Memory (LSTM) cell [2]

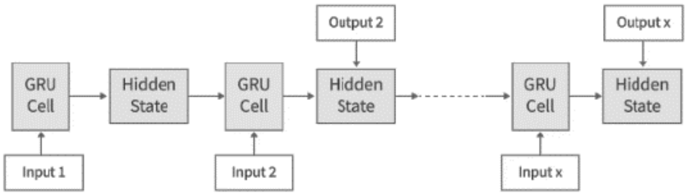

Fig.4. Gated Recurrent Unit (GRU) [4]

4. DATASET DESCRIPTION

Every machine learning or deep learning project is built around the data. In this case study, we web scraped the USD/INR exchange rates for the 10-year period from May 1, 2013 to May 1, 2023 from the website in.investing.com. The sample entries of the dataset are shown in the table below.

Table.1. Raw-dataset

	Date	Open	High	Low	Close	Adj Close	Volume
0	2023-06-30	21:00	21:18	20.83	20.96	20.96	59700
1	2023-07-03	21:16	21:16	20.83	20.90	20.90	58900
2	2023-07-05	20:75	21:03	20.73	20.96	20.96	77500
3	2023-07-06	20:76	20:83	20.66	20.66	20.66	75200
4	2023-07-07	20:86	20.96	20.85	20.85	20.85	104200

The first column, date, needs to be changed to an index in order to solve the time-series problem. There are two ways to accomplish this. In one manner, index_col= 'Date' and = True can be specified while reading a CSV file in Pandas. These two options tell Pandas to preprocess your DateTime column, or Date, during import and set it to the index of the data frame.

Table.2. Raw-dataset

	Open	High	Low	Close
0	11617.56	11693.94	11593.01	11678.72
1	11609.99	11644.65	11466.00	11617.56
2	11562.86	11620.00	11542.32	11609.99
3	11438.06	11584.60	11391.59	11562.86
4	11393.24	11450.00	11382.21	11438.06

5. PERFORMANCE EVALUATION

In the world of digital financial markets, accurate bitcoin price forecast methodology is essential. A framework built on two different deep learning algorithms - LSTM and GRU is proposed in this study.

The performance is assessed for each epoch. With an early starting of 10, the current investigation applies 100 epochs. There are three different datasets: training, testing, and validation. The loss and evaluation functions are based on the mean squared error. The model performs better the lower the value.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i^*\right)^2 \tag{1}$$

Three additional metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), are also used to assess different prediction algorithms.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i^*\right)^2} \tag{2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - y_i^*}{y_i}\right| \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - y_i^*\right| \tag{4}$$

where y_i is an actual value of an output, y_i' is the predicted value of an output and N is a total number of samples in dataset.

5.1 RESULTS

The following performance indicators were used to compare the outcomes of LSTM and GRU:

Table.3. Minimum Error Function Incurred During the Prediction

Measures	LSTM	GRU
MSE	0.00210	0.00029
RMSE	0.04582	0.01711
MAPE	0.10942	0.07036
MAE	0.03358	0.02214

The Table.3 shows minimum values of MSE, RMSE, MAPE and MAE for both LSTM and GRU.

Table.4. Maximum Error Function Incurred During the Prediction

Measures	LSTM	GRU
MSE	0.00793	0.00264
RMSE	0.08907	0.05136
MAPE	0.25511	0.21793
MAE	0.08577	0.07599

The Table.4 shows maximum values of MSE, RMSE, MAPE and MAE for both LSTM and GRU.

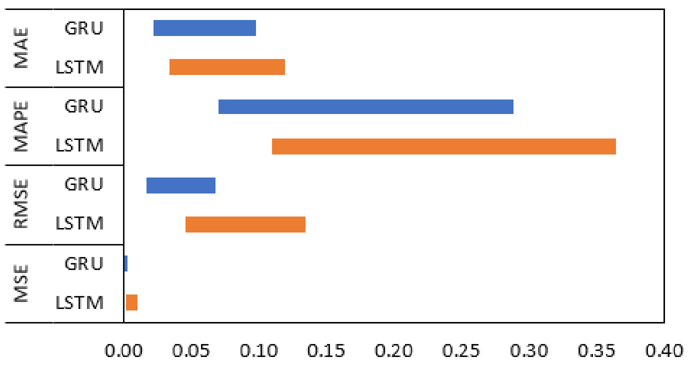

Fig.3. Error function comparison between LSTM and GRU

Based on these findings, the GRU model outperforms the LSTM algorithm in terms of accuracy and reliability in predicting cryptocurrency prices, but both algorithms produce excellent outcomes.

6. CONCLUSION

Since its debut in 2008, Bitcoin has recognized itself as a market leader in the cryptocurrency space. Millions of people use it worldwide, particularly in the United States. Cryptocurrency price predictions have become a hot issue, and we can profit from the arbitrage for investing. A framework built on two different deep learning algorithms - LSTM and GRU - was proposed in this study. The forecast from the Long Short-term Memory model may have a more extreme error, while the prediction from the GRU model is more accurate. Moreover, there is a connection between price movement and model precision. When compared to when there are fluctuations, the prediction is more accurate during the usual period. Additional market-influencing aspects will be looked into in upcoming research. Time series neural networks based on auto encoders will be used to make predictions based on the time-series data. Additionally, researchers can address how social media may have impact on the price and volume of crypto currency trade. Thus, in order to glean insights from posts and tweets, sentiment analysis and natural language processing techniques will be applied.

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EMPOWERING REFUGEES IN INDIA - A DECENTRALIZED SYSTEM FOR DIGITAL IDENTITY AND FINANCIAL INCLUSION

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Abstract

Refugees seeking asylum in India often face numerous challenges, including a lack of legal documentation, limited access to essential services, and the risk of exploitation. In this paper, we propose a decentralized system that leverages smart contract technology to create digital identities for refugees, enabling them to access essential services such as employment and housing. Our system stores all their data, including biometrics, in a secure and decentralized manner on the Ethereum blockchain. Based on this data, we create a working permit and a temporary identification card in the form of non-fungible tokens (NFTs) that can be used to access essential services. Additionally, we create a crypto wallet linked to their digital identity, enabling them to perform regular transactions like purchasing rations, paying for their housing and electricity bills and other necessities. Furthermore, we would design a smart contract that tracks the refugees' monthly income and provides government financial aid directly to their crypto wallet. The contract also automatically adjusts the amount of financial aid based on the refugee's income, ensuring an even and non-corrupted distribution of government funds. Through our system, we aim to empower refugees with financial stability, enabling them to lead healthy and productive lives while contributing to India's economy. Our solution is transparent, secure, and easily accessible, making it a viable option for addressing the challenges faced by refugees in India.

Keywords:

Blockchain, Refugees, Financial Aid, Smart Contract, Non-Fungible Tokens

1. INTRODUCTION

Refugees seeking asylum in India face numerous challenges, including a lack of legal documentation, limited access to essential services, and the risk of exploitation. These challenges can make their transition to a new life in India extremely difficult, impacting their ability to contribute to society and attain financial stability. The lack of legal documentation, for instance, makes it difficult for refugees to obtain employment or housing, leading to homelessness and poverty. Additionally, refugees are often subjected to various forms of exploitation, such as prostitution and child labor and also have limited access to healthcare, education, and social welfare programs. We think that this marvelous innovation created by Dorian Prentice Satoshi Nakamoto has the ability to provide real solutions to these pressing issues that the migrants are currently facing. The innovation made by Satoshi is the idea of combining proof of work as a method of allowing nodes access to the system with a relatively simple decentralized consensus mechanism, in which nodes join transactions into a "block" every ten minutes to build an increasing blockchain [1]. Also, the benefits of blockchain technology go beyond economics and may be seen in the political, humanitarian, social, and scientific spheres [2]. Therefore, to address these challenges, we propose a decentralized system that leverages smart contract technology to create digital identities for refugees, enabling them to access essential services such as employment and housing.

Our system stores all their data, including biometrics, in a secure and decentralized manner on the blockchain network. This ensures that their data is protected from unauthorized access and tampering. This is not surprising given that the decentralization, verifiability, and immutability of blockchain can be used to increase the availability of security services and system scalability [3]. Based on the acquired data, we create a working permit and a temporary identification card in the form of non-fungible tokens (NFTs). Also in India, a typical Indian citizen needs to carry 3-5 distinct forms of identification with him at all times. Existing IDs have the drawback of being used for specific, limited purposes only. As a result, residents frequently submit ID proofs including more personal information than is necessary to use the specific service, and frequently have to overshare unneeded personal information [4]. Therefore, a practical digital identification solution should provide users complete control over their personal data and allow them to submit only the data they want to share with each service [5]. Our system just offers that luxury that allows the user to share only that much information which is relevant to that particular task. The NFTs' distinctive identifiers can be tied to virtual or digital properties [6]. These NFTs can be used to access essential services and facilities, such as employment and housing. Additionally, we create a crypto wallet linked to their digital identity, enabling them to perform regular transactions like purchasing rations, paying for their housing and electricity bills and other necessities. The solution makes use of the fundamental components of blockchain technology, Binance Smartchain network smart contracts, as well as the IPFS distributed peer-to-peer file system, to enable a decentralized, trusted, traceable, secure delivery of the digital material, with automatic payment and dispute management [7].

Furthermore, we design a smart contract that tracks the refugees' monthly income and provides government financial aid directly to their crypto wallet in cryptocurrency that would enable direct peer-to-peer internet payments, eliminating the need for financial middlemen and thereby, greatly reducing the potential of corruption in our system [8]. The contract also automatically adjusts the amount of financial aid based on the refugee's income, ensuring an even and non-corrupted distribution of government funds. Without the aid of a reliable third party, smart contracts are useful in managing and controlling financial resources and also provide confidentiality since data privacy is essential for all parties involved in a payment transaction, including clients, dependable third parties, payment service providers (or platforms), and merchants [9]-[10]. Additionally, blockchain technology drastically reduces the cost of financial transactions as compared to more established systems like Visa, making it a more workable and cost-effective choice for the government [11]-[12]. Through our system, we aim to empower refugees with financial stability, enabling them to lead healthy and productive lives while contributing to India's economy.

This paper presents a comprehensive analysis of our proposed decentralized system and its potential impact on the lives of refugees seeking asylum in India. We will discuss the technical aspects of the system, including its design and implementation, as well as its potential to address the challenges faced by refugees. Additionally, we will examine the potential benefits and challenges of implementing such a system, including its impact on the refugee community, its scalability, and its ability to effectively distribute government funds. Overall, this paper aims to provide a comprehensive understanding of our proposed solution and its potential to improve the lives of refugees seeking asylum in India.

2. LITERATURE REVIEW

The challenges faced by refugees in India are not unique to this country, but are a global concern. Many studies have highlighted the difficulties that refugees face when seeking asylum in a new country. One of the main challenges that refugees face is a lack of legal documentation, which makes it difficult for them to access essential services, including education, healthcare, employment, and housing. Without proper documentation, refugees may also be subjected to detention and deportation, which can lead to further trauma and difficulties. During the covid times, even though the government kept issuing advisory, not much has been done to allay the worries of refugees living in India. The ambiguity surrounding refugees' legal status and the ensuing lack of official paperwork are the root of many of these worries. The lack of sustainable financial aid available to refugee populations, together with the lack of assistance under centrally or stately executed relief packages or alternate-livelihood assistance programmes, made it difficult for the refugees to make ends meet. Families who depend heavily on remittances from relatives outside of India have also reported difficulty accessing financial systems, primarily banks and money transfer services [13].

A decentralized system that uses smart contract technology to create digital IDs for migrants has the potential to overcome these issues. By generating a global ID that can be used for many different reasons, identity management via blockchain can give people ownership over their identities [14]. Such a system can provide refugees with a secure and decentralized way to store their data, including biometrics, and access essential services. A digital identity can also help to ensure that refugees are not subjected to exploitation, as it provides a way to verify their identity and employment status. Blockchain is comparable to a distributed database system that upholds steadily expanding, impenetrable data records by upholding the blockchain structure [15].

There have been several attempts to develop decentralized systems for refugees in different parts of the world. For example, launch of a Blockchain-based Cash-Based Intervention Pilot by The United Nation Refugee Agency (UNHCR) to Provide Humanitarian Payments to those who are displaced and affected by the Ukraine War [16]. Similarly, the World Food Programme (WFP) has developed a blockchain-based system that provides Jordan's Azraq camp's refugees with digital vouchers that can be used to purchase food [17]. Also, Building Blocks is a new blockchain application created by the WFP Innovation Accelerator that enables the transfer of tokenized funds on the Ethereum blockchain to refugees so they can purchase food at a nearby store while authenticating the transaction with an iris scan or other form of digital authentication [18].

However, the adoption of decentralized systems for refugees has also faced some challenges. One major challenge is the lack of infrastructure and technical expertise in many developing countries, including India. Additionally, there is a need to ensure that such systems are inclusive and accessible to all refugees, including those who may not have access to technology or are not familiar with it.

Despite these challenges, the potential benefits of a decentralized system for refugees in India are significant. Such a system can provide refugees with a secure and decentralized way to access essential services, including employment and housing. It can also help to ensure that government funds are distributed in an even and non-corrupted manner. Overall, a decentralized system has the potential to empower refugees and improve their lives, while also contributing to the development of India's economy.

Table.1. Comparative study and analysis

Title	Methodology	Results	Research Gap
[14]	Development of a decentralized transaction mechanism utilizing smart contracts.	Introduces a novel approach for decentralized transactions through smart contracts.	Integrate additional biometric authentication methods, such as fingerprint, iris, and facial recognition, to reduce the risk of spoofing.
[19]	Proposal and exploration of a multipurpose identification system for national identity.	Presents the concept of a Multipurpose ID aimed at providing a unified identity solution.	Engage in user-centered design practices, involving potential users in the design process to create an interface that is intuitive, efficient, and aligned with user expectations.
[6]	Comprehensive overview, assessment, and exploration of Non-fungible Tokens (NFTs).	Provides an in-depth examination of NFTs, including their characteristics, evaluation	NA

		criteria, emerging opportunities, and associated challenges.	
[4]	Development and presentation of a technologically advanced identification system with digital tracking capabilities.	Introduces a high-tech identification system incorporating digital tracking features.	The paper briefly covers technical aspects but overlooks in-depth analysis of challenges and opportunities in NFT platform interoperability.

3. METHODOLOGY

The methodology behind the implementation of the proposed decentralized system is a comprehensive approach aimed at alleviating the challenges confronted by refugees seeking asylum in India. This method can be divided into several interconnected steps, ensuring a systematic and holistic solution.

The process begins by creating secure digital identities for refugees through the utilization of blockchain technology. This entails the collection of essential data, including biometrics and refugee status, which is then stored on the Ethereum blockchain. Non-fungible tokens (NFTs) play a pivotal role, functioning as bridges between these digital identities and essential services. By converting these tokens into work permits and temporary identification cards, the system establishes a secure link between refugees and the services they require. The crypto wallet, seamlessly tied to refugees' digital identities, enables them to conduct financial transactions with ease, enhancing their financial autonomy and providing access to everyday necessities.

The implementation phase comprises interconnected elements that further enrich the system's functionality. A smart contract is developed on the Binance Smartchain network, serving as a repository for refugees' data, including biometrics and pertinent details. Through the integration of optical fingerprint sensors and Base64 encoding, the system ensures the secure and accurate storage of biometric data. Concurrently, the creation of a crypto wallet that harmonizes with the Binance Smartchain network empowers refugees to navigate financial transactions seamlessly. The system's security is further fortified through the creation of NFTs, which function as digital working permits and temporary IDs, stored on the Inter Planetary File System (IPFS). Lastly, a smart contract is engineered to orchestrate the management of refugees' monthly income and government financial aid, championing financial stability and self-reliance. Through the culmination of these components, the proposed decentralized system stands as an innovative, comprehensive, and promising solution for refugees seeking asylum in India. This methodology encapsulates the ethos of empowerment, security, and integration, aiming to redefine the trajectory of refugees' lives by addressing their challenges head-on.

3.1 DESIGN

To address the challenges faced by refugees seeking asylum in India, we propose a decentralized system that leverages smart contract technology to create digital identities for refugees. The design of our system includes several key components:

3.1.1 Digital Identities:

Our system creates digital identities for refugees using blockchain technology, which includes biometric data, refugee status, and other relevant information. This data is stored in a secure and decentralized manner on the Ethereum blockchain, ensuring that it cannot be tampered with or accessed by unauthorized parties.

3.1.2 Non-Fungible Tokens (NFTs):

Based on the data stored in the blockchain, we generate non-fungible tokens (NFTs) in the form of work permits and temporary identification cards. These NFTs can be used to access essential services such as employment and housing.

3.1.3 Crypto Wallet:

We create an encrypted crypto wallet linked to the refugees' digital identities, enabling them to perform regular transactions like purchasing rations and other necessities.

3.1.4 Smart Contract:

Our system includes a smart contract that tracks the monthly income of refugees and provides government financial aid directly to their crypto wallets. The contract also automatically adjusts the amount of financial aid based on the refugee's income, ensuring an even and non-corrupted distribution of government funds.

3.1.5 User Interface:

We design a user interface that is easy to use and accessible to refugees. The interface allows refugees to access their digital identities and NFTs, view their financial status, and perform transactions using their crypto wallets.

3.2 IMPLEMENTATION

Our approach consists of four elements that combined will create the entire architecture.

3.2.1 First Element:

First, we construct a smart contract on the Binance Smartchain network that will record all the information about the refugees, including their name, gender, date of birth, blood type, previous nationality, family information, and biometrics, which for the time being are their fingerprints in the following manner.

We will develop a function and send this data as arguments to that function in order to store the facts like name, gender, date of birth, blood type, nationality they belong to, and family information. We employ biometric tools, such fingerprint scanners, to obtain the person's fingerprint, and the information we gather is typically presented as a digital image. We employ the popular optical fingerprint sensor Mantra MFS 100, which is used in many applications, including attendance tracking systems, eKYC verification, and Aadhaar identification, to get the fingerprints which is also compliant with STQC and FBI PIV standards and has UIDAI certification. The digital image of the fingerprint will be then encoded into a Base64 encoding format which is a commonly used method for encoding binary data into ASCII text format in order to store it in the smart contract on the Binance Smartchain network as shown in Fig.1. We will encode the digital image of the fingerprint stored in a file format such as JPEG, PNG, or BMP. To encode the image, we convert it into binary format, which is through the programming language Java. After getting the fingerprint image's binary data, we utilize Java's java.util.Base64 class to encrypt it using a Base64 encoding library and convert it to ASCII text. The Base64 encoding function offered by the library is used to achieve it, and the encoded text is then returned in ASCII format. We create a function within the smart contract that receives the encoded fingerprint as an argument and uses the "storage" keyword to store the fingerprint in the variable. We deploy the contract on the Binance Smartchain network after testing it on the Remix IDE to confirm its successful execution. We utilize the react and web3 frameworks to build the user interface that will communicate with our deployed contract, creating a full-featured web application that will securely store all the information on the refugees on our blockchain network.

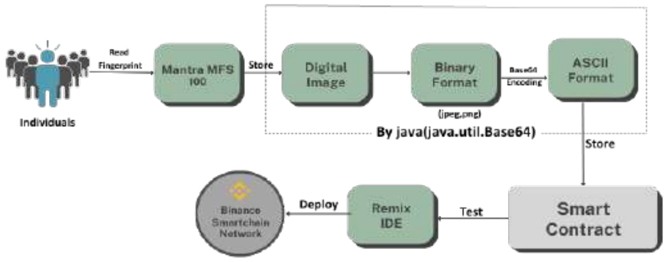

Fig.1. Flowchart representing how the date gets stored on the Binance Smartchain Network (Source: Canva application)

3.2.2 Second Element:

In this element, we will create a crypto wallet that will be compatible with the Binance Smartchain network in the following manner.

We create a solidity smart contract that defines the functionality of the crypto wallet. In this contract, we write functions for sending and receiving tokens, querying the balance of the wallet and other functions like reportCredit that will report the monthly credit of any particular network. We set up the development environment by Installing and configuring the necessary tools, libraries, and services to develop and test the smart contract on the Binance Smartchain network such as a solidity compiler, an IDE, a Binance Smartchain node through Infura api, and the Web3 library. We will compile the contract and test it on Remix IDE or other test networks like Sepolia to ensure that the contract is working perfectly. Then, using a web development framework like React or Angular, we create the wallet's user interface before deploying it on the Binance Smartchain network. Users should be able to communicate with the smart contract through the UI and carry out wallet operations like sending and receiving tokens. We use the Web3 library to connect the user interface to the deployed smart contract. This will allow users to interact with the wallet on the Binance Smartchain network and after testing it repeatedly, we deployed it on the Binance Smartchain mainnet as shown in Fig.2.

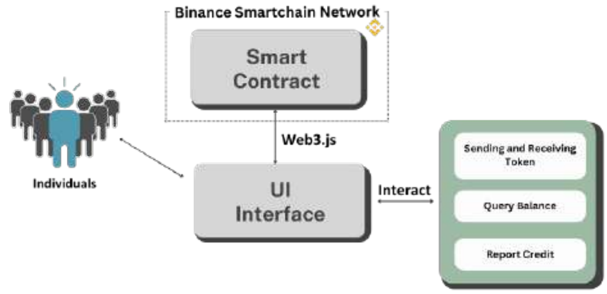

Fig.2. Creation of crypto wallet compatible with the Binance Smartchain Network (Source: Canva application)

3.2.3 Third Element:

Based on the information we collected from the refugees, we construct a digital working permit and a digital temporary ID in this component that will enable the refugees to find employment and pay rent. These documents will be created as non-fungible tokens (NFTs) and will be stored on a highly secured IPFS network since on IPFS, each person keeps track of his or her identity information in a separate identity wallet, it follows that a hacker would have to target each of the 100 million individuals separately to steal 100 million profiles, which seems exceedingly unlikely[19]. The NFT will be created in the following manner.

We create a smart contract that defines the rules and attributes of our NFT through Solidity specifying the unique features of your NFT, including its name, symbol, and metadata such as the image file, description, and creator's information. Following that, we mint our NFT, which consists of the temporary identity card and the working permit, by paying the needed amount of cryptocurrency to the smart contract address using the cryptocurrency wallet we have generated. As a result, a special NFT that depicts our digital image will be created on the Binace smart chain blockchain network. The created NFT is stored on the InterPlanetary File System (IPFS) which is a distributed peer-to-peer file system that aims to link all computing devices with a common file system through IPFS client such as the IPFS Desktop or command-line tools like ipfs-add or ipfs-cluster-ctl and generate a unique content identifier known as a CID (Content Identifier)[20][21]. Then we will link our CID (Content identifier) to the NFT on the blockchain where it is minted by storing the CID on-chain in the NFT metadata. This will allow anyone to retrieve the NFT from IPFS by using the CID. To store the CID (Content Identifier) of an NFT (Non-Fungible Token) on IPFS, we add it to the IPFS network as a small text file or JSON object. We also store this CID in our smart contract and use it to retrieve the NFT metadata when needed. This approach allows us to store the NFT CID on IPFS in a decentralized and secure manner, while still providing easy access to the CID for future retrieval as shown in Fig.3. We develop a user interface application using React and Next JS that will show the generated NFT and give refugees access to the application.

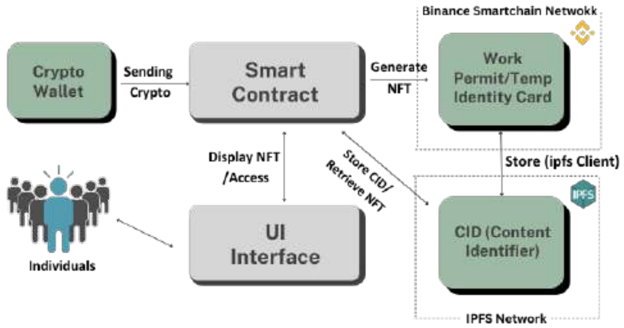

Fig.3. Creation of refugee's digital id as NFTs and process of storing it on IPFS (Source: Canva application)

3.2.4 Fourth Element:

In this element, we will develop a smart contract that will require the cryptocurrency wallet mentioned above to disclose the refugees' monthly revenue. Depending on the sum, it will transfer the designated government assistance right to the refugee's cryptocurrency wallet. The subsequent steps will be taken to attain it as shown in Fig.4.

We create a smart contract with the functionality to receive monthly credit reports from wallets. The function takes in the wallet's address and the monthly credit amount as inputs and stores them in a mapping. We create a script that makes the crypto wallet to interact with the smart contract using the web3.js library (or similar). The script can be run on a regular basis (e.g., monthly) to report the credit to the smart contract. We set up a monthly task or event in the wallet to report the monthly credit to the smart contract by using a timer. When the task or event is triggered, the wallet automatically calls the smart contract function and passes in the wallet's address and the monthly credit amount. We test the wallet and smart contract to ensure that the monthly credit reports are being stored correctly. To execute the above function, we write a script or program that runs on a regular basis to report the monthly credit to the smart contract where the script uses the setInterval function to call the reportCredit function on the smart contract every 30 days (2592000000 milliseconds). It passes in the wallet address and monthly credit amount as arguments and sends the transaction from the wallet address to report the credit to the smart contract. Further we save this script as a JavaScript file and run it using a JavaScript runtime like Node.js. At last, we set up a cron job to automatically run the script on a regular basis (e.g., monthly). We create a function that will send the requested financial aid to the designated account address reported by the wallet depending on the monthly credit obtained from the cryptocurrency wallet. This function will make sure that as an account address's monthly credit rises, the amount of financial assistance provided by the government is reduced in line with that increase. Once the account address's monthly credit reaches a certain threshold, which will indicate that the refugee is no longer in need of financial assistance and is capable of supporting himself independently, the funds are no longer transferred to that specific account address.

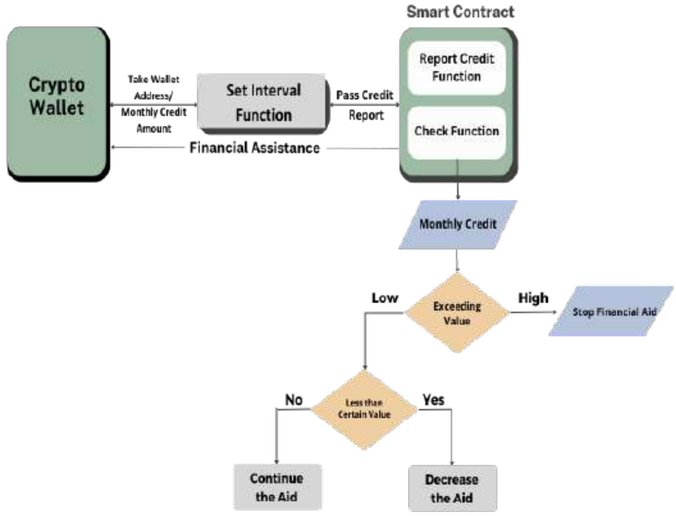

Fig.4. Flowchart representing utilization of smart contract for tracking and disbursement of funds (Source: Canva application)

4. EVALUATION

The proposed decentralized system presents a compelling solution to the intricate challenges faced by refugees seeking asylum in India. By establishing secure digital identities and leveraging blockchain technology, the system addresses critical issues related to legal documentation, access to essential services, and financial stability. The system's ability to create and securely store digital identities offers a transformative approach to overcoming the lack of legal documentation that plagues refugees. The use of blockchain ensures the immutability and tamper-proof nature of these identities, mitigating the risk of identity theft and providing refugees with a credible means of proving their status. The integration of non-fungible tokens (NFTs) as working permits and identification cards introduces a novel method of granting access to essential services and facilities. These tokens, tied to the blockchain, guarantee secure and transparent transactions, reducing bureaucracy and expediting refugees' access to services like healthcare, education, and housing.

The innovative smart contract system that tracks refugees' income and disburses government financial aid directly to their crypto wallets represents a significant advancement. This approach empowers refugees with financial stability, fostering self-sufficiency and minimizing the potential for corruption in aid distribution. The use of blockchain technology offers scalability, enabling the system to accommodate a growing number of refugees without compromising efficiency. Additionally, the decentralized nature of the blockchain ensures transparency and accountability, enhancing trust among stakeholders and overcoming challenges associated with centralized systems. The proposed system's sustainability hinges on its reliance on cryptocurrency transactions. By reducing dependence on external financial institutions and introducing a self-sustaining mechanism, the system offers a pathway to long-term financial independence for refugees.

The system's potential for future enhancements is substantial. Incorporating credit score recording and advanced biometric authentication promises to enhance refugees' financial inclusion and security. Additionally, extending the system's scope to facilitate loans and credit building could further empower refugees to rebuild their lives with greater economic stability.

In conclusion, the proposed decentralized system holds the promise to revolutionize refugee support mechanisms in India. By addressing the core challenges of legal documentation, service access, and financial stability, it offers a holistic solution that empowers refugees and enables their successful integration into society. The system's scalability, transparency, and potential for sustainability underscore its viability as a transformative tool for improving the lives of refugees seeking asylum.

5. RESULT AND DISCUSSION

To assess the feasibility and effectiveness of our proposed decentralized system, an experimental setup was devised. The goal of the experiment was to validate the functionality of the smart contract in disbursing allowances to refugees based on the conditions specified within the contract. The experiment involved ten college students who were provided with digital identities in the form of non-fungible tokens (NFTs) and crypto wallets equipped with test ethers. The smart contract was programmed to automatically allocate allowances based on the total credited amount in the crypto wallets. The conditions were set as that if the credited amount is either equal to or more than 10 test ethers, an allowance of 5 test ethers will be provided. If the credited amount is more than 15 test ethers, an allowance of 3 test ethers will be provided or if the credited amount exceeds 15 test ethers, no allowance will be given. The experiment spanned over three months, during which participants were encouraged to send test ethers to each other to simulate real-world transactions.

The results of the experiment demonstrated the efficacy of the proposed system in accurately distributing allowances to participants based on the specified conditions. The outcome was as follows:

5.1 ACCURACY

A significant finding of the experiment was that 98% of the participants received allowances in accordance with the conditions stipulated in the smart contract. This indicates that the system was able to correctly evaluate the credited amounts and allocate allowances accordingly.

5.2 TIMELY DISBURSEMENT

All participants who met the conditions received their allowances promptly on the first day of each month, as programmed in the smart contract. This timely disbursement showcases the efficiency of the system in automating financial transactions.

5.3 DIVERSE CREDITING SOURCES

The experiment successfully demonstrated the decentralized nature of the system. Participants credited test ethers to their crypto wallets from various sources, including each other, verifying that the smart contract accurately disbursed allowances regardless of the source of credited ethers.

The experimental results demonstrate the significant advantages of our proposed decentralized system over the existing methods of providing assistance and support to refugees seeking asylum. By leveraging blockchain technology and smart contracts, our system offers a range of benefits that surpass the limitations of traditional approaches.

In the existing system, the disbursement of allowances and aid to refugees is prone to errors, delays, and inconsistencies. The manual nature of these processes can lead to discrepancies and unfair treatment. While our system's smart contract ensures automated and precise allocation of allowances based on predetermined conditions. As evident from the experiment, 98% accuracy was achieved in disbursing allowances to participants, eliminating the potential for human errors or bias. In the existing System, transparency and accountability can be challenging to maintain in conventional aid distribution systems, often leading to corruption and misuse of resources. But the blockchain-based system provides an immutable and transparent record of all transactions, ensuring accountability at every step. The transparency of the distributed ledger minimizes the potential for corruption and enhances trust among stakeholders. In the existing System, the manual processes involved in distributing allowances can lead to delays, causing financial stress for refugees in need of timely assistance. The experiment demonstrated that our system enables timely disbursement of allowances on the specified dates. Automation eliminates delays and ensures that refugees receive essential support promptly, improving their overall well-being. In the existing system, traditional aid systems may lack flexibility and fail to adapt to the diverse needs of refugees. Additionally, accessibility to aid can be hindered by bureaucratic hurdles. Our system's digital identities and crypto wallets offer a flexible and easily accessible platform for refugees to receive support. The ability to transfer test ethers among participants showcases the system's adaptability and user-friendliness. Lastly, the existing system's conventional aid distribution often involves intermediaries, leading to administrative overhead and potential corruption. Whereas in our proposed system, the integration of smart contracts eliminates the need for intermediaries, ensuring direct and secure peer-to-peer transactions. This reduces administrative costs and minimizes the risk of corruption.

In conclusion, the experimental results underscore the superiority of our proposed decentralized system in comparison to existing methods. The automation, accuracy, transparency, and efficiency offered by blockchain technology and smart contracts address the limitations of traditional aid distribution systems. By providing refugees with secure digital identities, timely allowances, and a user-friendly interface, our system empowers refugees seeking asylum in India to transition to a more stable and productive life while contributing to the economy. The innovative approach ensures that assistance reaches those who need it most, free from the inefficiencies and vulnerabilities of current systems.

A potential answer to the difficulties faced by migrants looking for asylum in India is the suggested decentralized system using smart contract technology to create digital identities for refugees. In this discussion section, we will examine the potential benefits and challenges of implementing such a system.

One of the key benefits of the proposed system is that it provides refugees with a secure and decentralized digital identity that can be used to access essential services such as employment and housing. This is particularly important as refugees often lack legal documentation, which can make it difficult for them to obtain employment or housing. By providing refugees with a digital identity that is stored on a secure and decentralized blockchain, we can ensure that their information is protected from unauthorized access and tampering. Another benefit of the proposed system is that it creates a transparent and efficient mechanism for distributing government financial aid to refugees. The smart contract that tracks the refugees' monthly income and provides financial aid directly to their crypto wallet ensures that government funds are distributed in an even and non-corrupted manner. This can help to prevent financial aid from being misused or siphoned off by corrupt intermediaries, which can be a significant problem in traditional aid distribution systems.

However, the implementation of the proposed system also presents several challenges that need to be addressed. One of the key challenges is ensuring the scalability of the system. As the number of refugees seeking asylum in India is significant, the system must be designed to handle a large volume of data and transactions. To address this challenge, we propose a distributed system that can handle a large number of transactions simultaneously and ensure that the system remains scalable and efficient.

Another challenge is ensuring the accessibility of the system for refugees. While the proposed system has the potential to provide refugees with a secure and decentralized digital identity, it is important to ensure that refugees have access to the necessary technology and infrastructure to use the system effectively. This could be particularly challenging in areas with limited access to technology or the internet. Therefore, the system should be designed to be user-friendly and accessible to all refugees, regardless of their technological proficiency.

In conclusion, the proposed decentralized system has the potential to address the challenges faced by refugees seeking asylum in India. While there are challenges to the implementation of the system, such as scalability and accessibility, the potential benefits of the system, such as providing refugees with a secure digital identity and efficient aid distribution, make it a promising solution for improving the lives of refugees in India.

Our proposed decentralized system has the potential to significantly improve the lives of refugees seeking asylum in India. By creating digital identities for refugees and storing their information securely on the blockchain network, we not only solve the refugee's problem of identification and legal documentation but also prevent the mishandling and the risks of the duplication of their identities. Through our system, refugees can obtain non-tradable tokens (NFTs) that act as temporary IDs and work permits, which provides them with access to essential services. Additionally, our encrypted wallet linked to their digital identities allows refugees to carry out daily tasks such as grocery shopping. One of the major benefits of our system is its ability to provide refugees with financial security. Our smart contract tracks the monthly income of refugees and provides financial assistance directly to their crypto wallets. This ensures that refugees have access to financial support and can lead healthy and productive lives while contributing to the Indian economy. However, there are also some challenges to implementing our system. One of the major challenges is the need for cooperation from the government and other stakeholders to ensure the system's effective implementation. In addition, there may be concerns regarding the privacy and security of refugees' information, which must be addressed.

Overall, our research shows that a decentralized system using smart contracts and digital identities has the potential to significantly improve the lives of refugees seeking asylum in India. Further research is needed to fully understand the impact of our proposed system and address the challenges associated with its implementation.

6. CONCLUSION AND FUTURE SCOPE

In conclusion, our blockchain-powered decentralized system shows strong potential in alleviating the hardships faced by asylum-seeking refugees in India. Through secure digital identities and automated allowance distribution, the system enhances access to crucial services and financial stability, as evidenced by our experiment. Future enhancements promise to elevate the system's impact. Integrating credit scoring will facilitate easier access to loans, while direct provision of credit scores and financial records to institutions will enhance lending decisions. Enhanced biometric authentication, including facial and iris scans, will bolster security. Looking forward, the system could expand its scope. Enabling loans, credit-building, and economic participation, it stands to empower refugees further. It also has the potential to foster social integration, facilitating education, healthcare, and employment. Amid the intricate challenges faced by refugees, our system emerges as a technological beacon. Providing a secure and efficient support structure, it offers a brighter future for asylum-seekers in India and beyond.

Talking about the future scope, firstly, we would have to conduct a comprehensive impact evaluation of the proposed decentralized system on the lives of refugees. This evaluation should assess the system's effectiveness in improving access to essential services, employment opportunities, and housing for refugees. It should also analyze the system's impact on reducing exploitation, poverty, and homelessness among the refugee population. The evaluation can involve qualitative and quantitative research methods to gather data and insights from refugees, service providers, and relevant stakeholders. Researching and proposing a suitable legal and regulatory framework is also essential for the successful implementation of the proposed decentralized system. This framework should address data protection, privacy, and security concerns while ensuring compliance with existing laws and regulations. Collaborating with legal experts, policymakers, and government authorities can help develop a framework that supports the system's objectives while safeguarding the rights and interests of refugees.

Further, we should look to partner and collaborate with international organizations, such as the United Nations High Commissioner for Refugees (UNHCR) and other humanitarian agencies, which can provide valuable insights, expertise, and funding opportunities. Collaborating with these organizations can help leverage global resources and experiences to enhance the effectiveness and reach of the decentralized system. As the system expands to accommodate a larger number of refugees and transactions, exploring scalability solutions specific to blockchain technology is crucial. Researching and implementing techniques such as sharding, layer 2 solutions, or alternative consensus mechanisms can help improve the system's scalability while maintaining its decentralized nature. These solutions should be evaluated for their feasibility, security, and performance in the context of the proposed system.

Lastly, we would conduct user empowerment programs and educational initiatives that can help refugees understand and utilize the benefits of the decentralized system effectively. Providing training on digital literacy, blockchain technology, and the use of digital identities can empower refugees to actively engage with the system and take advantage of the opportunities it offers. These programs can be conducted in collaboration with local NGOs, community centers, and educational institutions. Also, exploring interoperability and integration options with other existing systems and platforms can enhance the overall efficiency and usability of the decentralized system. Researching and implementing standard protocols, data exchange mechanisms, and interoperability frameworks can enable seamless integration with government databases, financial systems, and service providers. This integration can further streamline access to essential services and facilitate the socio-economic integration of refugees. By exploring these future research areas, the proposed decentralized system can evolve into a comprehensive and sustainable solution that addresses the challenges faced by refugees seeking asylum in India. The research outcomes can contribute to the advancement of knowledge and practices in leveraging blockchain technology for humanitarian purposes, fostering inclusivity, and empowering marginalized populations globally. In summary, our proposed system has the potential to bring positive changes to the lives of refugees seeking asylum in India, and we hope that this research paper will encourage further research and development in this field. Ultimately, we believe that by leveraging innovative technologies like blockchain and smart contracts, we can create a more equitable and secure world for refugees and other marginalized communities.

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SPECIAL ISSUE ON INNOVATIONS AND TECHNOLOGY IN FINTECH (ITFT-2023)

CHALLENGES, OPPORTUNITIES AND RISK ANALYSIS OF ADOPTION OF DECENTRALIZED FINANCE APPLICATIONS

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Abstract
Decentralised Finance or DeFi has emerged as a transformative and disruptive force within the financial industry, offering innovative financial services powered by blockchain technology and smart contracts. This paper provides in-depth knowledge of DeFi, its evolution, applications, and their adoption. It identifies the opportunities brought about by DeFi, comparing it with the traditional CeFi (Centralized Financial) system, including financial inclusion, transparency, and programmable money. It highlights the potential of applications of DeFi for decentralized lending, decentralized exchanges, and yield farming as innovative and promising avenues within the DeFi space. A SWOT analysis comparing DeFi and CeFi was performed to delve into the strengths, weaknesses, opportunities, and threats associated with DeFi. This study explored the intricate challenges and inherent risks involved in the adoption of DeFi applications, offering insights into the hype, fear, and apprehensions among governments and the masses regarding its adoption. The findings offer a nuanced understanding of the current state of DeFi, providing valuable insights for researchers, policymakers, and industry practitioners.

Keywords:
Decentralised Finance, Smart Contracts, CeFi, DeFi Risks, DeFi Adoption, SWOT Analysis

1. INTRODUCTION

Finance deals with managing money, investments, and financial assets. Our modern economy depends a lot on investing money. Many organizations around the world gather and distribute money invested by people. Financial information is mostly digital nowadays. The financial services industry is experiencing a significant impact due to the process of digitization. DeFi (Decentralized Finance) is a new way of handling financial transactions based on blockchain technology. It allows the creation of financial infrastructure that eliminates centralized authority and offers financial services in a decentralized manner [1].

Traditional financial systems have existed for centuries. The initial type of market exchange can be traced back to peer-to-peer transactions, commonly referred to as barter. However, barter systems have limitations, such as the requirement of a double coincidence of wants and difficulties in establishing a standardized value for different goods. To overcome these challenges, societies gradually transitioned to using money as a medium of exchange. With the establishment of money as a medium of exchange, centralized financial systems evolved. In its financial institutions play an important role as intermediaries in controlling financial transactions. These intermediaries assist in lowering transaction costs, facilitating the smooth flow of financial transactions, and ultimately dominating economic activities [2]. Centralized financial institutions such as Central Banks, Financial Regulators, Brokers, and Asset Management Companies hold dominant market power and earn profits. These systems have relied on trust in centralized entities, regulatory frameworks, and physical infrastructure to operate.

CeFi (Centralized Finance) emerged as a response to the limitations and inefficiencies of traditional financial systems. It involved the digitization and automation of financial processes, bringing convenience and speed to transactions and services. CeFi entities, such as online banks and payment processors, acted as intermediaries, controlling users' funds and executing transactions on their behalf [3]. The global unbanked population stands at approximately 1.7 billion people, while small businesses face exclusion from traditional banking services and resort to expensive financing options like credit cards. This leads to significant costs for both small businesses and retailers, with the latter losing 3% on each credit card sales transaction. As a consequence, there is a reduction in investment and economic growth [4].

The term "Fintech", which emerged by combining the words "financial" and "technology", refers to the application of technology and innovation to improve and enhance financial service and is believed to have been introduced in the early 1990s by John Reed, the chairman of Citicorp [5]. Fintech seeks to enhance efficiency, accessibility, and convenience in traditional financial systems using various technological advancements. Fintech encompasses innovations such as mobile banking, digital payments, online lending platforms, robo-advisors, and more. Fintech's impact extends beyond traditional banking and finance, with its influence expanding into areas such as insurance, wealth management, regulatory compliance, and financial inclusion [6].

According to Saulo Dos Santos et al. [7], Innovative technologies in the finance field have the potential to revolutionize the financial ecosystem, posing competitive risks to established firms and creating opportunities for new entrants.

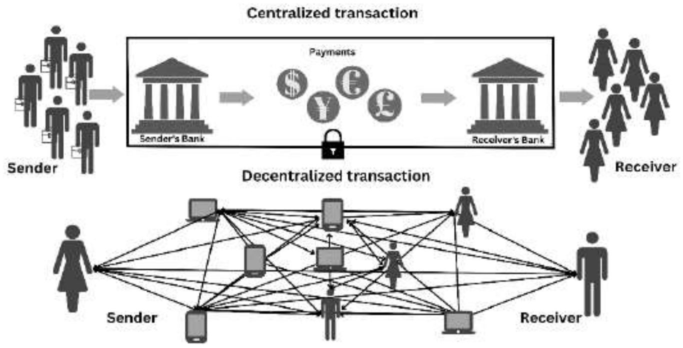

Fig.1. Working of the Centralized vs Decentralized transactions [7]

The advent of blockchain technology and cryptocurrencies has further propelled the fintech industry, giving rise to DeFi. DeFi is a financial system that is fundamentally different from traditional finance as it doesn't have a single authority governing the entire financial ecosystem. The Fig.1 contrasts the working of centralized and decentralized transactions.

A variety of protocols associated with DeFi make use of advanced software programs called "smart contracts" that enable the execution of traditional financial activities on top of the blockchain framework. Smart contacts [8] is a self-executing contract with the terms of the agreement directly written into lines of code. These contracts run on a blockchain network, such as Ethereum [9], and automatically execute when predefined conditions are met.

Blockchain employs multiple replicated immutable and secure copies of each transaction. If one version of the copy is modified, all of the remaining copies will be modified as well. Each message is encrypted before it is sent to the blockchain. Blockchain technology allows anyone to assess transactions, but due to clever design and being supplemented by cryptography and consensus mechanisms, the way data is recorded in the blockchain makes it extremely difficult to modify one piece of data without requiring changes to all subsequent data records. Distributed payment systems, like blockchain-based money transfers, seem to be more secure than CeFi.

DeFi plays a significant role within the broader realm of fintech. It represents a specific area of innovation and disruption within the financial technology landscape. Ethereum [9], as a decentralized blockchain platform, played a crucial and influential role in the evolution of DeFi. By introducing the concept of smart contracts, Ethereum enabled the creation of autonomous and self-executing financial agreements. This breakthrough empowered developers to construct decentralized applications (dApps) on the Ethereum network, thereby facilitating a diverse array of financial services like lending, borrowing, decentralized exchanges, and yield farming [9].

In DeFi, transactions are based on cryptographically secured digital currency. Satoshi Nakamoto in 2008 proposed the first decentralized digital cryptocurrency called bitcoin [10]. China declared all cryptocurrencies illegal in September 2021[11]. Many nations have outrightly banned cryptocurrency as of 2023. Bangladesh, Nepal, Qatar, and Ghana are among them. Forty-two nations have an implicit ban on the asset, typically by prohibiting local financial institutions from doing business with cryptocurrency companies. In contrast, 103 countries like Canada, Slovenia, and Germany have taken up initiatives to develop crypto regulations alongside their objectives for organizations dealing with cryptocurrencies [12]. El Salvador was the first nation to adopt bitcoin cryptocurrency as a legal tender on 9 June 2021 followed by the Central African Republic on 27 April 2022 [13], [14].

Fig.2. Timeline of the introduction of the most famous cryptocurrencies from 2009 – 2021 [12]

The Indian Government recently banned the use of cryptocurrencies in India as cryptocurrencies would lead to the dollarization of the Indian economy if they are legalized [15]. According to the KuCoin report [16], 115 million people in India own cryptocurrencies as of the year 2021. In the next section, we discuss some popular digital currencies.

1.1 DIGITAL CURRENCIES

Bitcoin introduced the concept of decentralized digital currency and addressed the need for a trustworthy electronic cash system without relying on a central authority. Since then, many Decentralized digital currencies have come up with their own features and applications. These cryptocurrencies have the potential for future adoption and use in DeFi applications. Fig.2 represents the timeline of the introduction of the most popular cryptocurrencies introduced between 2009 to 2021.

Bitcoin [17] was created by Satoshi Nakamoto, as a peer-to-peer electronic cash system that revolutionized the financial environment as the first decentralized cryptocurrency and payment system. It operates as a digital currency exchanged directly between parties, eliminating the need for intermediaries like banks or financial institutions.

Litecoin [18] was introduced as a faster and lighter alternative to Bitcoin. It functions on a distributed network and utilizes the Scrypt algorithm to expedite the creation of blocks. Litecoin, which has a limited supply of 84 million coins, stands out for its reduced transaction fees and broad acceptance in various transactions.

Namecoin [19] is a digital currency that serves as a decentralized name and censorship resistant domain registry service that allows for data storage on its dedicated blockchain. It is capable of registering bit domain names and storing associated values.

Peercoin [20] launched in 2012, is an alternative cryptocurrency based on the Bitcoin framework. It offers value storage, anonymity, and decentralized transactions. Peercoin pioneered the use of a hybrid proof-of-stake (PoS) and proof-of-work (PoW) consensus, combining energy efficiency with network security.

Ripple [21] is a cryptocurrency introduced by Ripple Labs Inc in 2013. The native XRP participates as a bridge currency on the Ripple network and facilitates exchanges of cryptocurrencies across borders, serving as an ecosystem medium for value transfer. It uses a consensus mechanism instead of mining to confirm transactions quickly. Ripple transactions are energy-efficient, fast, and cost-effective compared to Bitcoin.

Dogecoin [22] introduced in 2013, was introduced by Billy Markus and Jackson Palmer as an alternative to Bitcoin. Dogecoin utilizes the Proof of Work consensus mechanism, boasts a larger supply cap and has a faster block time of one minute, ensuring faster transaction confirmations in comparison to Bitcoin's ten-minute block time.

Primecoin [23] is a cryptocurrency launched in 2013 by Sunny King, the creator of Peercoin. It is an innovative digital currency that utilizes cryptography and decentralized mining. Inspired by Bitcoin, Primecoin introduces a novel proof-of-work mechanism centred around prime numbers. It is the first cryptocurrency designed to incorporate scientific computing as its primary function

Stellar [24] launched in 2014 by Jed McCaleb, is a decentralized ledger for transmitting digital currencies. Its native token is Stellar Lumens (XLM). Stellar utilizes a consensus algorithm that is faster, cheaper, and more energy-efficient compared to Bitcoin. However, critics argue that the Stellar blockchain is centralized due to the influence of the Stellar Development Foundation, which holds a significant portion of lumens tokens.

Monero [25] is an open-source cryptocurrency that prioritizes privacy by concealing transaction details and addresses. It offers CPU mining, eliminating the need for specialized hardware. While its privacy features have led to associations with illicit activities and the dark web, Monero also appeals to individuals seeking enhanced transaction confidentiality.

NEO [26] is a cryptocurrency and blockchain platform known as the “Chinese Ethereum.” Initially launched as AntShares in 2014 and later rebranded as NEO in 2017, it aims to create a smart economy by digitizing real-world assets and implementing features like digital identity and smart contracts.

MIOTA (Mega Internet of Things Application) [27] is a cryptocurrency that operates on an open-source smart contract platform called IOTA designed specifically for seamless transactions among internet connected devices. The platform utilizes the MIOTA cryptocurrency tokens to facilitate transactions. It aims to enable frictionless value and data transfer between humans and machines within the Internet of Everything, a concept for the next generation of the digital revolution. With feeless transactions, tamper-proof data, and low resource requirements, IOTA provides a scalable distributed ledger suitable for powering the Internet of Things (IoT) without extensive infrastructure investments.

Ether [28] is the primary digital currency of the Ethereum blockchain, a decentralized and open-source platform recognized for its smart contract functionality. With a powerful market presence as the second largest cryptocurrency, Ethereum operates independently, facilitating the automatic execution of smart contracts based on predetermined conditions within its blockchain.

Zcash [29] is a cryptocurrency launched in 2016 by Zooko Wilcox which focuses on privacy, built upon the codebase of Bitcoin. It follows Bitcoin’s model of a fixed total supply of 21 million units. Zcash transactions can either be transparent, resembling Bitcoin, or shielded, utilizing zero-knowledge proofs for enhanced anonymity. The option of “selective disclosure” allows users to prove payment for auditing purposes, aiding compliance with anti-money laundering and tax regulations for private transactors.

Firo [30], previously known as Zcoin, is a privacy-focused cryptocurrency launched in 2016 by Poramin Insom. It emphasizes user privacy and transaction anonymity, employing the Zerocoin protocol for encrypted transactions. With ongoing advancements, including the adoption of the Sigma protocol and preparations for a transition to Lelantus, Firo provides a privacy-centric alternative to other cryptocurrencies.

Cardono [31], also known as ADA, is a cryptocurrency utilized for digital transactions. It was developed by Charles Hoskinson and distinguishes itself through its “Scientific philosophy and research-driven approach.” This means that the coin undergoes rigorous examination by scientists and programmers to ensure its reliability and integrity.

Binance coin [32] is the proprietary cryptocurrency of Binance, a renowned and widely used crypto exchange established in 2017. With a view to improving transactions and reducing fees, BNB was created exclusively on the Binance platform. It is finding extensive use in the Binance ecosystem for selling fees, coin sales and a variety of transactions on the BNBChain blockchain. BNB’s value and popularity have soared, establishing it as a prominent cryptocurrency based on market capitalization.

Tezos [33] is a cryptocurrency and blockchain network that operates with its native digital token called Tez (XTZ). It enables user involvement in decentralized finance (DeFi), decentralized applications, and non-fungible token (NFT) initiatives. What distinguishes Tezos from other blockchains is its unique governance mechanism that eliminates the need for disruptive hard forks. Instead, Tezos employs a blockchain-based voting system where users can propose and adopt protocol upgrades based on their economic stake in the network. This approach ensures a more inclusive and streamlined development process for the Tezos ecosystem.

Terra [34] is a cryptocurrency that operates on the Terra blockchain network. It is a decentralized payment platform and blockchain protocol known for its algorithmic stablecoins. Terra’s objective is to provide users with a stable and efficient medium of exchange, achieved through its ecosystem of stablecoins. These stablecoins, like TerraUSD (UST), maintain a steady value by dynamically adjusting their supply based on market demand. LUNA, the governance and staking token, enables users to engage in network governance and earn rewards by participating in network security through staking.

Algorand [35] is a cryptocurrency and decentralized blockchain network designed to support various applications, offering security, scalability, and efficiency. It enables computations with reliable performance guarantees, fostering new levels of trust.

Avalanche [36] is a prominent cryptocurrency known for its exceptional transaction speed of 4,500 TPS and scalability. It operates on a proof-of-stake mechanism and employs a unique three-layered blockchain system, making it a prime example for Web 3.0 applications. The platform’s native token, AVAX, is extensively utilized for payments, security, and network connectivity within the Avalanche ecosystem.

Polkadot [37] is a cryptocurrency and blockchain project that seeks to provide a strong foundation for the development and integration of decentralized applications (dApps). Unlike focusing on specific applications, Polkadot aims to enable seamless communication between different blockchain ecosystems. It achieves this by acting as a network of networks, allowing diverse blockchain architectures to interact through specialized blockchains called parachains. The network utilizes a nominated proof-of-stake (PoS) consensus algorithm, drawing inspiration from the Ouroboros protocol.

DeSo [38] formerly known as BitClout, is a blockchain-driven social media platform and cryptocurrency. Its mission is to transform the landscape of social media by granting users direct ownership and authority over their content and influence. DeSo functions as the intrinsic cryptocurrency of the DeSo blockchain, enabling users to engage in transactions such as buying, selling, and supporting creators and their content. The platform presents an opportunity for individuals to invest in public profiles and reap the benefits of their growth, effectively establishing a decentralized social economy. DeSo aspires to challenge conventional social media models by empowering users and offering them the means to monetize their online presence.

SafeMoon [39] is a recently introduced cryptocurrency that operates on the Binance Smart Chain (BSC) and offers distinctive tokenomics. One notable feature is an automatic liquidity generation and reflection system, where a portion of transaction fees is distributed to current token holders, encouraging them to retain their tokens. SafeMoon also implements static rewards and the automatic burning of tokens. The project has gained attention due to its community-oriented approach, but it is essential to exercise caution and conduct thorough research before considering any investments in cryptocurrencies.

2. LITERATURE REVIEW

In [1], P. K. Ozili conducted a global review of DeFi research and development, revealing the advantages and risks including smart contract execution and the potential for illicit activities. According to them, observations show rising interest in DeFi in Europe, US, Asia, and Oceania, but regulatory apprehensions prevail, especially in Asia and African nations with cryptocurrency limitations.

Y. Chen and C. Bellavitis [2] examined the advantages of decentralized finance, identified current business models, obstacles and constraints and showcased the potential of decentralization as a foundation for new business models. S. D. Santos et al. [7] provide an overview of key financial services in DeFi, comparing them to centralized counterparts, and discussed associated technical and economic risks.

In [8], F. Schär spotlighted the possibilities and potential hazards within DeFi ecosystem and introduced a comprehensive framework for assessing the underlying architecture and diverse components of DeFi, encompassing token standards, decentralized exchanges, decentralized debt markets, blockchain derivatives, and on-chain asset management protocols.

Huang et al. [9] discussed applications of DeFi like supply chain management, crowdfunding, lending, and stable currency, which are implemented on the Ethereum platform, and how they will significantly revolutionize these industries.

In [40], Spinoglio discussed the idea of restructuring the banking system, with a new monetary policy to address macroeconomic concerns and enhance the traditional banking system. The proposed solution utilizes blockchain technology and decentralized DeFi 2.0 protocols to establish a sustainable and liberated banking model.

In [41] Auer et al. discussed the evolution and the current state of DeFi markets, the risks and benefits of DeFi including key risks such as regulation and compliance, and challenges around the governance of DeFi. In [42], a comparative analysis of the acceptance of cryptocurrencies in China and India was conducted. While China has invested in blockchain and created its own centrally-issued digital currency. India's stance on cryptocurrencies and blockchain was found to be intricate.

In [43] Daniel Ramos et al. conducted a comprehensive analysis of the evolving landscape of decentralized finance and its crucial elements, recent historical developments, significant project categories, present status, future prospects, and its responsiveness to cryptocurrency market trends. In [44] Amler et al. examine the challenges and potential of DeFi, emphasizing its ability to create an inclusive and transparent financial system. The authors propose pathways for DeFi's growth, emphasizing lending, payments, and insurance. They emphasize the need for interoperability among DeFi applications and better user interfaces for DeFi to revolutionize finance and fulfil its potential.

In [45] Jensen et al. highlight the significance of understanding the potential consequences, complexities, and risks associated with the widespread adoption of consumer oriented DeFi applications. F. Carapella et al. [59] explored a broad range of risk implications of DeFi and stability challenges that emerge when offering financial services through blockchain technology. Additionally, it underscores specific issues that stem from the evolution of DeFi, particularly those related to managing the code governing decentralized applications.

In [60] U. W. Chohan conducts a rigorous assessment of significant aspects like market manipulation, distortionary incentives, excess short-termism, Ponzi schemes, and money-laundering challenges to counter DeFi's experimental and disintermediated financial practice.

The Table.1 provides a comparative study of similar work done by others. This study highlights the promising avenues of the applications of decentralized finance and the role of smart contracts and blockchain in its implementation. It examines the features, architecture, challenges and opportunities presented by DeFi, compares it to the traditional financial system through SWOT analysis and delves into the intricacies of the potential risks inherent in this domain. It provides a complete summary of the DeFi landscape for researchers, academicians and corporates who want to invest in it.

Section 3, provides a comprehensive explanation regarding decentralized finance encompassing its features, architecture, and the pivotal role played by smart contracts and blockchain. In section 4, we conducted a SWOT analysis comparing DeFi and CeFi applications. Section 5 explores several well-known dApps that are utilized in financial services. In section 6, we delve into the global adoption of decentralized finance in diverse countries. In section 7, we discuss the current status of adoption of DeFi applications across the world. In section 8, we list various types of risks and potential security considerations associated with decentralized finance. In section 9, we discuss the future of DeFi landscape.

Table.1. Comparative study of Related works

References	Features	Challenges	Opportunities	Architecture	Applications	Adoption	Threats/ risks
[1]			✓		✓	✓	✓
[2]	✓						✓
[4]	✓						✓
[7]							
[8]			✓				
[9]		✓					
[40]		✓					
[41]							
[42]			✓				
[43]		✓					
[44]		✓					
[45]							
[47]			✓				
[59]	✓						✓
[60]	✓						✓
This Work		✓					

3. METHODOLOGY

The research methodology employed in this study is qualitative and exploratory in nature, utilizing a comprehensive review of existing literature. The study analyzed data gathered from diverse secondary sources like financial reports, government websites, reputable commercial platforms, scholarly articles, and academic journals. Extensive examination and thorough analysis were performed on this data to shed light on the Challenges, opportunities, and threats within the decentralized finance industry.

4. DECENTRALIZED FINANCE (DEFI)

DeFi, is an incredibly dynamic and diverse sector that thrives on the revolutionary power of blockchain technology and financial systems. Blockchain is a decentralized and distributed digital ledger technology that records transactions across multiple computers in a secure and immutable manner. A decentralized ledger is a type of digital record-keeping system that operates in a distributed and decentralized manner. Blockchain consists of a chain of blocks, where each block contains a list of transactions, and each block is linked to the previous one using cryptographic principles. This design ensures that once data is added to the blockchain, it cannot be altered or deleted retroactively without altering all subsequent blocks, making it highly resistant to tampering and fraud. Within the realm of DeFi, an assortment of innovative financial instruments, protocols, and systems merge together, all fuelled by distributed, consensus-driven blockchains. In decentralized finance, consensus algorithms play a crucial role in achieving agreement among network participants on the validity of transactions and the state of the blockchain or decentralized ledger. Consensus algorithms ensure that all nodes in the network come to a common understanding and maintain a consistent and immutable record of transactions without the need for a central authority.

4.1 FEATURES OF DEFI

A collection of fundamental values that define DeFi's essence and set it apart from conventional financial systems serve as its guiding features. The following is a description of the features that serve as the foundation of the DeFi ecosystem. The Fig.3 represents some popular features of DeFi.

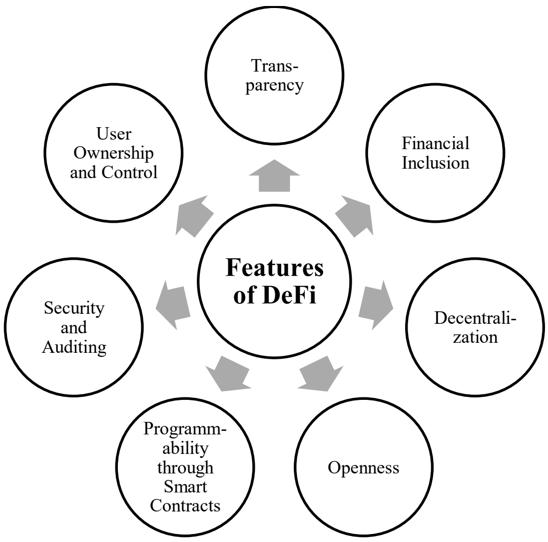

Fig.3. Features of DeFi

4.1.1 Decentralization:

DeFi operates on decentralized networks, utilizing blockchain systems. Its aim is to eliminate the need for trusted intermediaries, in contrast to traditional finance which heavily relies on centralized entities such as banks and financial institutions. Decentralization [2], [9] in DeFi fosters autonomy and reduces dependence on centralized entities, eliminating concerns like single points of failure, censorship, and control over user funds. Participants have complete control over their assets, making decisions and conducting transactions without requiring approval from a central authority.

4.1.2 Openness:

DeFi promotes transparency, collaboration, and community-driven development [2]. The accessibility of DeFi protocols, codebases, and infrastructure allows anyone to investigate, contribute, and enhance the ecosystem. This transparency enables programmers, auditors, and researchers to evaluate the logic, security, and fairness of the protocols.

4.1.3 Transparency:

It is a fundamental principle in DeFi, made possible by the inherent advantages of blockchain technology. All financial transactions, smart contract codes, and protocol specifications are publicly documented on an open and immutable blockchain ledger. This openness promotes accountability, and trust, and addresses information asymmetry. Users can review smart contract codes, verify transaction history, and assess the integrity of the system. It enables individuals to evaluate risks in DeFi and make informed decisions. Transparency [2] also encourages auditability and community involvement, allowing participants to examine protocols, identify weaknesses, and propose improvements. This cooperative approach enhances the security and reliability of the DeFi ecosystem.

4.1.4 Programmability through Smart Contracts:

The programmability of smart contracts is a central aspect of DeFi, enabling the automation and execution of predefined conditions and actions. DeFi platforms can offer cutting-edge financial instruments and protocols because of these self-executing agreements built on blockchain platforms. Smart contracts enable a wide range of financial operations, including sophisticated transactions, lending, borrowing, and decentralized exchanges, without the need for intermediaries. DeFi reduces reliance on centralized institutions and promotes peer-to-peer interactions by ensuring efficient and transparent execution of financial procedures through smart contracts.

4.1.5 Financial Inclusion:

DeFi aims to address the exclusivity inherent in traditional financial systems by providing open and unrestricted access to financial services. With DeFi protocols operating on public blockchains, anyone with internet access can participate, conduct transactions, and utilize financial tools. The inclusive nature of DeFi's services allows individuals who are unbanked, underbanked or have limited access to financial services to benefit from its offerings. DeFi promotes economic growth, empowers marginalized communities, and bridges the global financial divide by fostering financial inclusion.

4.1.6 Security and Auditing:

Security and auditing are crucial in DeFi to ensure reliability, integrity, and trust. Robust security measures mainly based on cryptography, hashing algorithms, and digital signatures are implemented in DeFi protocols to safeguard user assets and data. Independent third-party firms conduct audits to identify vulnerabilities and potential exploits in smart contracts, which serve as the foundation of DeFi applications. Through these audits, risks are mitigated, and the overall security of DeFi platforms is enhanced, ensuring the protection of user funds from malicious activities.

4.1.7 User Ownership and Control:

User ownership and control are fundamental principles in DeFi, setting it apart from traditional financial systems that rely on centralized intermediaries. In DeFi, users have complete ownership and control over all their assets during financial transactions. They interact directly with protocols using blockchain technology and smart contracts, eliminating the need for intermediaries. Users retain ownership of their private keys, ensuring the confidentiality of their funds. They actively participate in decision-making processes through voting or consensus mechanisms. DeFi platforms offer consumers the flexibility to engage in various financial activities without stringent eligibility requirements or intermediaries' permission. User ownership and control in DeFi encourage financial independence, personal empowerment, and a superior user experience.

These guiding principles form the foundation for the creation and management of DeFi projects, shaping the decentralized financial ecosystem and advancing the goal of establishing a more accessible, inclusive, and transparent financial system.

4.2 DEFI ARCHITECTURE

DeFi protocols are divided into a number of layers according to their functionalities within the ecosystem. The DeFi layering system is not precisely defined, and there may be overlap or variation in the classification of various layers and protocols deployed. There are 5 recognized layers in DeFi [8] as shown in Fig.4.

4.2.1 Settlement Layer:

The settlement layer, also known as the infrastructure layer or base layer, embodies the underlying blockchain network that establishes the fundamental framework for decentralized finance. This layer comprises the blockchain itself and its native protocol asset like ETH on the Ethereum blockchain. It enables the secure storage of ownership information within the network and ensures the adherence of any changes in the system state to its predefined ruleset. The blockchain functions as the cornerstone for trustless execution, operating as a settlement and dispute resolution layer. It facilitates robust and decentralized transaction processing, consensus mechanisms, and the execution of smart contracts.

4.2.2 Asset Layer:

The asset layer comprises all the assets that are generated on the settlement layer. This encompasses the native protocol asset and any supplementary assets issued on the blockchain, commonly known as tokens. Tokenization protocols facilitate the representation of real-world assets (such as real estate, art, and commodities) as digital tokens on the blockchain. Synthetic asset protocols create assets that emulate the value or performance of other assets, enabling users to attain exposure without possessing the underlying asset directly. Stablecoin protocols are responsible for furnishing price-stable cryptocurrencies, often pegged to a fiat currency or maintained through algorithmic mechanisms.

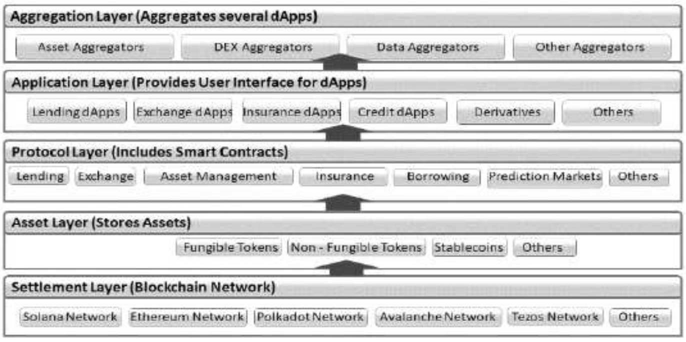

Fig.4. DeFi Stack [8]

4.2.3 *Protocol Layer:*

The protocol layer forms the foundational bedrock of DeFi, encompassing a multitude of decentralized protocols and smart contracts that facilitate precise financial functionalities. It establishes standardized frameworks for distinct use cases, such as decentralized exchanges, debt markets, derivatives, and on-chain asset management. These standards are typically implemented as a collection of smart contracts and are accessible to all users and DeFi applications. Consequently, these protocols exhibit a high degree of interoperability, enabling seamless integration and interaction across the DeFi ecosystem.

4.2.4 *Application Layer:*

The application layer of DeFi encompasses the user interfaces, applications, and decentralized applications (dApps) that enable users to interact with and leverage the functionalities offered by the underlying DeFi protocols. This layer facilitates the provision of user-friendly interfaces, often in the form of web-based interfaces, mobile apps, or dedicated dApps, which grant users access to features such as asset management, trading, lending, borrowing, yield farming, and more. The application layer creates user-centric applications that establish connections with individual protocols, while abstracting the smart contract interaction through web browser-based front ends, thereby enhancing the usability of the protocols

4.2.5 *Aggregation Layer:*

The aggregation layer focuses on platforms or aggregators that consolidate and integrate various DeFi protocols and services, extending the capabilities of the application layer. Aggregators construct user-centric platforms that establish connections with multiple applications and protocols. They typically offer tools to compare and rate services, enabling users to execute complex tasks by simultaneously interacting with several protocols, while presenting pertinent information in a concise and easily understandable manner. These platforms streamline the user experience by amalgamating liquidity, data, and services from multiple protocols into a unified interface. Aggregators assist users in identifying the optimal prices, routes, and opportunities across diverse protocols.

4.3 SMART CONTRACTS

The decentralized finance (DeFi) landscape has been significantly impacted by the revolutionary power of blockchain technology and smart contracts. DeFi, powered by the potential of smart contracts, aspires to upend conventional financial services by promoting inclusivity and creating solutions for their customers, regardless of their asset holdings. In order to understand how DeFi uses smart contracts, here is a step-by-step explanation:

4.3.1 *Smart Contract Creation:*

Programmers use blockchain programming languages to create smart contracts, such as Solidity for Ethereum. Specific financial operations, rules, conditions, logics, or protocols are defined by smart contracts.

4.3.2 *Deployment on the Blockchain:*

Smart contracts are deployed to blockchains once they have been written. A contract address is created on the blockchain corresponding to the contract's code. The contract address identifies the smart contract.

4.3.3 *Interacting with the Smart Contract:*

Smart contracts can be accessed by sending transactions to their blockchain addresses. Wallets that support blockchain transactions or web interfaces can be used for these types of interactions

4.3.4 *Validation and Execution:*

Blockchain networks verify the authenticity of transactions sent to smart contracts. The sender is verified to have the necessary funds and permissions. Based on the parameters of the transaction and the contract's code, a smart contract executes its predefined instructions.

Financial transactions are transparent, immutable, and automated using smart contracts on the blockchain powered by DeFi. With these characteristics, individual access to decentralized financial services is wide open, permissionless financial systems can be investigated, and assets can be managed without intermediaries.

4.4 BENEFITS OF SMART CONTRACTS AND BLOCKCHAIN TECHNOLOGY IN DEFI

Smart contracts and blockchain technology play crucial roles in the functioning of DeFi. The Fig.5 displays the benefits of using smart contracts and blockchain technology.

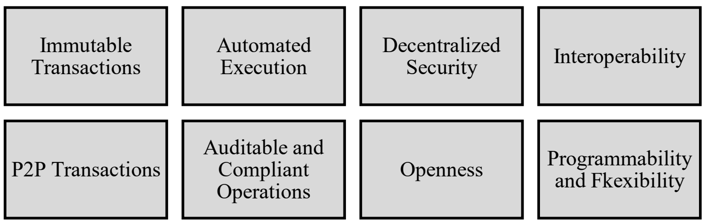

Fig.5. Benefits of Smart contracts and blockchain

4.4.1 *Immutable Transactions:*

Once recorded data cannot be easily corrupted as blockchain-based financial transactions are linked and secured through hashing algorithms which make sure that data cannot be altered once deployed. Immutability not only increases transparency and confidence but also makes it possible to audit and verify transactions and lowers the risk of fraud.

4.4.2 Automated Execution:

When certain circumstances are met, smart contracts completely execute themselves and carry out a prescribed set of operations. The efficiency of financial transactions and operations is increased because of this automation, which also decreases human involvement and eliminates potential errors.

4.4.3 Decentralized Security:

Smart contracts enforce the agreed-upon rules and enhance security and reduce the risk of malicious activity.

4.4.4 Interoperability:

With the help of smart contracts based on blockchain technology, different protocols, and applications can interoperate seamlessly. As a result of DeFi's platform's composability, financial products, and services can be created using multiple building blocks that are integrated and complex.

4.4.5 P2P Transactions:

P2P transactions are facilitated using smart contracts without the need for any intermediaries, unlike centralized finance. They eliminate counterparty risk. Using trustless transactions, users will be able to lend, borrow, trade, or provide liquidity directly to one another.

4.4.6 Auditable and Compliant Operations:

Smart contracts on the blockchain provide a transparent and auditable record of financial operations. Regulations and standards can be monitored and audited using this feature, which is especially useful for compliance purposes.

4.4.7 Openness:

Smart contracts and blockchain technology are open and accessible and provide a permissionless infrastructure. Any individual can participate in the DeFi ecosystem, create or use DeFi protocols, and access financial services, regardless of geographical location or centralized financial system limitations with a good internet connection.

4.4.8 Programmability and Flexibility:

Smart contacts are very flexible & programmable in nature, allowing developers to create sophisticated financial logic and customize the behaviour of DeFi applications. This flexibility enables the creation of various financial instruments and tools, lending protocols, decentralized exchanges, and other DeFi functionalities.

5. SWOT ANALYSIS

In this section we provide a comparative SWOT analysis of CeFi and DeFi applications. The Fig.6 provides a SWOT analysis of Centralized Finance applications and Fig.7 provides a SWOT analysis of Decentralized Finance applications.

Strengths	Weaknesses
• Provide Seamless customer services • Supports cross-chain services • Reduces excessive processing	• More Expensive • KYC is mandatory to access the Cefi Service • Less secure • Vulnerable • Monopolistic behaviour
Opportunities	**Threats**
• More Transparent financial transactions • Assist in the process of conducting audits • Established Regulatory framework and infrastructure	• Unpredictability and Inefficiencies • Higher security risk • Restricted financial freedom and autonomy

Fig.6. SWOT analysis of Centralized Finance applications

Strengths	Weaknesses
• Eliminates the need for intermediaries • More secure and permissionless • The user has sole control over the fund • Less expensive • Reduces inefficiency • DeFI data is tamper-proof, secure and auditable	• Lack of privacy • Delays in transaction due to higher complexity • Time and money consuming • Does not provide customer service • No centralized authority, volatility may be a problem
Opportunities	**Threats**
• Faster Transactions • Globally accessible through the internet • Provides transparency and the ability to track transactions • Promotes cross-chain interoperability • Greater Acceptability	• High-security risk and higher volatility • Smart contract risks • User error problem • No consumer protection • Privacy issue • DeFI's energy-intensive nature threatens environmental sustainability

Fig.7. SWOT analysis of Decentralized Finance applications

5.1 STRENGTH

The weaknesses of Centralized Finance (CeFi) lie in its higher costs due to intermediary fees, mandatory KYC requirements, security vulnerabilities, potential fraud and data corruption, and the risk of monopolistic behaviour. However, these weaknesses were resolved in DeFi. DeFi eliminates the need for intermediaries, resulting in lower costs and increased accessibility. It operates on a decentralized network, enhancing security through cryptographic protocols and providing a tamper proof and auditable system. Unlike CeFi, DeFi does not mandate KYC, ensuring greater privacy and inclusivity.

Users have complete control over their funds in DeFi, mitigating the risk of third-party mismanagement or fraud. Thus, the weaknesses of CeFi act as catalysts for the strengths exhibited in DeFi, including cost-efficiency, enhanced security, privacy, user control, and a more competitive and inclusive financial ecosystem [46]-[47].

5.2 WEAKNESS

The strengths of Centralized Finance (CeFi), such as providing seamless customer services, supporting cross-chain transactions, facilitating fiat-to-cryptocurrency exchanges, and reducing excessive processing, can transform into weaknesses when compared to Decentralized Finance. DeFi does not have centralized authority and customer service in place, which makes it more difficult for users to use. The complexity of decentralized protocols can result in delays in transactions, posing a challenge to efficiency. Privacy concerns may also arise from DeFi's decentralized nature, as transactions are recorded on the blockchain. Furthermore, while DeFi aims to streamline operations, it may require a certain degree of time and further steps in some cases. Moreover, participants may risk their own security by being exposed to the intrinsic volatility of decentralized systems. As a result, the strengths of CeFi have become weaknesses of DeFi, highlighting the drawbacks of the decentralized model in terms of convenience, speed, privacy, complexity, and volatility.

5.3 OPPORTUNITY

The threat of centralized finance arises from higher security risks, limited financial freedom, and dependence on central authorities, despite being globally accessible through the Internet. However, these threats become opportunities for decentralized finance to address and provide alternative solutions. DeFi offers faster transactions compared to CeFi, leveraging blockchain technology. It provides transparency and traceability of transactions through immutable records on the blockchain. Furthermore, DeFi offers greater acceptability as it does not require a traditional bank account, expanding access to financial services and promoting financial inclusion. By addressing the limitations and inefficiencies of CeFi, DeFi creates an opportunity for a more efficient, transparent, and accessible financial ecosystem. Cross-chain interoperability in DeFi refers to the ability of different blockchain networks to seamlessly communicate, share data, and interact with one another. Cross-chain interoperability presents significant opportunities in the DeFi space. It refers to the seamless interaction and exchange of assets and data between different blockchain networks. It allows users to access and utilize decentralized finance applications and services across multiple blockchains, enhancing liquidity, expanding opportunities, and unlocking the potential for diverse financial activities. It's important to remember that attaining cross-chain interoperability is a challenging technological task. Numerous projects and protocols are currently creating ways to successfully connect various blockchains while upholding security and decentralization [48], [49].

5.4 THREATS

The opportunities presented by centralized finance, including more transparent financial transactions, assistance in conducting audits, and an established regulatory framework and infrastructure, can become threats for implementing decentralized finance. The lack of centralized control in DeFi introduces higher security risks, as the absence of a central authority increases the potential for vulnerabilities and attacks. Higher volatility in DeFi can lead to significant losses for investors, as price fluctuations can occur rapidly and without centralized interventions. The use of smart contracts in DeFi introduces the risk of coding errors or vulnerabilities that could be exploited. Additionally, the absence of consumer protection mechanisms and the potential for user errors pose risks to participants in DeFi. Privacy issues can also arise in DeFi, as blockchain transactions are generally transparent and visible to all participants. The energy-intensive mechanism in DeFi poses a significant environmental threat due to its larger carbon footprint compared to centralized systems. Neglecting sustainability concerns may lead to negative public perception, increased regulatory scrutiny, and hinder the growth of DeFi networks. Proactive measures, such as exploring energy-efficient consensus algorithms, are essential to address this issue. Therefore, while CeFi opportunities initially attract users, they also create concerns and threats when transitioning to the decentralized model of DeFi.

SWOT analysis of DeFi reveals its immense potential for transforming the financial landscape. Its strengths in accessibility, transparency, and empowerment make it an attractive alternative to traditional systems. However, it must address weaknesses related to scalability and regulatory uncertainty. By capitalizing on opportunities like decentralized lending and asset management, DeFi can shape the future of finance. Nevertheless, it must navigate threats such as regulatory challenges, security vulnerabilities, and market volatility. With continued innovation, collaboration, and adaptation, DeFi has the potential to revolutionize the way we think about and interact with finance.

6. DECENTRALIZED FINANCIAL APPLICATIONS

Decentralized applications, also known as dApps, refer to software applications that operate on blockchain technology or peer-to-peer platforms. Financial applications are software programs specifically created to access, facilitate, and secure personal or business financial data. Its purpose is to effectively manage, analyze, process, and store financial records and information. The Fig.8 shows some of the popular dApps used in financial services.

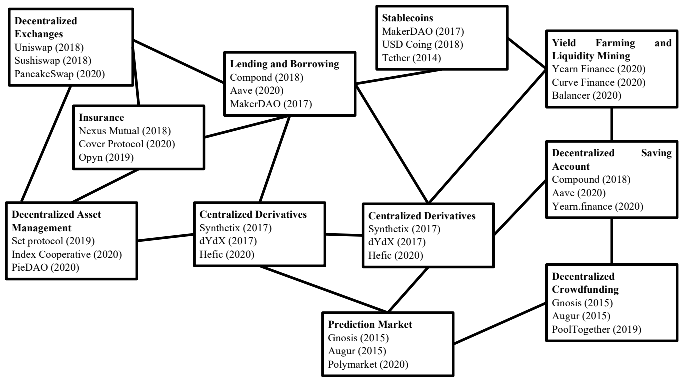

Fig.8. dApps based on DeFi

6.1 DECENTRALIZED EXCHANGES

DEXs (decentralized exchanges) [50]-[51] are trading platforms that improve the exchange of digital assets without a centralized authority. Instead of relying on traditional exchanges, they use a robust algorithm to dynamically update prices and execute trades based on available liquidity. These platforms typically use automated market makers (AMMs) to efficiently execute orders. Users can trade one cryptocurrency or token for another on these exchanges while maintaining full ownership and control of their crypto assets. Those who provide liquidity to token pools on these platforms will be rewarded.

Uniswap [52] operating on the Ethereum blockchain, holds the position of being the most extensive decentralized exchange (DEX). It enables global users to engage in cryptocurrency trading directly, eliminating the need for intermediaries or middlemen.

6.2 INSURANCE

DeFi insurance offers policyholders the opportunity to receive a significant compensation for covered events by paying a fixed premium. In this type of insurance, the entire life cycle, including risk assessment and management, for specific risks like smart contract attacks, is managed and coordinated using decentralized transaction and governance systems. Currently, there are decentralized insurance protocols operating on blockchain networks that provide on-chain coverage for various risks, allowing users to purchase protection against unintended use of code in any smart contract listed on the protocol.

Nexus Mutual [53] is a decentralized insurance application that offers individuals the opportunity to join and collectively bear risks. It offers various insurance products to its members, safeguarding them against different types of risks. Built on the Ethereum blockchain, the Nexus Mutual protocol serves as the foundation for members to acquire coverage, evaluate risks, process claims, and even establish risk management enterprises.

6.3 DECENTRALISED ASSET MANAGEMENT

Decentralized Asset Management [8], [43] in DeFi involves the management of digital assets through blockchain based protocols and smart contracts, bypassing conventional financial intermediaries. It gives individuals direct control over their assets, enabling them to invest in diverse financial products using self-executing smart contracts. These decentralized platforms ensure transparency and efficiency, automating investment choices without the need for banks or centralized entities.

6.4 STABLECOINS

Stablecoin plays a vital role in DeFi applications by providing stability and reducing the volatility commonly seen in cryptocurrencies such as Bitcoin and Ethereum. These digital assets are specifically designed to maintain a constant value by pegging themselves to specific assets or a combination of assets, ensuring a 1:1 value ratio with traditional currencies like the US Dollar. As a result, stablecoins are favoured in DeFi for enhancing liquidity in various aspects, including liquidity pools. Their steady value also makes them appealing to investors seeking consistent yields and a reliable choice for participating in DeFi.

USD Coin (USDC) [54] is a stablecoin that maintains a fixed value, always equivalent to one U.S. Dollar. This ensures that the worth of one USDC remains constant and equal to one dollar at all times.

6.5 LENDING AND BORROWING

In DeFi lending and borrowing play crucial roles within the rapidly expanding decentralized financial ecosystem [7], [8], [47]. These innovative applications utilize blockchain technology and smart contracts, allowing users to lend their cryptocurrencies and earn interest or borrow assets with collateral. Users deposit digital assets into lending protocols, contributing to liquidity pools accessible by borrowers. Borrowers can then obtain loans by providing collateral from these pools, and lenders earn interest on their deposited assets. Smart contracts efficiently manage interest payments, collateral requirements, and other aspects, ensuring transparency and effectiveness without intermediaries. These DeFi lending and borrowing platforms foster financial inclusion and empower users to access loans and generate passive income while retaining control over their assets. Nonetheless, users must be cautious of associated risks with DeFi protocols and conduct thorough research before engaging in these activities.

MakerDAO [55] is one of the pioneering DeFi protocols that holds the distinction of being the first Ethereum based project to provide secure and dependable lending services. With its peer-to-peer structure, MakerDAO leverages blockchain technology for creating innovative solutions in cryptocurrency borrowing, saving, and lending. Through its platform, users can access a robust ecosystem that facilitates decentralized financial transactions while promoting transparency and trust.

6.6 DECENTRALIZED DERIVATIVES

DeFi brought a revolutionary change to the financial world by introducing tokenized derivatives on the Ethereum blockchain. These derivatives [8] are usually linked to an underlying asset, and their value fluctuates based on the performance of that asset. DeFi derivatives offer the flexibility to represent a wide range of real-world assets, including bonds, currencies, commodities, and cryptocurrencies. Through the use of DeFi derivatives, people can securely gain exposure to various financial instruments and assets.

6.7 YIELD FARMING & LIQUIDITY IN DEFI

Yield farming, also known as liquidity mining, involves users supplying liquidity to DeFi protocols by depositing funds into liquidity pools. As compensation, they receive rewards in the form of additional tokens or fees generated by the protocol. This practice enables individuals to generate passive income by actively participating in the DeFi ecosystem and contributing to the liquidity of diverse protocols Liquidity in DeFi refers to the ample availability and extensive variety of tradable assets within a market. In the context of decentralized exchanges (DEXs) and lending platforms, liquidity plays a critical role in ensuring the efficient operation of these protocols. Users have the opportunity to provide liquidity by depositing their digital assets into liquidity pools, where others can access them for trading or borrowing purposes. In return for their contribution, liquidity providers receive rewards or fees. Liquidity serves as a fundamental element for promoting smooth market operations, establishing price stability, and facilitating the provision of various financial services within the DeFi ecosystem.

6.8 DECENTRALIZED SAVING ACCOUNT

In DeFi, a decentralized savings account enables users to securely store and earn interest on digital assets through blockchain and smart contracts. By depositing cryptocurrencies into a smart contract, users can automatically earn interest based on predefined rules, with interest rates determined algorithmically by the platform's supply and demand factors. This decentralized method offers enhanced control, transparency, and accessibility compared to traditional bank-provided savings accounts.

6.9 DECENTRALIZED CROWDFUNDING

Decentralised crowdfunding, also known as blockchain based fundraising, is an innovative method of generating money that uses cryptocurrencies and blockchain technology to enable direct communication between project creators and backers. By using smart contracts, creators can specify their project details and funding objectives, while backers can make contributions directly to the project's smart contract address. This transparent and secure process eliminates the involvement of middlemen, resulting in lower fees and increased accountability. By embracing decentralized crowdfunding, creators gain the ability to reach a global audience and foster community participation.

6.10 DECENTRALIZED IDENTITY

Decentralized identity is a concept that seeks to give individuals greater control over their digital identities and personal data through the use of decentralized systems and blockchain technology. Decentralized identity enables individuals to determine their own identities, unlike the conventional identification systems that depend on centralized databases and trusted intermediaries. Through the use of cryptographic keys and blockchain, users can establish unique and verifiable digital identities, known as self-sovereign identities. These self-sovereign identities, represented by Decentralized Identifiers, offer users complete ownership and authority over their identity information, ensuring advanced security and the ability to selectively share data.

6.11 PREDICTION MARKET

The advent of prediction markets has profoundly impacted the realm of decentralized finance, ushering in a new era of speculation where participants can engage in a wide array of events, ranging from elections and sports outcomes to cryptocurrency price movements. These markets operate on the robust foundation of blockchain technology, employing smart contracts to create decentralized and transparent platforms. Within these platforms, users can trade prediction tokens that signify the probability of specific outcomes. This innovative approach empowers users to contribute real-time information, thereby fostering a collective intelligence that informs decision making. As a result, DeFi prediction markets facilitate more precise forecasts and risk evaluations, leading to heightened efficiency and liquidity within the ecosystem. In effect, participants are now equipped with novel financial instruments and opportunities to leverage the power of these prediction markets.

Augur [56] is one of the earliest and most well-known decentralized prediction market platforms. It enables users to create and participate in prediction markets on various events using the Ethereum blockchain.

Polymarket [57] is a prediction market platform that gained popularity in 2020. It allows users to speculate on various topics, including political events, sports outcomes, and more, using blockchain technology.

7. ADOPTION OF DEFI

The adoption of DeFi has been growing rapidly in recent years. One of the main driving forces behind its adoption is the potential for greater financial inclusivity which leads to a greater level of accessibility to the financial services. It has been observed that the total value locked in DeFi protocols has increased significantly over the past few years. An indicator of adoption is how many cryptocurrency assets are locked into DeFi applications, which is called TVL. Users are increasingly recognizing the opportunity in DeFi and investing their assets in a variety of protocols, including decentralized exchanges, yield farming, and liquidity providers. In developing countries, individuals without access to banking services may find traditional financial systems to be out of reach. Many countries are not allowing decentralized finance to mature in their country and have banned it despite having a good banking system.

Cryptocurrency, a type of digital or virtual currency that relies on cryptography for security and operates independently of a central bank, has garnered substantial global attention and popularity. Many jurisdictions are still debating or are in the process of changing the legal status of cryptocurrencies. While cryptocurrency usage is not illegal in most countries, its status and usability as a means of payment (or as a commodity) varies greatly, with differing regulatory implications. The legal status of cryptocurrency varies across countries and is subject to continuous regulatory developments [58].

In numerous nations like the United States and Canada, cryptocurrency is generally acknowledged as a legal form of currency, accompanied by regulations that govern its use and trade. These regulations primarily concentrate on concerns such as money laundering, taxation, and safeguarding consumers. In the United States, for example, there exists a comprehensive framework for cryptocurrency, overseen by regulatory bodies such as the Securities and Exchange Commission (SEC) and the Financial Crimes Enforcement Network (FinCEN). In contrast, Canada has embraced a more progressive stance by recognizing cryptocurrency as a legitimate method of payment and implementing regulations to ensure its proper operation [58].

In Europe, countries such as Germany and the United Kingdom have acknowledged the legality of cryptocurrency and have put in place regulatory measures to enable its utilization. Germany treats cryptocurrency as a recognized unit of account, permitting individuals and businesses to conduct transactions using digital currencies like Bitcoin. Similarly, the United Kingdom has implemented regulatory guidelines specifically targeting cryptocurrency exchanges and custodian wallet providers to counteract money laundering and prevent terrorist financing [58].

In Asia, Japan has emerged as a significant participant in the cryptocurrency realm by officially recognizing it as a legal form of tender. The country has established a comprehensive regulatory framework to oversee cryptocurrency exchanges, implement measures for consumer protection, and ensure appropriate governance. On the other hand, South Korea, while legalizing cryptocurrency, has imposed stringent regulations to combat illegal activities and safeguard investors. These regulations include requirements such as Know Your Customer (KYC) procedures and the use of real-name banking accounts.

Nevertheless, there are countries that have not embraced cryptocurrency. Bolivia has completely prohibited cryptocurrency, deeming it illegal and forbidding its usage in any way. Similarly, Nepal has implemented a blanket ban on cryptocurrency transactions. Certain countries, such as China and India, have adopted restrictive measures and taken strong actions against cryptocurrency trading and initial coin offerings (ICOs) due to concerns surrounding financial stability and the potential for illicit activities.

Several countries find themselves in a grey area regarding cryptocurrency, where its legal status is neither explicitly permitted nor prohibited. These countries, such as Australia, Brazil, France, and Russia, have issued cautionary warnings concerning the risks associated with cryptocurrency transactions and encourage individuals to exercise prudence. Additionally, they are currently in the process of formulating regulatory frameworks to tackle the challenges and capitalize on the opportunities presented by cryptocurrencies [58].

It is important to highlight that the legal status of cryptocurrency can undergo rapid changes as governments and regulatory bodies frequently reassess their positions in light of the increasing impact of this digital asset. Consequently, it is vital for individuals and businesses involved in the cryptocurrency industry to remain informed about the most recent legal developments in their specific jurisdictions.

Overall, the legality of cryptocurrency varies worldwide, ranging from acceptance and regulation to complete prohibition, reflecting the diverse approaches taken by different countries and territories in adapting to this emerging form of currency. The landscape of cryptocurrency regulations is dynamic and constantly evolving, shaping the future of this digital financial ecosystem.

8. RISK ANALYSIS

DeFi presents a multitude of advantages, but it is imperative to acknowledge the accompanying uncertainties and potential security concerns. The Fig.9 displays the different types of risks and potential security considerations related to decentralized finance.

Fig.9. Risk and Security Considerations of DeFi

8.1 CODE VULNERABILITIES AND SMART CONTRACTS VULNERABILITIES

Smart contracts [8], [47] are intricate pieces of code, and if they are not meticulously audited or tested, they may harbour vulnerabilities that could be exploited. Flaws or loopholes in the code have the potential to result in financial losses or hacking incidents. These risks stem from coding errors, design flaws, and malicious intent, leading to potential exploits such as re-entrance attacks, where a contract can be called repeatedly before it completes previous executions, enabling attackers to drain funds. Other threats include arithmetic overflows, improper input validation, and weak access controls, allowing unauthorized access to sensitive functions.

DeFi's interconnected nature exacerbates the impact of any smart contract breach, highlighting the need for thorough audits, formal verification, and continuous monitoring to bolster the robustness of smart contracts and fortify the security of DeFi platforms. To mitigate these risks, extensive code auditing, formal verification, and rigorous testing are indispensable.

8.2 SCALABILITY AND NETWORK CONGESTION

As the popularity of DeFi surges, the surge in network congestion and scalability issues could ensue, leading to increased transaction fees & slower confirmation times. These challenges can affect the usability & cost-effectiveness of DeFi applications. Blockchain networks, particularly those experiencing high levels of activity like Ethereum, may encounter scalability obstacles. Continuous efforts are being made to enhance blockchain scalability [8].

8.3 REGULATORY AND COMPLIANCE CHALLENGES

The regulatory landscape surrounding DeFi is still evolving, with different jurisdictions adopting varying approaches [7]. As the industry matures, the possibility of heightened scrutiny, regulatory interventions, or changes in regulations that may impact the operation of DeFi protocols and applications increases. Compliance with existing regulations and adaptation to new regulatory requirements which will be crucial for ensuring the long-term viability of DeFi projects. In a decentralized environment, compliance with existing financial regulations like KYC (Know Your Customer) and AML (Anti-Money Laundering) can be arduous [7]. Striking a balance between innovation and regulatory compliance remains an ongoing consideration.

8.4 EXTERNAL DEPENDENCIES

While smart contracts are self-executing, they often interact with external data oracles to access off-chain information [8]. Relying on these oracles introduces potential security risks if they are compromised or manipulated. Efforts are underway to develop secure and decentralized oracle solutions to mitigate these risks.

8.5 USER ERROR, PHISHING ATTACKS, AND SCAMS

DeFi platforms frequently require users to manage their private keys, navigate unfamiliar interfaces, and make complex financial decisions. This elevates the risk of user error, including inadvertent loss of funds or falling prey to scams. Addressing these challenges necessitates robust education and user-friendly interfaces. User errors such as typographical errors in addresses or improper security practices can result in irretrievable loss of funds. Phishing attacks, fraudulent websites, and fake token offerings also pose risks that users must remain vigilant about [7]. Adequate education, appropriate security measures, and user-friendly interfaces can help mitigate these risks.

8.6 PRICE VOLATILITY AND MARKET RISK

DeFi tokens and assets can exhibit high volatility, subject to rapid price fluctuations. This volatility introduces risks for investors and users alike. Price manipulation, pump-and-dump schemes, and market speculation can impact the value and stability of DeFi assets. Before engaging in DeFi activities, investors and users must carefully evaluate and manage these risks, taking into account factors such as market liquidity, token supply, and project fundamentals. Diversification and risk management strategies can help mitigate the impact of price volatility.

8.7 GOVERNANCE AND CONSENSUS RISKS

Many DeFi protocols rely on decentralized governance mechanisms, involving token holders in decision-making processes [8]. However, this presents risks related to governance attacks, manipulation of voting systems, or the concentration of power among influential stakeholders. Malicious actors could amass a significant number of tokens to influence decisions or manipulate protocol parameters. Mitigating these risks and ensuring fair decision-making processes in DeFi protocols necessitates effective governance frameworks, transparent voting mechanisms, and strong community engagement.

8.8 LIQUIDITY RISKS

DeFi protocols heavily depend on liquidity providers to facilitate trading and maintain efficient markets. Insufficient liquidity or sudden withdrawal of liquidity can lead to price slippage, reduced trading opportunities, and potential losses for users. Additionally, low liquidity can hinder users from entering or exiting positions without significantly impacting market prices [8]. Well-designed tokenomics, incentivization mechanisms, and liquidity management strategies are essential to maintain adequate liquidity and mitigate risks associated with liquidity fluctuations in DeFi protocols.

8.9 ORACLE RISKS

In the dynamic landscape of DeFi, the term “oracle risk” highlights a critical concern rooted in the dependence on external data sources to initiate automated smart contract actions [3], [59]. Within DeFi ecosystems, smart contracts play a pivotal role in executing transactions based on real-world data, such as asset prices. However, the susceptibility arises when these Oracle data streams are compromised or tampered with, potentially enabling malicious entities to exploit this vulnerability and manipulate contract outcomes to their advantage. The resulting financial losses for users emphasize the utmost importance of making judicious choices in adopting robust and reliable Oracle solutions. Doing so becomes instrumental in upholding the integrity of DeFi protocols, thwarting potential disruptions, and fortifying the overall stability of the DeFi space.

8.10 SANDWICH ATTACKS

A sandwich attack exploits token price volatility by swiftly conducting transactions on both sides of a targeted trade. Some DeFi platforms attract potential participants with the promise of high-interest rate instruments. Nevertheless, it’s crucial to view these offerings within a risk-adjusted framework. Despite their appealing high interest rates, especially in today’s low-inflation and low-interest rate environment, they also come with questionable risks. [60] Sandwich attack is a form of price manipulation attack that occurs in a short period around a transaction, particularly in the context of Automated Market-Making (AMM) platforms [61]. In this manoeuvre, a malicious actor strategically places substantial buy and sell orders around a legitimate trader’s transaction, seeking to profit from the price fluctuations triggered by the trader’s move. By essentially “sandwiching” the genuine trade, the attacker induces the trader to buy or sell at an unfavourable rate due to the momentary price distortion arising from the attacker’s rapid manoeuvres. This technique has the potential to lead to financial setbacks for the unsuspecting trader, underscoring the imperative for robust strategies that counter such susceptibilities within DeFi ecosystems.

8.11 FLASH LOANS ATTACKS

Flash loans [47] pose a serious threat to the DeFi ecosystem as they lack collateral and offer borrowers the means to exploit price disparities and manipulate markets within a single transaction block. These loans are a type of price manipulation attack [62]. Such loans can pave the way for arbitrage attacks, market manipulation, and oracle exploits, resulting in significant losses for other participants and draining liquidity from the underlying protocols. Furthermore, discovering smart contract vulnerabilities during the loan period opens the door for malicious users to inflict further harm. Although certain platforms attempt to implement limitations, the simplicity of accessing flash loans makes them an alluring instrument for potential attackers, necessitating ongoing security measures and utmost vigilance when engaging with such loans in the DeFi space.

8.12 ETHICAL CONSIDERATIONS SURROUNDING DEFI

DeFi offers numerous advantages, it also raises several ethical considerations, including potential risks of exploitation, financial inclusion ethics, and privacy concerns. Let’s delve into each of these aspects:

8.12.1 Exploitation Risks:

DeFi platforms, driven by self-executing smart contracts with predefined rules, facilitate a wide range of financial activities, including lending, borrowing, and trading. The allure of reducing intermediaries and enhancing transparency through smart contracts is tempered by their susceptibility to exploits and attacks. The staggering financial losses witnessed in previous DeFi hacks underscore the gravity of smart contract bugs or vulnerabilities. Especially those users who are less familiar with technology, find themselves unintentionally involved in these risks due to the uncertain nature of these complexities. Minimizing the threat of exploitation necessitates paramount importance to security audits, comprehensive testing, and robust disclosures by DeFi developers and platform operators.

8.12.2 Financial Inclusion Ethics:

DeFi opens its virtual doors to anyone with an internet connection, it presumes users possessing indispensable technology are aware of how to engage in it meaningfully. Consequently, a digital gap emerges, further marginalizing vulnerable communities. Tackling this issue demands that DeFi platforms embrace user-friendly interfaces, empower with educational resources, and fortify support systems, thereby ensuring genuine accessibility to a diverse populace. Moreover, it is essential to implement strict measures to prevent any exploitative actions aimed at financially vulnerable individuals.

8.12.3 Privacy Concerns:

Every transaction in the realm of decentralized finance is recorded on immutable public blockchains, creating a transparent audit trail [47]. Although this quality is meant to foster confidence and strengthen monitoring, it paradoxically raises concerns about individual privacy. Users are put at risk by free access to financial data since it may reveal their whole financial history and portfolio, making them vulnerable to malicious groups. This dangerous breach of confidentiality seriously affects people living in places with restrictive fiscal laws or oppressive governments. DeFi systems must thus quickly implement cutting-edge privacy-enhancing technology, such as zero-knowledge proofs or anonymity-preserving blockchain networks, in order to protect user data and give them complete control over their financial information.

8.12.4 Regulatory Compliance:

DeFi works in a highly unregulated industry, and this may have positive and negative consequences. On the one hand, it promotes financial inclusiveness and accessibility by enabling quick innovation and experimentation. On the other hand, it can encourage fraudulent individuals to take advantage of the system without being held accountable. An important ethical issue involves figuring out how to strike a balance between innovation and regulatory oversight. Concerns concerning compliance may be addressed without limiting innovation with the support of responsible self-regulation by DeFi initiatives and industry participants and cooperation with regulatory organizations.

Participants in the DeFi ecosystem, including investors, users, and developers, must be aware of these risks and implement appropriate risk management strategies. Diligence, continuous monitoring, security audits, and community engagement are vital for identifying and addressing these risks. Additionally, regulatory frameworks and industry standards are evolving to address some of these concerns and enhance the overall security and stability of the DeFi space.

9. CONCLUSION

Currently, the DeFi industry is in its infancy but is constantly evolving despite many apprehensions regarding its adoption. A lot of research and development work is being done to promote DeFi applications and many such applications are running successfully. In this paper, we analyzed the various fields and applications where DeFi is being currently utilized, in which form, and how it will transform financial transactions of the future. We also did a risk analysis of its adoption and found out the driving reasons such as regulatory challenges, Financial stability concerns, Loss of control and lack of Monetary policy, Tax Evasion, & Illicit Activities, and most importantly customer protection as main reasons why some governments are fearing to adopt it. The risks such as Code Vulnerabilities and Smart Contracts Vulnerabilities, Scalability, Network Congestion, Regulatory and Compliance Challenges, External Dependencies, User Error, Phishing Attacks, and Scams, Price Volatility and Market Risks, Governance Consensus Risks, and Liquidity Risks in the DeFi Ecosystem makes it a cause of threat to privacy. Overcoming these risks and challenges will be crucial for DeFi adoption.

9.1 FUTURE OF DEFI

The future of DeFi is incredibly promising and filled with potential. Its ongoing development positions DeFi to play a pivotal role in reshaping the financial sector, fundamentally transforming conventional financial services. The general public and governments are looking towards its adoption and use in future financial applications with a lot of anticipation and curiosity. Despite the risks involved, the future of DeFi still looks bright, with improved scalability, widespread acceptance, regulatory clarity, and introduction of the new avenues of DeFi. Over time, there will be an increase in DeFi exchange offerings which will accelerate the trend toward alternative protocols, scaling, and infrastructure solutions. Opportunities for DeFi innovation are abundant, opening the door to new and improved methods to serve clients. DeFi has the capacity to democratize finance, granting broader global access to financial offerings, especially for individuals currently underserved by conventional banking systems. However, to reach its full potential and become a more mainstream and inclusive financial ecosystem, it must overcome challenges and obstacles, such as regulatory hurdles, scalability constraints, and requirements for user-friendly interfaces.

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TAXONOMY OF FINTECH ECOSYSTEM – A RESEARCH STUDY

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Abstract

Fintech ecosystem is developing at a fast pace with inclusion of all kinds of services within its ambit. In order to understand the fintech ecosystem, one has to understand the taxonomy of fintech ecosystem. This paper discusses the two most comprehensive taxonomies on fintech ecosystem developed by Imerman and Fabozzi (2020) and Ratecka (2020), for its advantages and disadvantages. Based on that discussion, the researcher develops his own taxonomy of fintech ecosystem and explains the rationale and also the theoretical foundations for that taxonomy. This paper is divided into four sections: (a) overview of fintech innovations; (b) Taxonomy developed by Imerman and Fabozzi; (c) taxonomy developed by Ratecka (d) synthesis of these two taxonomies and based on that the taxonomy developed by the researcher. The last section concludes the paper.

Keywords:

Fintech, Fintech Ecosystem, Financial Innovations, Taxonomy

1. INTRODUCTION

Fintech as a word has been catching up attention and interest. Fintech is an acronym of 'Financial Technology'. Fintech includes all those applications and softwares that will automate the transactions made in businesses. It has been having significant impact on all the stakeholders associated with business including employees, consumers, technology providers, vendors and the government. Functionally, Fintech makes the entire transaction faster and more accurate. Fintech efficiently handles volumes of data in a beneficial and meaningful way. Fintech is already creating the next financial revolution in India and abroad. Many startups and entrepreneurs are planning to start their Fintech ventures in order to be a part of this revolution. There are also many variations of innovations taking place in the Fintech space. Some of them are based on verticals of solution that are on offer, while some are on functional domain. To understand the scope of Fintech innovations, the authors feel that understanding the taxonomy of Fintech innovations becomes extremely essential. This article examines the taxonomy of Fintech Innovations happing across the world. This article is based on the literature review conducted by the author as part of his doctoral PhD work on Fintech industry. The outcome of such literature review is presented as a journal article.

1.1 FINTECH INNOVATIONS - AN OVERVIEW

We might see that as Fintech innovations; further, it is essential to know that there are so many options in the technologies in the software of transactions or events of activities in the industry and the businesses. It is essential to know that these software options should benefit the stakeholders and the corporations. If it is not, that will fail to succeed as an application or a go-to solution, the Fintech solution. It provides an alternative to the current traditional way of doing the particular activity as an exciting aspect of the entire Fintech.

In order to understand the nature of innovations taking place in the Fintech space, one has to understand the taxonomy of such ecosystem. The researcher has found two taxonomies that describe the Fintech ecosystem: (a) By Michael Imerman and Frank Fabozzi (2020); (b) By Patrycja Ratecka (2020). This article provides an quick summary of both these taxonomies of Fintech innovations. Based on these two taxonomies, the researcher has created an improvised version of the taxonomy of Fintech innovations, which is presented in the last section of this article.

1.2 TAXONOMY OF FINTECH ECOSYSTEM BY MICHAEL IMERMAN AND FRANK FABOZZI

Imerman and Fabozzi mentions about the Fintech ecosystem with its classification of the taxonomy of the different ecosystems with some verticals, some of which are so-called Fintech Verticals, including payments technology, digital banking, digital wealth management, capital markets, Fintech lending, equity crowdfunding, InsurTech and PropTech. They also mention about Fintech Horizontals, which is subcategorized into two subsets of the Functional Areas and the Emerging Technologies for financial services. In the functional areas we have the Financial Regulation, Risk Management, Funding and Valuation. The emerging financial services technologies would range from distributed ledger technology or blockchain, the IoT, AI, big data analytics, cyber security, biometrics, open-source computing or the API's, cloud computing, quantum computing and some virtual operated realities or automation robotics. The same is illustrated in the Fig.1.

A snapshot of the article; looking up such a taxonomy of the Fintech ecosystem or Fintech landscape helps us to understand the breadth and depth of Fintech as a revolution.

In fact, the most popular vertical of all the verticals, which is impacting all of us in the payment-related area, is the technology which is used for payments. So, we're all using those apps for making payments through smartphones or mobile electronic devices is termed as 'Payment Technology'.

So, money is transferred in a different mode than earlier. Money is transferred with a click or with a scan using mobile numbers, something unheard of or unseen has happened in the digital transformation primarily because of the pandemic. The pandemic forced us to have alternate sources of transactions. Because the scare of the pandemic was so large that people did not want to use cash.

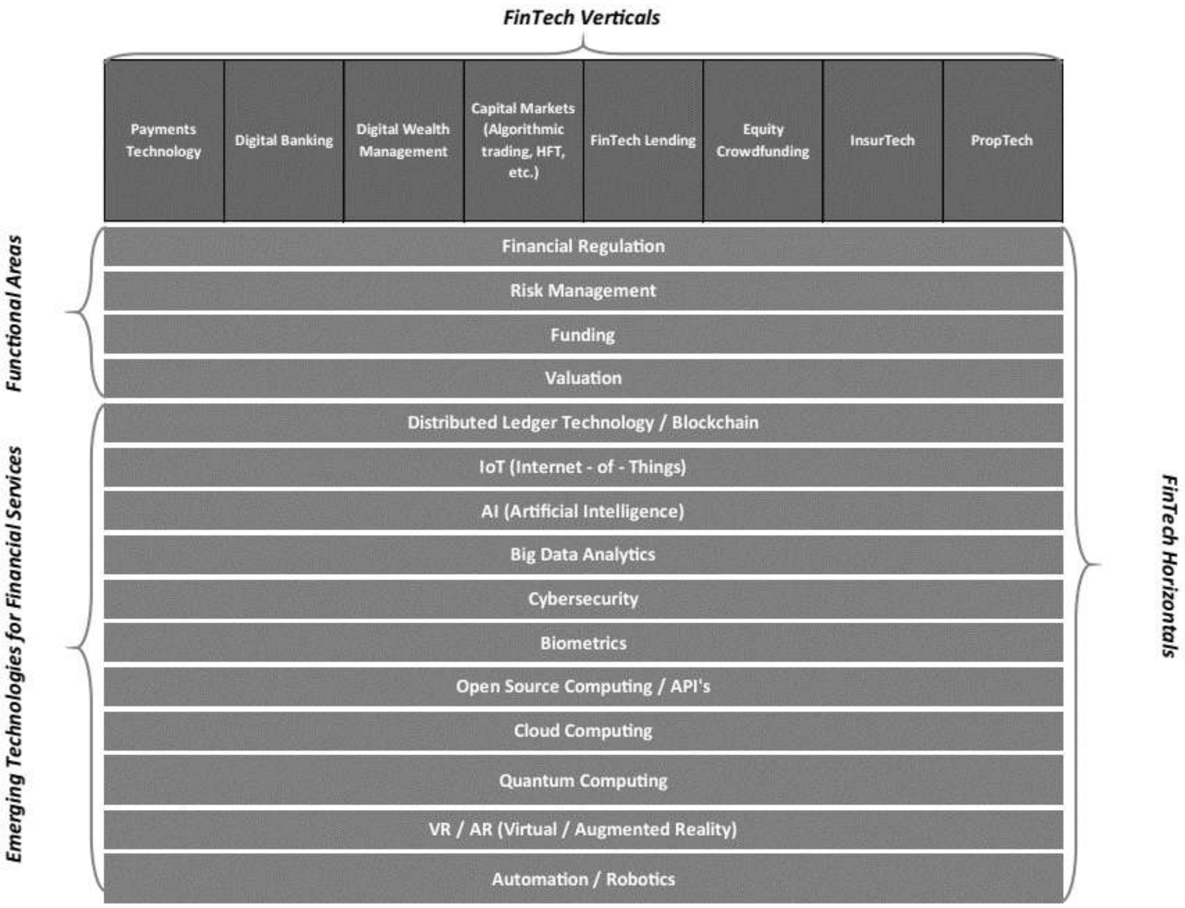

Fig.1. Fintech Ecosystem [1]

For Example, we didn't see notes as an exchange or a mode of exchange. The practical alternative came not wanting to touch the currency notes but scanning without transferring money or currency notes. In this arena, many companies came up with many options for helping people make payments.

This is a preferred type of payment software and technology for many investors. This type of software provided a large amount of acquisition funds. There were many funds raised in the form of public offers. A lot of these acquisitions started in the era of 2010-2019; maybe that's why it's called the 'Financial Revolution Time Zone'.

The second vertical of Fintech, payment technology is an essential aspect of what we discussed. This payment technology has a logical extension of doing banking transactions not by visiting the branch but in a digitized way.

Digital Banking would be of having transactions on online mode either through the computer or mobile, so all the traditional commercial and retail banks started operating differently compared to what they had been doing all these years. It has an impact on how the operations of banks happen. It is essential to know how banks operate. Banks have had their physical branches facilities in terms of cheque processing, having some computers clearing those payments, or some call centres trying to understand the customers.

The queries managing all of these had many resources, including demand power resources. It's essential to note and observe that there was a revolution and how they operate the Fintech revolution which is an extension of a digital revolution. The Fintech revolution would be an extension of a digital process because the way the banks operate now would be completely different, everybody's comfortable using a banking app and mobile banking.

Every bank offers us technology or an interface that is safe, friendly and easy to handle for transactions. Mobile banking is important where real solutions have to be driven by an important aspect known as Data Storage or Data Capture, or Data Retrieval-Related Technologies. So, terms like cloud computing and artificial intelligence-driven become a standard reference here because there's so much of an inflow of technology-driven businesses. The startups offering services to banking and these new-age banks, which have a lot of software and technology-driven services, are giving tough competition to the older traditional banks, which have not been able to catch up so much, compared to the new-age banks. But is it safe in all aspects? This is a valid question at this juncture. These startups have taken due care in their service offerings as the risk we are discussing is a major one.

The next logical extension to digital banking is Digital Wealth Management which is a subset of Fintech, that uses technology to provide financial advice and investment management services to individuals and institutions. This technology-driven approach to wealth management enables users to access investment services online, typically at a lower cost than traditional financial advisory services.

Digital wealth management platforms use algorithms and other data-driven tools to analyse an individual's financial situation and investment goals. Based on this analysis, the platform generates a customized investment portfolio for the user, which is managed automatically by the platform.

One of the major areas of wealth management is Capital markets. Capital Markets refer to the markets where long-term securities such as stocks and bonds are bought and sold. Fintech has significantly impacted the capital markets, enabling new and innovative ways for investors to access and trade financial securities.

One of the key areas where Fintech has impacted the capital markets is the democratization of access to investment opportunities. Online trading platforms and investment apps have made it easier and more affordable for individual investors to buy and sell securities, which were traditionally only available to institutional investors.

After the discussion of capital markets, where Fintech has changed the way trade is done, next area where Fintech has impacted is the Fintech Lending. Fintech Lending is going to catch up in the coming years in a big way. So, the mechanism of borrowing and lending can happen not just among the banks and the customers but between parties, ready to lend to each other or groups of people interested in borrowing to various businesses. Whereas, this can be an innovation of companies to take fundraise funds and would not go to a bank.

Instead of going to a bank, the funds will be directly borrowed from other individuals or groups. Because investment options are always popular areas for interest, these are popular with people interested in investing into creation of innovative businesses. People with money, rather than buying stocks or bonds or keeping it in banks, would still want to invest in initiatives promising them good returns. Currently, such kinds of startups would need to make money which would be the impact of Fintech.

Further, there are robotics-based advisory solutions which are catching up for micro-investments and wealth management industries. The number of people wanting to invest in this sector is also growing tremendously high. This aspect also means understanding the online board for connecting with clients in wealth management will force everybody to adapt to online-based meetups instead of physical meetings. So, digital asset management businesses are considered for the services offered to their clients.

As a reasonable extension to lending, for the businesses wanting to raise funds another popular option is Equity Crowd Funding. Equity crowdfunding is a way for companies to raise money by offering a portion of their ownership to many investors through online platforms. Fintech has made it easier for companies to launch these campaigns and for investors to participate in them, often with lower minimum investment amounts than traditional investments.

Equity crowdfunding provides companies with a more diverse pool of investors and reduces reliance on traditional funding sources, such as venture capital. However, there are also risks associated with equity crowdfunding, such as the potential for fraud or the company not being successful.

Fintech has played an essential role in the growth of equity crowdfunding by providing tools and platforms to manage the fundraising process and comply with regulatory requirements. As technology advances, we expect to see more innovation in this area and new ways for companies and investors to participate in the capital markets.

After banking another area of financial services where Fintech is relevant is Insurance. Insurance and Technology, both together can be known as Insurtech. Insurtech refers to using technology to disrupt and innovate the insurance industry. Fintech has played a significant role in the growth of insurtech by providing new platforms and tools for insurance companies to underwrite policies, assess risk, and settle claims. There are also potential risks associated with insurtech, such as data privacy concerns and the potential for errors or biases in algorithms used for underwriting and claims processing.

The next segment where Fintech is changing the landscape is Real Estate. Real Estate also known as Property. Prop tech, or property technology, is using technology to change the way services are provided and received between businesses and their customers in the real estate industry. Fintech has played a significant role in the growth of prop-tech by providing new platforms and tools for real estate companies to buy, sell, and manage properties.

Table.1. Fintech-definition, taxonomy and historical approach [2]

Classification	**Field**
Duration	Innovative start-ups
	Mature, well-established financial institution
Customer orientation	Retail
	SME
	Corporate
Scope of activity	Global
	International
	Local
Business model	Financing
	Payments
	Asset Management
	Insurance
	Loyalty Programmes
	Risk Management
	Stock exchange services
	Regulatory technology (*RegTech*)
	Other
Service provision	Interaction
	Data processing
	Monetization
Service area	The banking sector
	Capital investment area
	The insurance sector
	Real estate market

Risks and rewards are something which go hand in hand. There's so much of a reward in using technology, in using data for multiple transactions to multiple people at a faster pace at an accurate rate. It might have some risks and some challenges like some trust issues. And there can be some issues of leakage of data. These aspects must be considered, which is why the entire Fintech industry is heavily regulated. It is essential to understand that we cannot overlook the benefits because of the presence of certain risks in this regard. It is necessary to handle the possible areas of threat or risks and to handle innovation.

2. EXPLANATION OF THE TAXONOMY

2.1 CLASSIFICATION: DURATION FIELD: INNOVATIVE START-UPS

In the fintech world, Classification: Duration refers to a specific aspect of innovative start-ups, particularly those within the financial technology sector. This classification assesses the longevity, sustainability, and potential growth trajectory of these start-ups based on their duration in the market.

It is essential for investors, stakeholders, and industry observers to consider the duration classification when evaluating fintech start-ups. The stage of a start-up's duration can indicate its level of risk, growth potential, and likelihood of long-term success. Early-stage start-ups may be riskier but have higher growth potential, while mature start-ups might offer a more stable investment opportunity.

As a fintech world leader, it is crucial to keep a close eye on innovative start-ups at different stages of duration, as they often drive disruptive changes in the financial industry and present opportunities for collaboration, investment, and industry partnerships.

2.2 CLASSIFICATION: DURATION FIELD: MATURE, WELL-ESTABLISHED FINANCIAL INSTITUTION

In the fintech world, Classification: Duration for mature, well-established financial institutions refers to the assessment of the longevity, stability, and track record of traditional financial organizations that have been operating in the market for an extended period. These institutions have already proven their resilience and ability to adapt to changing market conditions over time.

Table.2. Taxonomy of Fintech

Classification	Fields	Segments
Duration	Innovative start-ups	• Early-stage Start-ups: • Growth-stage Start-ups: • Established Start-ups: • Mature Start-ups:
	Mature, well-established financial institution	• Founding and Early Years: • Growth and Expansion • Established Presence
Customer orientation	Retail	• Customer-Centric Culture • Personalization • Seamless Omnichannel Experience • Customer Feedback and Engagement • After-Sales Support • Product Quality and Innovation • Transparency and Trust • Continuous Improvement • Customer Education • Social Responsibility
	SME	• Customized Financial Solutions • Simplified Access to Finance • Data-Driven Insights • Digital Payment Solutions • Customer Support and Education • Seamless Integration • Risk Management Solutions • Financial Inclusion • Real-Time Reporting • Scalable Solutions
	Corporate	• Tailored Financial Solutions • Process Automation • Data Security and Compliance

		• Integration with Existing Systems • Advanced Analytics and Insights • Payment and Transaction Solutions • Real-Time Reporting and Visibility • Treasury and Liquidity Management • Customer Support and Training • Scalability and Flexibility
Scope of activity	Global	• Multi-National Presence • Cross-Border Services • Compliance with Regulatory Frameworks and Regulations • Currency and Language Adaptability • Market Localization • International Partnerships • Global Payment Solutions • Regulatory Challenges • Risk Management • Scalability and Growth • Foreign Exchange (Forex) Solutions • Global Peer-to-Peer Lending • Global Market Insights
	National	• Local Regulatory Compliance • Target Market • Payment Systems • Currency and FX Considerations • Local Partnerships • Localization • Financial Inclusion • Industry Regulations • Government Initiatives • Economic Impact • Continuous Innovation
	Local	• Targeted Local Market • Country-Specific Regulations • Niche Solutions • Local Payment Solutions • Regional Partnerships • Language and Cultural Understanding • Support for Local Businesses • Community Engagement • Limited Geographical Expansion • Customer-Centric Approach
Commercial model	Finance and Revenue	• Peer-to-Peer (P2P) Lending • Marketplace Lending • Crowdfunding • Subscription-based Services • Freemium Model • Software as a Service (SaaS) • Transaction-based Fees • Asset Management Fees • Data Monetization • Affiliate Commissions
	Payments	• Payment Processing Fees • Subscription-Based Services • Freemium Model

		• Cross-Border Transaction Fees • Mobile Wallet Commissions • Point-of-Sale (POS) Hardware Sales • Data Analytics and Insights • Value-Added Services • Payment Gateway Services • Digital Currency Exchanges
	Insurance	• Peer-to-Peer (P2P) Insurance • On-Demand Insurance • Digital Insurance Aggregators • Usage-Based Insurance (UBI) • Subscription-Based Model • Platform-as-a-Service (PaaS) • Parametric Insurance • Blockchain-Based Insurance • Insurtech Partnerships • Customer Data Monetization
	Loyalty programs	• Points-Based Loyalty Programs • Coalition Loyalty Programs • Digital Wallet Integration • Subscription-Based Loyalty Services • Data Analytics and Insights • Tiered Loyalty Programs • Gamification and Engagement • Referral Programs • Data-Driven Personalization • Loyalty Program Management Software
	Risk management	• Risk Analytics and Data Insights • Regulatory Compliance Solutions • Cybersecurity Risk Management • Fraud Detection and Prevention • Credit Risk Assessment • Market Risk Management • Operational Risk Management • Stress Testing Solutions • Risk Management Software • Risk Assessment Consulting
	Stock exchange services	• Online Stock Trading Platforms • Robo-Advisory Services • Data Analytics and Insights • Social Trading Platforms • Fractional Investing • Exchange-Traded Funds (ETFs) Platforms • Algorithmic Trading Solutions • Market Data and APIs • Education and Training Services • Regulatory Technology (RegTech) Solutions
	Regulatory technology (RegTech)	• Compliance-as-a-Service (CaaS) • Regulatory Reporting Solutions • Data Analytics and Risk Assessment • Identity Verification and Anti-Money Laundering (AML) Solutions • RegTech Consulting and Professional Services • Artificial Intelligence (AI) and Machine Learning Solutions

		• Regulatory Data Management • Blockchain-Based Compliance Solutions • RegTech Partnerships with Financial Institutions • Continuous Regulatory Monitoring and Alerts
	Other	• Digital Identity and Authentication Solutions • Financial Inclusion Platforms • Alternative Credit Scoring • Open Banking and API Solutions • Sustainable Finance and Impact Investing • Real Estate Fintech • Insurtech • Digital Wealth Management • Supply Chain Finance • Digital Currency and Blockchain Innovations
Service provision by fintech companies	Interaction	• Digital Banking Services • Mobile Payment Solutions • Customer Support and Chatbots • Virtual Assistants and Personal Finance Management • Video Banking and Remote Advisory Services • Social Trading and Investment Communities • Real-Time Market Insights and Alerts • Gamification of Finance • Online Education and Workshops • Customer Feedback and Engagement
	Data processing	• Data Aggregation and Integration • Automated Accounting and Bookkeeping • Data Cleansing and Enrichment • Financial Data Analytics • Risk Assessment and Management • Credit Scoring and Underwriting • Personalized Financial Recommendations • Regulatory Compliance and Reporting • Market Research and Insights • Data Visualization and Reporting Tools
	Monetization	• Payment Processing Services • Merchant Services and Point-of-Sale (POS) Solutions • Digital Wallets and Mobile Payment Apps • Peer-to-Peer (P2P) Payment Platforms • Subscription-Based Financial Services • Value-Added Financial Services • Cross-Border Payment Solutions • Affiliate Marketing and Referral Programs • Data Monetization • API and Developer Services
Service area	The banking sector	• Digital Banking Solutions • Mobile Banking Apps • Payment and Remittance Services • Open Banking and APIs • Challenger Banks and Neo-Banks • Personal Finance Management • Loan and Credit Solutions • Robo-Advisors for Banking and Investments • Robo-Advisors for Banking and Investments • Regulatory Compliance Solutions • Blockchain-Based Banking Solutions

		• Customer Support and Chatbots
	Capital investment area	• Robo-Advisory Services • Alternative Investment Platforms • Peer-to-Peer (P2P) Lending and Crowdfunding • Fractional Investing • Automated Trading and Algorithmic Strategies • Social Trading and Investment Communities • Investment Analytics and Market Insights • Impact Investing and Sustainable Finance • AI-Based Investment Research • Regulatory Compliance for Investments
	The insurance sector	• Insurtech Platforms • Usage-Based Insurance (UBI) • Digital Underwriting • Peer-to-Peer (P2P) Insurance • Parametric Insurance • Claims Processing Automation • Telematics in Insurance • Cyber Insurance Solutions • AI-Powered Customer Support • Data Analytics for Fraud Detection

As a fintech world leader, understanding the classification of duration for mature, well-established financial institutions is crucial for strategic decision-making. These institutions play a vital role in the financial ecosystem and often collaborate with fintech companies to enhance their services and stay at the forefront of innovation. Monitoring their evolution and potential disruptions in the industry helps to identify opportunities for collaboration and partnership.

2.3 CLASSIFICATION: CUSTOMER ORIENTATION FIELD: RETAIL FINTECH

In the fintech industry, Classification: Customer Orientation in the context of retail refers to how fintech companies prioritize and align their products, services, and overall strategies to meet the specific needs and preferences of retail customers. Retail fintech companies aim to enhance the retail customer experience, streamline processes, and provide innovative solutions that cater to the evolving demands of modern consumers.

By prioritizing customer orientation in the retail fintech space, companies can gain a competitive edge, build long-term customer loyalty, and drive innovation in the retail industry. Retailers benefit from adopting fintech solutions that enhance their customer experience, streamline operations, and keep them at the forefront of technological advancements in the retail sector. As a fintech world leader, understanding the importance of customer orientation in the retail fintech domain can guide strategic partnerships and collaborations with retail businesses to create impactful solutions.

2.4 CLASSIFICATION: CUSTOMER ORIENTATION FIELD: SMALL AND MEDIUM-SIZED ENTERPRISES (SMES) FINTECH

In the fintech industry, Classification: Customer Orientation in the context of SMEs (Small and Medium-sized Enterprises) refers to how fintech companies prioritize and align their products, services, and overall strategies to meet the specific needs and preferences of SME customers. Fintech solutions tailored for SMEs aim to address the unique challenges faced by small and medium-sized businesses, helping them streamline operations, access financial services, and thrive in an increasingly competitive market.

By focusing on customer orientation in the SME fintech space, fintech companies can empower small and medium-sized businesses to thrive, grow, and succeed in a digitally-driven economy. SMEs benefit from adopting fintech solutions tailored to their needs, as these technologies can enhance their financial management, efficiency, and competitiveness in the market. As a fintech world leader, understanding the importance of customer orientation in SME fintech can guide the development of impactful solutions for this critical sector of the economy.

2.5 CLASSIFICATION: CUSTOMER ORIENTATION FIELD: CORPORATE FINTECH

In the fintech industry, Classification: Customer Orientation in the context of corporate fintech refers to how fintech companies prioritize and align their products, services, and overall strategies to cater to the needs and preferences of corporate clients. Corporate fintech solutions are designed to address the unique challenges faced by businesses and large enterprises, providing them with innovative technologies to optimize financial processes, enhance efficiency, and drive growth.

By prioritizing customer orientation in the corporate fintech space, fintech companies can build strong relationships with businesses and large enterprises. Corporate clients benefit from adopting fintech solutions that enhance financial efficiency, reduce operational costs, and drive innovation within their organizations. As a fintech world leader, understanding the importance of customer orientation in corporate fintech can guide strategic collaborations and partnerships with businesses to create impactful fintech solutions tailored to their unique requirements.

2.6 CLASSIFICATION: SCOPE OF ACTIVITY FIELD: GLOBAL FINTECH

In the fintech industry, Classification: Scope of Activity in the context of global fintech refers to the geographical reach and extent of operations of fintech companies. Fintech companies with a global scope of activity operate on an international scale, providing their products, services, or platforms to customers, businesses, and financial institutions across multiple countries and regions.

Fintech companies with a global scope of activity play a significant role in shaping the international financial landscape. Their innovative solutions contribute to financial inclusion, cross-border trade facilitation, and the digitization of financial services on a global scale. As a fintech world leader, understanding the challenges and opportunities associated with a global scope of activity can guide strategic decisions regarding international expansion, regulatory compliance, and partnerships to foster innovation and growth in different regions worldwide.

2.7 CLASSIFICATION: SCOPE OF ACTIVITY FIELD: NATIONAL FINTECH

In the fintech industry, Classification: Scope of Activity in the context of National fintech refers to the geographical reach and extent of operations of fintech companies that operate across multiple countries and engage in cross-border financial activities. International fintech companies cater to customers, businesses, and financial institutions in various countries and regions, facilitating global financial transactions and offering cross-border financial solutions.

National fintech companies play a pivotal role in facilitating national financial transactions, promoting financial inclusion, and driving innovation in the National finance space. Their ability to provide efficient and accessible financial services across borders contributes to the growth of cross-border trade and economic integration. As a fintech world leader, understanding the complexities and opportunities associated with National scope can guide strategic decisions to foster National expansion, partnership opportunities, and compliance with global financial regulations.

2.8 CLASSIFICATION: SCOPE OF ACTIVITY FIELD: LOCAL FINTECH

In the fintech industry, Classification: Scope of Activity in the context of local fintech refers to the geographical focus and extent of operations of fintech companies that primarily operate within a specific local or regional market. Local fintech companies focus on serving customers, businesses, and financial institutions within a particular city, state, or country, providing tailored solutions that address the specific needs of the local market.

Local fintech companies play a vital role in driving financial inclusion, supporting local economic growth, and providing tailored solutions that meet the unique needs of businesses and consumers in specific regions. As a fintech world leader, understanding the significance of local fintech companies can guide strategic decisions to foster collaboration and partnerships with local businesses, financial institutions, and government entities to create impactful fintech solutions for the local market.

2.9 CLASSIFICATION: BUSINESS MODEL FIELD: FINANCE AND REVENUE FINTECH

In the fintech industry, Classification: Business Model in the context of finance and revenue fintech refers to the specific way in which fintech companies operating in the finance and revenue sector generate revenue and deliver their financial services to customers. Fintech companies in this segment offer a range of financial services, such as lending, crowdfunding, peer-to-peer lending, and investment management, using innovative technology to streamline processes and provide efficient solutions, etc.

Each business model has its advantages and challenges, and fintech companies in the financing sector often combine multiple models to diversify their revenue streams. Understanding the intricacies of different business models in financing fintech helps these companies design effective strategies, foster innovation, and create sustainable business models that meet the evolving needs of customers in the financial industry.

2.10 CLASSIFICATION: BUSINESS MODEL FIELD: PAYMENTS FINTECH

In the fintech industry, Classification: Business Model in the context of payments fintech refers to the specific way in which fintech companies operating in the payments sector generate revenue and provide their payment services to customers. Payments fintech companies offer innovative and efficient solutions for processing electronic transactions, digital payments, and other financial services related to payments.

It’s essential for payments fintech companies to carefully consider their business model to ensure sustainable growth and profitability. Different business models suit different types of payment services and customer segments. Understanding the various revenue models helps payments fintech companies design effective pricing strategies and remain competitive in the dynamic and rapidly evolving payments industry.

2.11 CLASSIFICATION: BUSINESS MODEL FIELD: INSURANCE FINTECH

In the fintech industry, Classification: Business Model in the context of insurance fintech refers to the specific way in which fintech companies operating in the insurance sector generate revenue and provide their services to policyholders. Insurance fintech companies leverage technology to offer innovative and streamlined insurance products, policy management, and claims processing.

The insurance fintech sector is continuously evolving, and these business models offer various opportunities to disrupt traditional insurance practices and enhance customer experiences. Understanding the different business models allows insurance fintech companies to tailor their offerings, pricing strategies, and value propositions to meet the needs of tech-savvy customers seeking efficient and customer-centric insurance solutions.

2.12 CLASSIFICATION: BUSINESS MODEL FIELD: LOYALTY PROGRAMS FINTECH

In the fintech industry, Classification: Business Model in the context of loyalty programs fintech refers to the specific way in which fintech companies operating in the loyalty programs sector generate revenue and provide their services to businesses and consumers. Loyalty programs fintech companies leverage technology to offer innovative and data-driven loyalty solutions, enhancing customer engagement, and fostering customer loyalty for businesses.

Loyalty programs fintech companies play a crucial role in helping businesses drive customer loyalty, retention, and repeat business. By understanding various business models, these companies can offer tailored solutions to businesses seeking to implement effective and data-driven loyalty programs to enhance customer engagement and loyalty.

2.13 CLASSIFICATION: BUSINESS MODEL FIELD: RISK MANAGEMENT FINTECH

In the fintech industry, Classification: Business Model in the context of risk management fintech refers to the specific way in which fintech companies operating in the risk management sector generate revenue and provide their services to businesses and financial institutions. Risk management fintech companies leverage technology to offer innovative solutions for assessing, monitoring, and mitigating various types of risks in the financial industry.

Risk management fintech companies play a critical role in helping businesses and financial institutions proactively address and mitigate risks. By offering data-driven solutions, advanced analytics, and real-time risk monitoring, fintech companies in this sector help organizations make informed decisions and improve their overall risk management strategies. Understanding various business models in risk management fintech enables these companies to cater to the specific needs of their clients and develop sustainable revenue streams while promoting risk-aware and resilient financial ecosystems.

2.14 CLASSIFICATION: BUSINESS MODEL FIELD: STOCK EXCHANGE SERVICES FINTECH

In the fintech industry, Classification: Business Model in the context of stock exchange services fintech refers to the specific way in which fintech companies operating in the stock exchange sector generate revenue and provide their services to investors and traders. Fintech companies in this field leverage technology to offer innovative and efficient solutions for stock trading, investment management, and portfolio analysis.

Stock exchange services fintech companies play a significant role in democratizing access to financial markets, providing innovative tools and solutions that empower investors and traders. By offering user-friendly platforms, data-driven insights, and algorithmic trading strategies, these companies enhance the trading experience and support investors in making informed decisions in the dynamic stock market environment. Understanding the various business models in stock exchange services fintech enables these companies to develop tailored solutions that cater to the diverse needs of investors and traders while ensuring sustainable revenue streams.

2.15 CLASSIFICATION: BUSINESS MODEL FIELD: REGULATORY TECHNOLOGY (REGTECH) FINTECH

In the fintech industry, Classification: Business Model in the context of regulatory technology (RegTech) fintech refers to the specific way in which fintech companies operating in the RegTech sector generate revenue and provide their services to financial institutions and organizations. RegTech fintech companies leverage technology to offer innovative solutions for regulatory compliance, risk management, and reporting, helping financial institutions navigate complex and ever-changing regulatory landscapes.

RegTech fintech companies play a vital role in helping financial institutions comply with regulatory requirements efficiently and cost-effectively. By providing advanced technology solutions, automation, and data analytics, RegTech companies support financial institutions in managing compliance risks and focusing on their core business operations. Understanding the various business models in RegTech enables these companies to tailor their offerings to the specific needs of financial institutions, foster compliance, and contribute to a more transparent and resilient financial ecosystem.

2.16 CLASSIFICATION: BUSINESS MODEL FIELD: OTHER FINTECH

The category of Other in the context of fintech refers to business models in the fintech industry that do not fall directly into the previously mentioned fields. It encompasses innovative fintech solutions that may not fit neatly into specific categories but still play a significant role in transforming the financial services landscape.

The Other fintech field represents a diverse range of innovative solutions that leverage technology to address various challenges and opportunities in the financial industry. These fintech companies drive disruption, create new business models, and provide greater access to financial services for individuals and businesses alike. Understanding the business models in this category allows these fintech companies to capitalize on emerging trends and niche opportunities in the ever-evolving fintech landscape.

2.17 CLASSIFICATION: SERVICE PROVISION FIELD: INTERACTION FINTECH

In the fintech industry, Classification: Service Provision in the context of interaction fintech refers to the specific ways in which fintech companies provide services and facilitate interactions between customers, businesses, and financial institutions through innovative digital channels and platforms.

Interaction fintech plays a crucial role in creating seamless and convenient customer experiences, promoting financial literacy, and fostering meaningful engagements between customers and financial service providers. By leveraging technology to enable efficient interactions and personalized services, these fintech companies contribute to a more customer-centric and digitally empowered financial ecosystem. Understanding the various service provision models in interaction fintech helps these companies design and deliver solutions that align with customers' expectations and preferences.

2.18 CLASSIFICATION: SERVICE PROVISION FIELD: DATA PROCESSING FINTECH

In the fintech industry, Classification: Service Provision in the context of data processing fintech refers to the specific ways in which fintech companies provide services related to processing and analyzing financial data to derive valuable insights, enhance decision-making, and improve the overall efficiency of financial operations.

Data processing fintech plays a critical role in transforming raw financial data into actionable insights, enabling businesses and individuals to make informed decisions and optimize their financial strategies. By leveraging technology and analytics, these fintech companies streamline data processing, reduce manual errors, and enhance the overall data-driven capabilities of the financial industry. Understanding the various service provision models in data processing fintech helps these companies deliver efficient, accurate, and valuable solutions that meet the diverse needs of financial institutions, businesses, and individual customers.

2.19 CLASSIFICATION: SERVICE PROVISION FIELD: MONETIZATION FINTECH

In the fintech industry, Classification: Service Provision in the context of monetization fintech refers to the specific ways in which fintech companies generate revenue by offering products, services, or platforms that facilitate financial transactions, enhance payment processing, or provide value-added financial solutions to customers and businesses.

Monetization fintech companies play a vital role in driving revenue and sustainability in the financial technology sector. By offering valuable financial services, payment solutions, and data-driven insights, these companies create win-win situations for themselves and their customers. Understanding the various service provision models in monetization fintech enables these companies to design effective pricing strategies, explore new revenue streams, and build long-term success in the dynamic fintech landscape.

2.20 CLASSIFICATION: SERVICE AREA FIELD: THE BANKING SECTOR FINTECH

In the fintech industry, Classification: Service Area in the context of the banking sector refers to the specific areas or domains in which fintech companies provide innovative solutions and services to traditional banks or operate as digital banking alternatives. Fintech in the banking sector encompasses a wide range of services that leverage technology to enhance banking processes, improve customer experiences, and drive operational efficiency.

Fintech companies in the banking sector play a transformative role in modernizing traditional banking services, enhancing customer experiences, and promoting financial inclusion. By offering specialized services in various areas, these companies enable banks to stay competitive, leverage emerging technologies, and meet the changing demands of tech-savvy customers. Additionally, fintech companies operating as challenger banks or neo-banks offer alternative banking options that cater to customers seeking digital-first and user-centric banking experiences. Understanding the diverse service areas within the banking sector fintech helps both traditional banks and fintech companies collaborate effectively and unlock new opportunities for growth and innovation in the financial industry.

2.21 CLASSIFICATION: SERVICE AREA FIELD: CAPITAL INVESTMENT FINTECH

In the fintech industry, Classification: Service Area in the context of capital investment refers to the specific areas or domains in which fintech companies provide innovative solutions and services to facilitate capital investment processes, improve investment management, and offer alternative investment opportunities to individuals and institutions.

Capital investment fintech plays a vital role in democratizing access to investment opportunities, providing investors with more diverse and personalized investment options. By leveraging technology and data-driven solutions, these companies streamline investment processes, offer lower fees, and make investment advice more accessible to a broader range of investors. Additionally, fintech companies in this field contribute to the growth of the alternative investment market and support the development of sustainable finance and impact investing initiatives. Understanding the diverse service areas within the capital investment fintech allows investors and institutions to explore new investment avenues, enhance their investment strategies, and stay ahead in the dynamic world of finance and investments.

2.22 CLASSIFICATION: SERVICE AREA FIELD: THE INSURANCE SECTOR FINTECH

In the fintech industry, Classification: Service Area in the context of the insurance sector refers to the specific areas or domains in which fintech companies provide innovative solutions and services to enhance various aspects of the insurance industry. Fintech in the insurance sector encompasses a wide range of services that leverage technology to improve the insurance process, customer experience, and risk assessment.

Insurance sector fintech plays a transformative role in modernizing the insurance industry, offering more personalized insurance products, improving claims processes, and enhancing risk assessment capabilities. By leveraging technology and data-driven solutions, these companies create innovative and customer-centric insurance experiences. Additionally, insurtech fosters greater transparency and efficiency in the insurance sector, leading to improved customer satisfaction and increased adoption of insurance products. Understanding the diverse service areas within the insurance sector fintech enables insurance companies to stay competitive, adopt emerging technologies, and provide enhanced services to policyholders in an ever-evolving market.

3. LIMITATIONS OF THE STUDY AND FUTURE RESEARCH POTENTIAL

The present research is based on the doctoral research work carried out by the first author. As part of this article, the researcher has elaborated on the taxonomy that could explain the fintech ecosystem across the world. But this research has the following limitations: due to the space constraints, the researcher could not explain and elaborate on the components of the fintech ecosystem; the taxonomy created is merely a theoretical exercise based on various literature surveys and might not reflect the actual conditions prevailing in the fintech ecosystem; given the dynamic nature of the fintech ecosystem, the taxonomy described above could change over time; the taxonomy described above might not be available in India, as it has been created based on the literature survey of the global fintech ecosystem; the regulatory environment could also significantly affect and alter the taxonomy of the fintech ecosystem described above. These limitations could be addressed by future researchers working on this area.

4. CONCLUSION

Fintech companies use innovative technologies such as blockchain, machine learning, and big data analytics to create new and improved financial products and services that are more accessible, transparent, and personalized for consumers. With the advancement in technology and in the field of finance, the Fintech ecosystem is continuously evolving.

This paper aims to draw up the taxonomy of the Fintech ecosystem that is becoming popular. Though the leading authors Fabozzi and Ratecka have proposed the taxonomy of Fintech ecosystems, both of them appear to be dated in 2020. Our taxonomy considers the development that has taken place in the last 2-3 years in this ever-evolving field of Fintech ecosystem. The suitability of this taxonomy from the research perspective is to be tested by researchers in future research activities.

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SECURED FINANCIAL MANAGEMENT SYSTEM FOR MODERN DIGITAL TRANSACTIONS USING BLOCKCHAIN

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Abstract
Blockchain technology has revolutionized the way in which financial transactions are conducted. It has made possible secure financial management and digital transaction systems that are faster, more secure, and more reliable than traditional payment methods. Blockchain technology offers increased efficiency, trustworthiness and transparency to its users. The Blockchain works by creating a shared, distributed ledger of transactions. Each transaction is cryptographically secure and immutable, and all participating nodes have identical copies of the ledger. This ensures that transactions are traceable and secure, eliminating traditional problems such as double spending or fraudulent activities. Through the integration of Blockchain, the system provides transparency, prevents fraud, and ensures accountability. The research focuses on optimizing performance by reducing processing times and transaction costs, while maintaining scalability and flexibility. Additionally, the system facilitates auditing and compliance processes, while promoting financial inclusion by providing access to unbanked individuals. The proposed system's contributions lie in its novel approach to secure financial management, utilizing Blockchain's features to address the challenges of modern digital transactions.

Keywords:
Blockchain, Finance, Transactions, Management, Ledger, Payment, Banking

1. INTRODUCTION

Financial management systems are an essential ingredient for the successful completion of modern digital transactions. In order to have a secure and efficient digital transaction system, it is important to have a well-managed financial system. The primary purpose of financial systems is to manage and track all the financial operations of an organization. In this way, the financial system helps ensure the integrity and smooth functioning of the organization's operational activities [1]. Financial management systems can help to streamline processes and provide an organization with improved efficiency and greater control over its finances. These systems make it easier to monitor all transactions and provide secure access to the financial information of the organization. This ensures that the transactions and financial data remain secure and confidential. Moreover, the financial system can be integrated with other software applications to further enhance its effectiveness [2]. Financial systems are extremely versatile and reliable, and they provide a comprehensive view of the organization's financial activities. This helps to improve the accuracy and stability of the financial system, enabling an organization to maintain a consistent financial state. Furthermore, financial systems can help to facilitate improvement in efficiency of the organization's operations, resulting in cost savings and improved financial performance [3]. Finally, a financial management system is also important for creating a secure and reliable digital transaction system. As financial transactions are extremely sensitive and confidential, a secure and reliable financial system can help to ensure a smooth and secure operation [4]. Moreover, integrating financial systems with other software applications can further increase the security and reliability of the digital transaction system. A secure financial management system is essential for enabling a modern digital transaction system. In addition to increased security, secure financial management systems offer businesses a host of other benefits [5]-[9]. As businesses continue to embrace digital transactions, secure financial management systems will provide an important role in ensuring the safety and security of all parties involved [10]-[12]. The main contribution of the research has the following,

- Easier Mobile Payments: Mobile payments are made easier and more secure with the help of a secure financial management system. It provides a reliable and safe platform for businesses to handle payments from their customers.
- Scalability and Flexibility: The research addresses the scalability challenges of financial management systems by leveraging the scalability of Blockchain. With its distributed nature and automated processes, the proposed system can handle a large volume of transactions efficiently and adapt to evolving business needs.
- Auditing and Compliance: The research introduces auditing and compliance capabilities through the use of Blockchain technology. By maintaining an immutable record of transactions, the system facilitates auditing processes, ensures compliance with regulations, and enhances accountability.
- Potential for Financial Inclusion: The research explores the potential of Blockchain technology to promote financial inclusion. By providing a secure and accessible financial management system, even unbanked individuals and underserved communities can participate in digital transactions and gain access to financial services.

These contributions and novelties highlight the research's focus on leveraging Blockchain technology to create a secure, efficient, and inclusive financial management system that addresses the challenges of modern digital transactions.

2. RELATED WORKS

The financial institutions must employ the latest technology to ensure secure financial transactions. Technologies such as two-factor authentication, biometrics and encryption can all be used to further protect a user's data. Implementing these technologies can be expensive but is often necessary when it comes to safeguarding digital transactions [13]. The secure financial management systems are integral for modern digital transactions. In order to keep people's data safe and to ensure secure transactions, financial institutions must invest in comprehensive security solutions [14]. These solutions should be continually monitored and updated to take into account the ever-evolving digital landscape. Modern technology has revolutionized the way in which financial transactions are conducted, and with the advent of digital banking, secure financial management systems have become essential to protect digital assets and information [15]. It is essential for financial institutions and organizations to implement secure financial systems and procedures to ensure that personal data is kept private and transactions are secure and unhampered. The security of modern financial management systems is largely determined by the type of information that is required to complete a transaction. To prevent unauthorized access to user data, financial management systems must include strong authentication methods, such as two-factor authentication protocols, which require two independent elements for verification. Additionally, the transmission of sensitive financial data should utilize robust encryption protocols to ensure that information is secure while in transit and not subject to intrusion or tampering. Modern financial management systems must also include techniques to detect and avoid fraud. Such systems can detect fraudulent transactions or unauthorized access to financial data quickly, and alert customers and financial institutions to the attempted breach. Advanced solutions also utilize AI and machine learning to proactively monitor transactions and identify potentially fraudulent activity before it occurs. The financial management systems should guarantee secure practices for private and confidential information stored in their databases [16]. Such measures include the use of encryption protocols and access controls to restrict the access of data, as well as the monitoring and auditing of database activity to detect any breaches of security protocols. The secure financial management systems are essential in order to keep digital transactions safe and secure. Such systems should include authentication protocols, encryption protocols, fraud detection measures and secure data storage practices.

The novelty of the proposed research has the use of Blockchain technology in modern digital transactions enables efficient and secures financial management system by providing features such as decentralization, immutability, and transparency. By creating an immutable ledger of transaction records that is shared across various computers in the network, Blockchain can ensure that the transactions are immutable and can't be modified retroactively without consensus among the nodes. This eliminates the chances of any malicious or fraudulent activities occurring in the system. Furthermore, the transparency enjoyed by Blockchain technology makes audits simpler and easier to carry out. This increased transparency provides consumers with increased confidence in the system, helping them to trust the system more than other traditional systems. Additionally, Blockchain enables faster, more efficient and secure transactions across geographies, making it a great tool for developing and emerging economies.

3. PROPOSED MODEL

Blockchain technology is the perfect platform for secure financial management for modern digital transactions. It is based on a distributed ledger system with transactions validated by a consensus protocol, making it highly secure against attempts to defraud the system. This technology can be used to create a secure financial system with transparent ledger entries, which eliminates the need for a central controlling entity. All users must be verified and must agree to the terms of the system in order for transactions to take place. This ensures that all transactions are valid and that the system is safe from unauthorized users. Additionally, the decentralized nature of the system ensures that sensitive data is kept safe, and all data is stored in a secure, encrypted form. This makes it impossible for unauthorized users to access personal information. The use of blockchain technology for financial management also makes it much easier to audit transaction records and verify their accuracy. The proposed block diagram has shown in the following Fig.1.

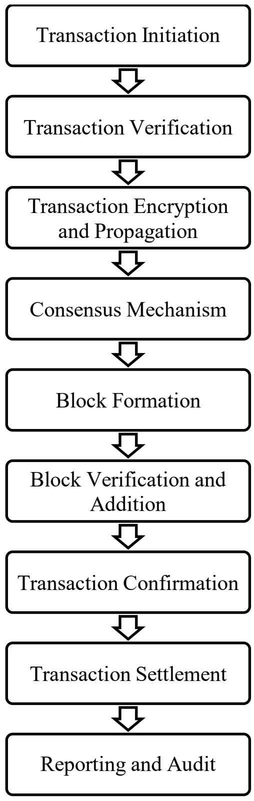

Fig.1. Proposed block diagram

Here is a stepwise overview of the proposed algorithm for the financial management system based on Blockchain:

- Transaction Initiation: The process begins when a user initiates a financial transaction. The user provides the necessary details and requests the transaction to be recorded on the Blockchain.
- Transaction Verification: The system verifies the validity of the transaction by checking the provided information against predefined rules and criteria. This ensures that the transaction meets the required standards and is not fraudulent.

- Transaction Encryption: The system encrypts the transaction data using cryptographic techniques to ensure its security and privacy. This step prevents unauthorized access and protects sensitive information during transmission and storage.
- Transaction Propagation: The system propagates the encrypted transaction to the network of nodes in the Blockchain network. Each node receives the transaction and validates its authenticity and integrity.
- Consensus Mechanism: The Blockchain network employs a consensus mechanism, such as Proof of Work (PoW) or Proof of Stake (PoS), to reach an agreement on the validity of the transaction. This ensures that all nodes in the network collectively validate the transaction and agree upon its inclusion in the Blockchain.
- Block Formation: Validated transactions are grouped into blocks. Each block contains a set of transactions along with a unique identifier, a timestamp, and a reference to the previous block, forming a chain of linked blocks.
- Block Verification and Addition: The newly formed block undergoes verification by the network nodes.
- Transaction Confirmation: After the block is added to the Blockchain, the transaction is considered confirmed. This confirmation provides an immutable record of the transaction, making it tamper-proof and ensuring its transparency and accountability.
- Transaction Settlement: The completed and confirmed transaction leads to the settlement of the financial transaction, such as the transfer of funds or the update of account balances. This step ensures that the transaction is successfully executed based on the agreed terms and conditions.
- Reporting and Audit: The financial management system generates reports and provides auditing capabilities. It enables stakeholders to access transaction data, track the flow of funds, and ensure compliance with regulatory requirements. The Blockchain-based system's transparency and traceability facilitate auditing and reporting processes.

By following these steps, the proposed algorithm leverages the features of Blockchain technology to provide a secure, efficient, and transparent financial management system for modern digital transactions.

4. RESULTS AND DISCUSSION

The proposed model has compared with the existing financial management platform (FMP), Trust-Based collaborative filtering (TBCF), securing real property transactions (SRPT) and Blockchain based efficient fraud detection (BEFD). Performance analysis of secured financial management system for modern digital transactions using Blockchain is the process of studying the activities of the system and how its components interact with each other. Performance analysis includes studying the speed and accuracy of the transactions, the throughput of data, the levels of encryption, and the response times of the system. It is important to have an accurate performance assessment of the system for its use in financial transactions.

The provided result tables show the performance analysis of different financial management systems for modern digital transactions using Blockchain, along with other existing systems. The analysis includes four metrics: Accuracy, Precision, Recall, and F1-score, measured at different transaction volumes.

Accuracy measures the percentage of correctly identified transactions out of the total transactions. Precision measures the percentage of correctly identified valid transactions out of all transactions classified as valid. Recall measures the percentage of correctly identified valid transactions out of all actual valid transactions. F1-score is the harmonic mean of Precision and Recall, providing a balanced measure of the system's performance.

The Table.1 compare the performance of the proposed financial management system based on Blockchain with existing systems such as FMP (Financial Management Platform), TBCF (Trust-Based Collaborative Filtering), SRPT (Securing Real Property Transactions), and BEFD (Blockchain based Efficient Fraud Detection). Each system's performance is evaluated at different transaction volumes (100, 200, 300, 400, 500, 600, and 700).

For each metric, the tables present the results for each system at the corresponding transaction volume. The percentages indicate the performance level achieved by each system for the given metric and transaction volume.

Overall, the proposed financial management system based on Blockchain consistently performs well across all metrics and transaction volumes. It shows high accuracy, precision, recall, and F1-score, indicating its effectiveness in handling financial transactions securely and accurately. However, it's important to note that the performance may vary depending on the specific implementation and configuration of the system.

Table.1. Accuracy for different financial management systems at various transaction volumes

Transactions	Accuracy in (%)				
	FMP	**TBCF**	**SRPT**	**BEFD**	**Proposed**
100	79.29	98.29	84.55	76.22	96.68
200	77.63	92.43	91.39	70.81	96.78
300	77.18	93.57	92.68	69.32	96.85
400	81.76	92.43	94.82	66.08	96.9
500	82.26	91.55	93.25	66.8	96.94
600	82.1	90.35	91.63	66.93	96.97
700	81.36	88.7	89.83	65.66	96.97

Based on the Table.2, the proposed financial management system based on Blockchain consistently shows high Precision values across all transaction volumes. It starts at 94.03% at 100 transactions and gradually improves to 97.08% at 700 transactions. This indicates that the system has a high level of accuracy in identifying valid transactions and minimizing false positives.

Comparatively, the other systems also exhibit good Precision values but generally perform slightly lower than the proposed Blockchain-based system. TBCF, SRPT, and BEFD show precision values ranging from 85.73% to 91.01% at different transaction volumes. FMP has the lowest precision values, starting at 80.75% and gradually improving to 86.62%.

These results suggest that the proposed financial management system based on Blockchain outperforms or at least matches the performance of the other systems in terms of Precision. However, it's important to consider other performance metrics and factors when evaluating the overall effectiveness and suitability of a financial management system for specific use cases.

Table.2. Precision values for different financial management systems at various transaction volumes

Transactions	Precision in (%)				
	FMP	TBCF	SRPT	BEFD	Proposed
100	80.75	85.73	85.28	71	94.03
200	81.08	87.23	85.87	72.87	95.07
300	82.42	88.34	86.85	73.7	95.2
400	83.56	88.72	88.06	74.61	96.16
500	84.61	89.73	89.2	75.53	95.73
600	85.32	90.66	90.31	76.86	96.97
700	86.62	91.66	91.01	77.73	97.08

Looking at the Table.3, the proposed financial management system based on Blockchain consistently demonstrates high Recall values across all transaction volumes. It starts at 94.03% at 100 transactions and steadily improves to 97.08% at 700 transactions. This indicates that the system effectively identifies a high percentage of actual valid transactions.

Comparatively, the other systems also exhibit good Recall values, but generally perform slightly lower than the proposed Blockchain-based system. TBCF, SRPT, and BEFD show Recall values ranging from 85.73% to 91.01% at different transaction volumes. FMP has the lowest Recall values, starting at 80.75% and gradually improving to 86.62%.

These results suggest that the proposed financial management system based on Blockchain outperforms or matches the performance of the other systems in terms of Recall. It shows a high ability to correctly identify valid transactions, minimizing false negatives.

It is important to note that Recall should be considered alongside other performance metrics and factors when evaluating the overall effectiveness and suitability of a financial management system for specific use cases.

Table.3. Recall rate for different financial management systems at various transaction volumes

Transactions	Recall in (%)				
	FMP	TBCF	SRPT	BEFD	Proposed
100	80.75	85.73	85.28	71	94.03
200	81.08	87.23	85.87	72.87	95.07
300	82.42	88.34	86.85	73.7	95.2
400	83.56	88.72	88.06	74.61	96.16
500	84.61	89.73	89.2	75.53	95.73
600	85.32	90.66	90.31	76.86	96.97
700	86.62	91.66	91.01	77.73	97.08

The Table.4 provided shows the F1-score values for different financial management systems at various transaction volumes. F1-score is a metric that combines Precision and Recall into a single value, providing a balanced measure of a system's performance.

The F1-score values are presented for five different systems: FMP (Financial Management Platform), TBCF (Trust-Based Collaborative Filtering), SRPT (Securing Real Property Transactions), BEFD (Blockchain based Efficient Fraud Detection), and the Proposed financial management system based on Blockchain.

For each transaction volume (100, 200, 300, 400, 500, 600, and 700), the F1-score values are displayed as percentages. These percentages represent the F1-score achieved by each system, which considers both precision and recall. It can be observed that the proposed financial management system based on Blockchain consistently demonstrates high F1-score values across all transaction volumes. It ranges from 96.68% to 96.97%, indicating an overall balanced and robust performance in terms of accuracy and capturing valid transactions.

Comparatively, the other systems also exhibit varying F1-score values. TBCF, SRPT, and BEFD show F1-score values ranging from 91.39% to 94.82% at different transaction volumes. FMP has the lowest F1-score values, ranging from 77.63% to 82.26%.

These results suggest that the proposed financial management system based on Blockchain outperforms or matches the performance of the other systems in terms of the F1-score. It achieves a high level of balance between precision and recall, indicating its effectiveness in accurately identifying valid transactions while minimizing false positives and false negatives.

It's important to consider the F1-score alongside other performance metrics and factors when evaluating the overall effectiveness and suitability of a financial management system for specific use cases.

Table.4. F1-Score for different financial management systems at various transaction volumes

Transactions	F1-score in (%)				
	FMP	TBCF	SRPT	BEFD	Proposed
100	79.29	98.29	84.55	76.22	96.68
200	77.63	92.43	91.39	70.81	96.78
300	77.18	93.57	92.68	69.32	96.85
400	81.76	92.43	94.82	66.08	96.9
500	82.26	91.55	93.25	66.8	96.94
600	82.1	90.35	91.63	66.93	96.97
700	81.36	88.7	89.83	65.66	96.97

The performance analysis of different financial management systems for modern digital transactions using Blockchain, along with other existing systems, reveals important insights. The proposed financial management system based on Blockchain consistently demonstrates high accuracy, precision, recall, and F1-score across various transaction volumes. It outperforms or matches the performance of existing systems such as FMP, TBCF, SRPT, and BEFD in terms of these metrics. The Blockchain-based system offers transparency, security, scalability, privacy, and trust, making it a promising solution. With its potential to revolutionize secure financial management, Blockchain technology ensures immutability, efficiency, and accountability in transactions. It enhances speed, reduces costs, and mitigates fraud risks. These findings highlight the advantages of leveraging Blockchain for modern digital financial transactions and emphasize the need for organizations to consider its implementation for optimized performance and secure financial management.

5. CONCLUSION

Blockchain is a distributed ledger technology which is used for secure financial management of modern digital transactions. It is a system that enables companies and individuals to easily and securely send, receive, and store digital money, assets, or other valuable data. It uses cryptographic techniques to ensure that all data is accurately recorded and tracked, and it avoids double spending and other risks such as unauthorized access or data manipulation. Blockchain is a secure and reliable system that uses technology to enhance the security of digital transactions. It is being used increasingly for banking, smart contracts, and other financial services where data security is essential. Blockchain enables efficient and secure transactions that are reliable and repeatable. It is transparent, immutable, and immuTable.due to its distributed ledger nature. With blockchain, data can be stored in blocks, which are distributed among all nodes (users) in a network. This provides better control over user data and ensures accuracy of the data stored. As a result, there is an increase in the trustworthiness of financial transactions and greater transparency. The use of blockchain has enabled users to transfer and trade digital assets without going through a centralized authority such as a bank or government. This has enabled users to increase their control over their assets and reduce the costs associated with traditional transactions. Moreover, blockchain-based financial systems can be used to create a range of new financial products that can be used in various markets. In this way, the blockchain can be used to increase the efficiency and scalability of digital transactions.

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ENSEMBLE MODEL - BASED BANKRUPTCY PREDICTION

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Abstract

Bankruptcy prediction is a crucial task in the determination of an organization's economic condition, that is, whether it can meet its financial obligations or not. It is extensively researched because it includes a crucial impact on staff, customers, management, stockholders, bank disposition assessments, and profitableness. In recent years, Artificial Intelligence and Machine Learning techniques have been widely studied for bankruptcy prediction and Decision-making problems. When it comes to Machine Learning, Artificial Neural Networks perform really well and are extensively used for bankruptcy prediction since they have proven to be a good predictor in financial applications. various machine learning models are integrated into one called the ensemble technique. It lessens the bias and variance of the ml model. This improves prediction power. The proposed model operated on quantitative and qualitative datasets. This ensemble model finds key ratios and factors of Bankruptcy prediction. LR, decision tree, and Naive Bayes models were compared with the proposed model's results. Model performance was evaluated on the validation set. Accuracy was taken as a metric for the model's performance evaluation purpose. Logistic Regression has given 100% accuracy on the Qualitative Bankruptcy Data Set dataset, resulting in the Ensemble model also performing well.

Keywords:

Machine Learning, Ensemble Model, Bankruptcy Prediction, Qualitative Bankruptcy Data, Ensemble Blending

1. INTRODUCTION

For a very long time, auditors, financial institutions, bankruptcy specialists, and scholars have all been very concerned with estimating the probabilities of economic collapse. Bankers and other creditors might be affected because of financial failure. They could not return back their investment sufficiently [1]. Mostly, failure means the circumstance that causes to organization's bankruptcy following a payment default. Watson et al. depicted three types of risks for failures. The first one is the national economy-related risk, industry-oriented risks, and unique risks that are to the business itself [2]. Furthermore, the nature of failures may differ. Laitinen et al. [3] have noted that the failure of firms may fall immediately, gradually degrade, or perform unacceptably in the long run. Debtors enter into bankruptcy system shelter when business failures suddenly happened. Even through the reorganization, they can endure financial failure [4]-[6].

To manage the risk in corporate, many things are taken into consideration. one thing that poses a threat to risk management, is corporate failure prediction. Banks and other financial institutions have taken this as a serious issue. They may come with an effective alert algorithm to predict bankruptcy. In the modern era, vast amounts of present economic data about firms are gathered from the sources of Big data emerging, Information Technology, and Social media. Decision-makers do not give proper direction to attain goals by using enormous amounts of information. Pre-processing is needed to find crucial information among enormous amounts of information. thus, a prediction model in an effective way needs to be constructed without affecting desired quality output. The feature selection step is employed in Machine Learning (ML) techniques to attain crucial information. It is one of the pre-processing algorithms in general [7].

eXtreme Gradient Boosting (XGBoost) adopted feature selection, which helps to predict bankruptcy prediction. In this paper, we proposed AS-XGBoost which contains XGBoost with Attribute Selection. It is a distributed, scalable, gradient-boosting decision tree technique. An efficient way of predicting bankruptcy is through the use of this technique. The contribution of this paper is devised in two ways. The first one is an XGBoost tree incorporating important features that enhance accuracy. It is a suitable machine learning model to determine financial distress. Another contribution is to compare the proposed AS-XGBoost with established machine learning models like SVM, NB, Decision Tree, and Logistic Regression(LR) to identify ML that is sensitive to feature selection from comparisons made. This gives guidelines to banks and financial institutions to identify suitable models for bankruptcy.

In this paper, Section 2 deals with the literature review. Section 3 explains the methodology utilized. Part 4 gives the results of the proposed method along with its analysis. Section 5 concludes.

2. LITERATURE REVIEW

A crucial area of finance is the identification of bankruptcy. The possibility of a company becoming bankrupt is, in fact, a concern for numerous players for obvious factors, including executives, shareholders, or financiers. As a result, numerous research on the subject of bankruptcy prediction have been conducted. Beaver (1966) provided a univariate analysis in the late 1960s, giving financial ratios their first statistical explanation for their capacity to account for default [8]. In Altman's research, he employed multiple discriminant analysis (MDA) techniques to calculate the probability of bankruptcy for a sample of businesses. Due to its widespread use and popularity, Altman's Z-Score model is regularly used by auditors, accountants, courts, banks, and other creditors. The MDA technique assumes that there is a Gaussian distribution for the variables which was afterwards embraced by many other researchers [9]-12]. The idea that parameters have multiple normal distributions is then challenged in support of the hypothesis that the factors that explain something have distinct distributions. The probit, as well as logit models, were subsequently often applied to the prediction of bankruptcy. The second phase of the narrative started in the 1990s with the development of AI techniques, particularly those in the machine learning field like neural networks or genetic algorithms [13-15]. They achieved impressive, predicted outcomes without any statistical constraints. Indeed, using data from North American firm's data from 1985 to 2013, Barboza et al. assessed five machine learning models and contrasted their ability to forecast bankruptcy with more established statistical methods (discriminant analysis and logistic regression) [16]. From the literature survey, [17] reached this conclusion.

The use of financial ratios can improve bankruptcy prediction accuracy. Using principal component analysis (PCA) or least absolute shrinkage and selection operator (LASSO), one can identify the most relevant predicted features based on a subset of explanatory variables [18]. In order to form a list of 50 ratios, detailed information was taken from the Balance Sheet [19]. Du Jardin et al. employ feature selection [20]. To predict bankruptcy, Glen et al. used quarterly data rather than annual data [21]. Data about the bankruptcy process may include other attributes besides financial information, such as relational and textual data, market evaluations, and corporate governance information. In their study, Retznakova et al. examined average ratios for a number of years prior to bankruptcy. In addition, Pump et al. found that Bankruptcy model outcomes have an impact on economic limit periods as well. A bankruptcy prediction model is commonly used in small businesses and listed companies.

Table.1. Existing methods in the prediction of Bankruptcy

Authors	Algorithms	Characteristics	Limitations
[21]	XGBoost, SVM, and DNN	Three financial ratios are taken to classify bankruptcy from non-bankruptcy firms	No Hybrid techniques were used to categorize bankruptcy firms
[22]	Mathematical model	The model to assess financial risk	It estimates risks and then forms clusters and does not classify them.
[23]	SVM and KNN	Noisy training samples were removed with the help of SVM and KNN	Compared model with only traditional SVM
[24]	Magnetic Optimization Algorithm (MOA) and Particle Swarm Optimization (PSO)	Bio-inspired algorithms and ANN applied to bankruptcy data. It reduces training time	Standard Data Repository was not taken for the experiment
[25]	multi-criteria decision-making (MCDM) based approach	The standard ML classifier's performance was evaluated on an imbalanced dataset	Four evaluation criteria were not considered imbalanced data ratios
[26]	Hybrid switching particle swarm optimization (SPSO) and support vector machine (SVM)	Finding optimal parameter values of the Radial basis function of SVM	Comparison made against hybrid SVM and GA only
[27]	A hybrid ANN based on variables selection techniques	Multivariate discriminant analysis (MDA), Logistic Regression, and Decision Tree (DT) combined with ANN are used to distinguish bankruptcy or not.	The Moroccan firm's financial data statement was utilized. It may be an imbalanced classifier.

In order to improve bankruptcy prediction accuracy, a robust machine learning method is needed that can generalize well on financial data. As a result, many models rely on categorization methods like the Support Vector Machine (SVM). However, in financial situations, especially in bankruptcy prediction [23], it is difficult to make conclusions and choose effective solutions based on inadequate, imprecise, and noisy data. These authors offer a method for filtering out noisy training data by combining a Support Vector Machine with a K-nearest neighbor (KNN-SVM). The experimental findings demonstrate that, when applied to engineering tasks, the proposed method greatly improves generalization performance and classification accuracy by 12% over the standard SVM classifier. Potentially beneficial in computerized system applications, a composite classifier based on these variables may improve outcomes in company bankruptcy prediction.

Bankruptcy prediction is a paramount thing for financiers, investors, and also organizations. For an efficient prediction model to be constructed, Machine learning and other factors are utilized. The trained dataset containing financial ratios as features are acquired from the financial statements of various companies. Using Genetic Algorithms that determine the most weightage financial ratios helps in bankruptcy prediction. The input as financial ratios have been given to the random forest model, implemented in R. This predicts accurate results on various test cases [22].

Predicting whether or not a corporation will declare bankruptcy is a crucial step in establishing the viability of a business. For this reason, Artificial Neural Networks (ANNs) and other machine learning approaches have become increasingly popular in recent years.

For the purpose of predicting financial risk, many classifiers have been proposed. This research developed a multi-criteria decision-making (MCDM) based technique for rating insolvency prediction models, which considers numerous performance measures concurrently [24]. Seven financial unbalanced binary data sets were obtained from the UCI Machine Learning repository and used in an experiment aiming to test the suggested method. In this study, we apply four common classifiers (LR, SVM, MLP, and C4.5) in conjunction with three sets of unbalanced techniques: cost-sensitive learning, resampling (RUS and SMOTE), and hybrid methods.

Strength training is a crucial step in the process of learning a network. Strength training with ANN is more effective. Many recent works have used metaheuristic algorithms including Evolutionary Algorithms (EA) and Swarm Intelligence (SI) techniques to enhance ANN's weight training in order to better forecast insolvency [25].

This research improves upon two existing metaheuristics algorithms - the Magnetic Optimisation Algorithm (MOA) and the Particle Swarm Optimisation (PSO) - by proposing a hybrid of the two. It has been shown that hybrid algorithms can solve optimization issues more quickly and accurately. An improved prediction speed of up to 99.7 percent is demonstrated by the suggested hybrid MOA-PSO method. The next step is to test the method with more up-to-date data sets that are just as reliable. For bankruptcy forecasting, other MOA variants such the Functional Sized Population MOA (FSMOA) should be explored.

In this study, we forecast insolvency using a PSO and SVM hybrid algorithm [26]. At first, they analyzed data from the UCI Machine Learning Repository's sample bankruptcies. Then, a switching PSO technique is used to optimize the SVM's parameters. The included model has been effectively used to provide bankruptcy forecasts.

The noisy based tolerant method has not been updated to include more current datasets of equivalent quality. Instead of analyzing each and every issue, focus on the ones that matter most when making a bankruptcy determination. When compared to another hybrid algorithm, the accuracy is drastically lower. It was determined that the KNN-SVM classifier, and not the hybrid methods, would benefit most from the use of the five financial ratios chosen. The average accuracy of other algorithms is just 92.5%, which is much lower. Furthermore, a hybrid method consisting of neural networks and two optimization techniques obtained 99.728% accuracy. However, this investigation relied on historical data with only a few observations rather than more current, reliable datasets.

This paper's primary contribution is Bank collapses may be predicted with the highest accuracy possible. To lay forth the factors of becoming bankrupt. Finding the Critical Ratios for bankruptcy

3. METHODOLOGY

Machine learning techniques are often utilized for bankruptcy forecasting. Support Vector Machines, Artificial Neural Networks, Gaussian Process, Classification and Regression Trees, Logistic Regression, Decision Tree, Random Forest, Linear Discriminant Analysis, and Ensemble Learning Techniques are some of the most used methods. Additionally, several recent research agrees on the merits of combining mechanisms from various search strategies. In both operations research and AI, the development of hybrid methods is a current trend.

In the realm of managing financial risks, bankruptcy is the single most important procedure. Predicting whether or not a company will go bankrupt is an important step in figuring out the health of an organization's finances. Because it has such far-reaching consequences for a bank's personnel, customers, management, shareholders, asset-sale valuations, and bottom line, it has been the subject of many studies. The findings have implications for the lending decisions made by financial organizations and their bottom lines. A bank's ability to foresee an organization's potential is critical for preventing loan defaults. This means that banks urgently need factors related to bankruptcies and more accurate data from the present to anticipate bankruptcies.

The Ensemble models are meta-algorithms that integrate many machine learning approaches into a single predictive model to either reduce variance (bagging), bias (boosting), or enhance predictions (stacking). Using a preset qualitative bankruptcy data set and a quantitative bankruptcy data set in an ensemble model with several models, the proposed model will give important causes and key ratios relating to insolvency. After that, we'll examine the data with a number of popular categorization models including Naive Bayes, Support Vector Machines, and Logistic Regression. Finally, we use multiple measures (accuracy, precision, recall, etc.) to evaluate the models' performance on the validation datasets and rank them appropriately. As a result, banks will have a higher level of awareness and access to highly connected aspects.

3.1 DATA MODELING

With the goal of developing a predictive model that can accurately forecast the bankruptcy state of a given (unseen) bank, we will examine the various categorization models that we have examined for training on both datasets independently in this section. The following 5 models were taken into consideration: Logistic Regression, Support Vector Machine, Gaussian Naïve Bayes, Decision Tree and Random Forests.

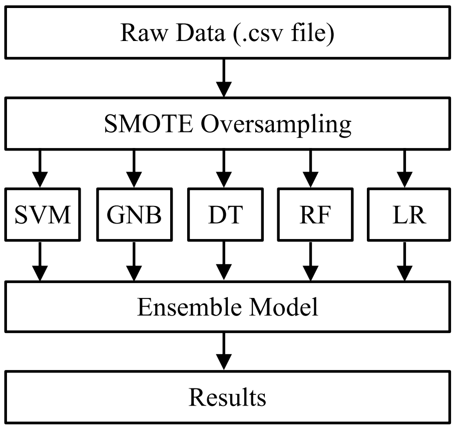

Fig.1. Pipeline for data modeling

3.1.1 Logistic Regression Classifier:

The purpose of logistic regression in statistics is to make predictions about discrete categories. The outcome or metric of interest is a binary variable. In a binary classification system, there are just two options. It's a kind of linear regression when the dependent variable is a discrete set of categories. The dependent variable is a log of the odds. The logit function is used in Logistic Regression to make predictions about the likelihood of a binary event occurring.

$$p = 1/(1+e^{-(\beta 0+\beta 1\, X1+\beta 2X2\ldots\ldots\beta nXn)}) \tag{1}$$

3.1.2 Support Vector Machine:

Although Support Vector Machines are more commonly used for classification issues, they may also be used for regression. It works well with both continuous and categorical data. To differentiate between groups, support vector machines (SVMs) create a hyperplane in a dimensional space. The ideal hyperplane for minimizing the error is generated via SVM in an iterative fashion. Finding the maximum marginal hyperplane (MMH) that most effectively separates the dataset into classes is important to SVM.

3.1.3 GNB Classifier:

A supervised learning method, the Naive Bayes classifier takes the 'naive' assumption of independence between each pair of characteristics and applies Bayes' theorem to the data. For a categorical outcome y and a set of features $x_1 \ldots x_n$,

$$p(y|x_1,\ldots x_n)= (P(y)P(x_1,\ldots,x_n)|y))/(P(x_1,\ldots,x_n)) \tag{2}$$

Based on the simplistic notion of autonomy,

$$P(x_i|y,x_1,\ldots,x_{i-1},x_{i+1},\ldots,x_n) = P(x_i|y) \tag{3}$$

for all i, this relationship is simplified to:

$$P(y|x_1,\ldots,x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_i,\ldots,x_n)} \tag{4}$$

The following categorization rule may be applied since P is independent of the input:

$$P(y \mid x_1,\ldots,x_n) \propto P(y)\prod_{i=1}^{n} P(x_i \mid y) \tag{5}$$

$$\hat{y} \propto \arg\max P(y)\prod_{i=1}^{n} P(x_i \mid y) \tag{6}$$

The Gaussian Naive Bayes classification algorithm is implemented in Gaussian Naive Bayes. The feature probabilities are assumed to follow a Gaussian distribution.

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma^2 y}} \exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma^2 y}\right) \tag{7}$$

Maximum likelihood is used to estimate the values of the parameters σ_y and μ_y.

3.1.4 Decision Tree Classifier:

A decision tree is a type of flowchart in which each node represents an individual feature or characteristic, each branch an individual decision rule, and the individual leaf nodes the final results. The 'root' node is the node at the very top of a decision tree. It figures out how to divide things apart according to their attribute values. Recursive partitioning is a method through which the tree is divided in a self-referential fashion. This decision-making 'flowchart' will serve you well. A flowchart-like visual representation that can be used to represent complex ideas in the same way a human brain can.

In Random Forest, it works in four steps: Gather shuffled representations of data. Generate a forecast from each sample by building a decision tree. Put each expected outcome to a vote. Choose the most popular forecast as the final forecast.

3.1.5 Attribute Selection – XGBoost (Ensemble Model):

By combining many models into a single, more accurate prediction, ensemble learning aims to boost predictive model performance. The term 'Ensemble Learning' refers to a technique whereby numerous machine learning models (such as classifiers) are systematically built to address a specific issue.

Diverse Ensemble Learning methods exist, distinguished mostly by the models they employ (homogeneous vs. heterogeneous models), the methods they use to sample data (replacement vs. non-replacement, k-fold, etc.), and the decision function they employ (voting, average, meta-model, etc.). Therefore, there are several ways to categorize Ensemble Learning methods: Stacking, Blending, Voting and Blending.

The concept of blending may be traced back to the more general method of stacking. The sole distinction is that in Blending, the meta-model's training data is not generated using the k-fold cross-validation method. In order to blend, a 'one-holdout set' is used.

Predictions made using a fraction (validation) of the whole training set are 'stacked' to create the meta-model's training set. The meta-model test data is also formed by making predictions based on the test data.

The Fig.2 depicts a Blending architecture, which consists of a final classifier and three basic models (weak learners). The meta-model (yellow boxes) is formed by using predictions (blue boxes) from the training data. The predictions made from the green boxes are utilized to create the purple boxes of meta-model test data.

4. RESULTS OF ANALYSIS

4.1 DATA

In this study, we examined two datasets: the qualitative one to identify causal variables in bank failure and the quantitative one to identify correlations between those causal factors and ratios derived from bank financial statements.

4.2 QUALITATIVE BANKRUPTCY DATA

The Qualitative bankruptcy data from the UCI Machine Learning Repository has been considered for the bankruptcy prediction problem. This repository is a large collection of freely available datasets which can be used in different domains such as Machine Learning and Data Science community.

Data and questionnaires were used to separate quantitative and qualitative aspects of the analysis of the failed banks. The bankruptcy prediction data set is ideal for our study since it contains several advantageous econometric indicators as characteristics (features).

4.3 QUANTITATIVE BANKRUPTCY DATA

This data set was generated with the help of Altman Bankruptcy Model and Ratios. The bankruptcy equation of Altman bankruptcy model is given below,

$$X = 0.012\ A1 + 0.014\ A2 + 0.033\ A3 + 0.006\ A4 + 0.999\ A5$$

where A1 is ratio of working capital to total assets, A2 is the ratio of retained earnings to total assets, A3 is called as earnings before interest divided by total assets, A4 is the ratio of equity market value to total liabilities, A5 is division of sales and total assets, and X is Altman Bankrupt value.

4.4 IMPLEMENTATION

Python v3.6 is used as a working programming environment in this work. We used an Intel Core i3 Core processor with 4 GB Memory (RAM) and 1 TB of storage (disk space) to run our experiments. Our code workflow exactly mimics the data modeling pipeline shown in Fig.6. We used the libraries listed in Table.3 to run our experiments and achieve our results. Libraries mentioned in Table.3 are imported. Dataset in the form of raw data (.csv files) as pandas data frames is loaded. Features are numeric in this dataset and labels for each class are binary. These data types need to be converted into appropriate ones for data frames to store and process data efficiently. So, the numeric data type was changed to float and binary data type was changed to integer type.

Now we start the data analysis. We apply SMOTE oversampling on quantitative dataframes to get fresh dataframes of oversampled dataframes and store them in a dictionary.

Table.2. Comparative analysis with existing works

Authors	G-mean	F-measure	AUC	Accuracy
Song et al. [25]	0.9193	0.9189	0.9619	-
Ansari et al. [26]	-	-	-	99.728
Y. Lu et al. [27]	-	-	-	99.2063
Fatima et al. [28]				99.2063
Proposed Method	-	-	-	100

Instantiation of the 5 classifier models (GNB, LR, SVM DT, RF, XGB, BB) is done and stored in a dictionary. We iterate the best classifier in ensemble models - validation using Metrics.

4.5 MODEL PERFORMANCES

Accuracy and ROC of seven models for Qualitative datasets was given below: Fig.2 and Fig.5. In Qualitative data, every model depicts 100% accuracy. It is pure data for Bankruptcy prediction.

4.6 FEATURES

From Qualitative data set, we can infer from tree chart and correlation matrix that Financial Flexibility, Credibility, Competitiveness has high correlation. These factors have a high impact on bankruptcy prediction. And these factors are relatable to Altman ratios. i.e., Management Risk is a core feature of Working capital / Total assets (X1), Financial Flexibility is a core feature of Retained earnings / Total assets (X2) and Earnings before interest and taxes/ Total assets (X3), Operating Risk is a core feature of Market value of equity / Book value of total liabilities(X4) and Sales / Total assets(X5). From the relation, we can infer that X2, X3 has high impact on bankruptcy prediction. The decision tree structure is formed to make classification shown in Fig.3. The dataset correlation is shown in Fig.4. Accuracy and ROC of seven models for Quantitative datasets is given in Fig.5.

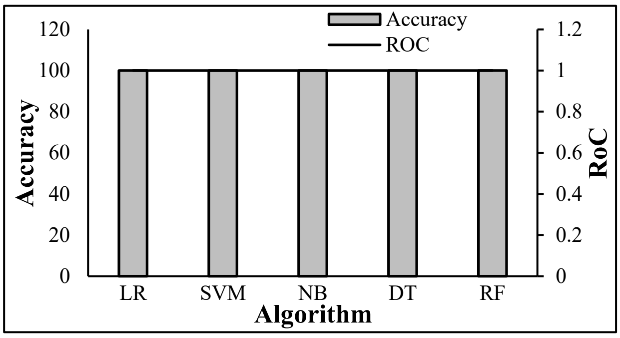

Fig.2. Qualitative Accuracy Chart

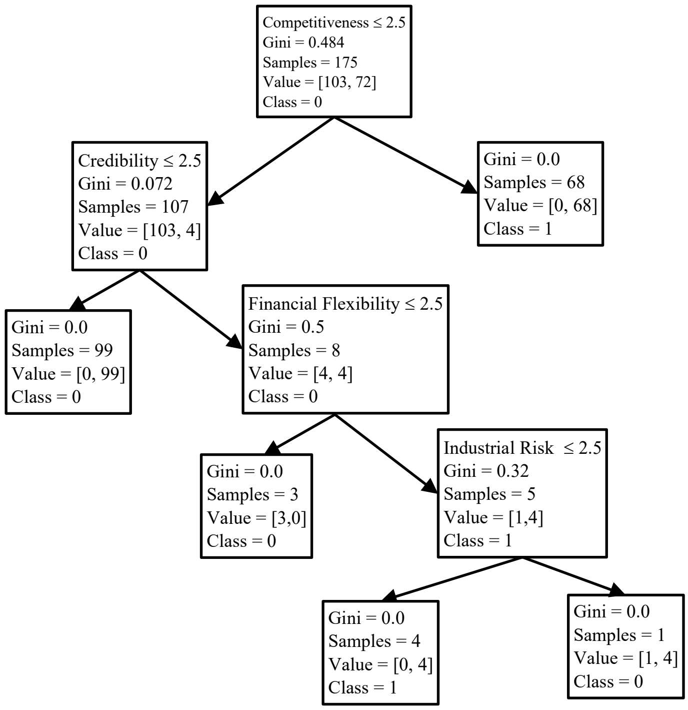

Fig.3. Tree Structure

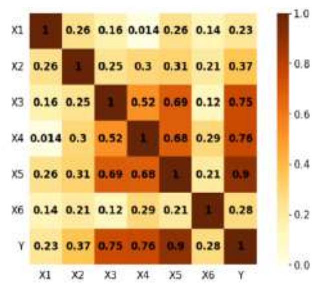

Fig.4. Qualitative Features Correlation Score

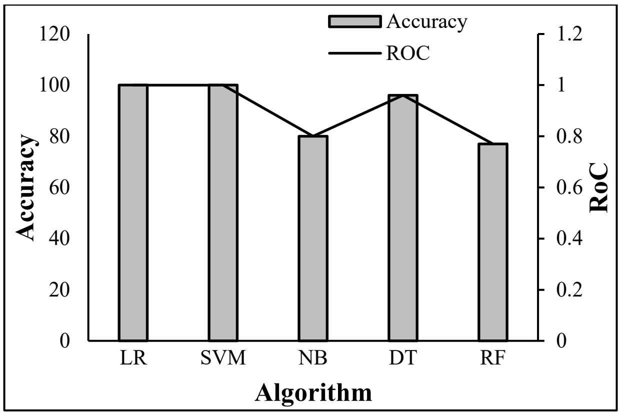

Fig.5. Quantitative Accuracy Chart

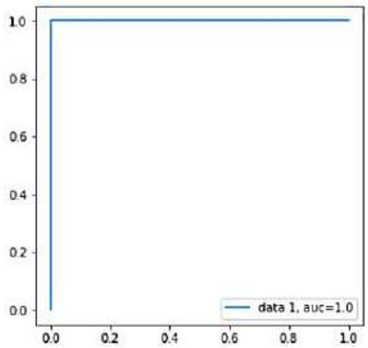

Fig.6. Blending Result of AUC curve

From the results, we can infer that Logistic Regression, Support Vector Machine, Random Forest are the best classifiers. We can infer there is drastic change in accuracy of every model due to involvement of low correlation. This model achieved accuracy of 100 due to combination of qualitative and quantify nature of dataset. For the nature of the structured dataset and ensemble technique, classification of bankruptcy from non-bankruptcy was performed more accurately shown in Fig.6.

5. CONCLUSION

Classification models, including the Gaussian Naive Bayes, Support Vector Classifier, Logistic Regression, Decision Tree, Random Forest, Extreme Gradient Boosting, and Balanced Bagging classifiers, were used to inform the formulation of the ensemble model. Using the Synthetic Minority Oversampling method, we ensured that the training sets had an equitable distribution of class labels. Predicting insolvency using indicators other than financial numbers present in firms' balance sheets requires extensive research and validation. We've done a thorough job of documenting our findings and offering our best recommendation for a bankruptcy prediction model The Deep-learning model may be used for large unstructured datasets that will be feature work.

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AN INTER-DISCIPLINARY APPROACH TO AUTOMATION TECHNOLOGY IN FINANCE - WHAT CAN HISTORY, LAW AND DATA SCIENCE TEACH US?

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Abstract
The year 2008 is etched in human history as the year of the 'Global Financial Crises'. Post the crises, Historians and financial commentators alike rushed to impute blame. Some blamed securitizations, some the banks and some Lehman Brothers and AIG. However, in the midst of all of this humbug, a key epicentre of the crises escaped academic scrutiny; 'Automation Technology'. The paper therefore aims to present an alternative view of financial history; one which impleads 'automation technology in finance' i.e., Risk Modelling Algorithms and RegTech. However, the underlying aim of this paper is to make a case against systemic automation bias in finance and to achieve that end, the paper employs an inter-disciplinary approach and uses history, law and data science to show case the multifarious perils of using automation technology blindfold in finance whilst also proposing possible solutions such as the incorporating of design thinking and systems theory in finance. Expired data sets, human assumptions, turning code in law, and a lack of standardized financial semantics as but some of these 'perils'. On the law front; it presents a twofold challenge under constitutional and anti-trust law and aims to reconcile law and technology. Lastly the paper aims to guide regulators by categorizing multiple stages of technological complexity and recommends application of different regulatory approaches to regulating automation. Therefore, the paper shall maintain a 'solution' oriented approach throughout.

Keywords:
RegTech, Algorithms, Regulator, Automation, Risk-Modelling

1. INTRODUCTION

1.1 RESEARCH PROBLEM

Fintech and technology in Financial Markets is largely regarded as 'infallible' and the algorithmic accuracy and fallibilities largely remain un-addressed by academia. Furthermore, a lack of an inter-disciplinary approach within academia with regards to the perils of automation precludes scholars, regulators and firms alike from cohesively understanding the risks of automation, ultimately leading to a veil automation bias. Policy decisions to regulate fintech therefore, remain largely unguided, un-informed and without nuance. The paper therefore aims to analyse the aforementioned research problems within academia using an interdisciplinary approach of law, history and data science.

1.2 BACKGROUND

Since the inception of mankind, technology has driven human progress. The integration of technology in human life is at its apogee today. Some scholars have even gone so far as to view human life itself as a self-replicating information-processing system whose information software (in the context of DNA) determines both its behaviour and the blueprints for its hardware [1]. Max Tegmark, an MIT professor, argues in his book 'Life 3.0: Being Human in the Age of Artificial Intelligence' that singularity (self-learning and reproducing capabilities) of AI is but a progression stage of life called 'life 3.0'.

This integration is especially pronounced in financial markets where the technology post the 2008 Financial Crises has been rapidly advancing without any regulatory oversight. The purpose of these new technologies is purportedly to 'automate' specialized human financial analysis and are therefore placed under the umbrella term 'automation technology'. The technology started taking the market at an unprecedented pace during the 2000's. However, post the Global Financial Crises (GFC) in 2008, due to a result of the new "process based" regulatory regime with ever increasing compliatory dictums, parallel breakthroughs in AI and Machine Learning, and lastly, calls for better, more "scientific" risk modelling systems; private firms finally turned wholesale to automation technology for their legal compliance and risk modelling strategy. This led to the age of "RegTech and Automated Risk modelling" which even the regulators wholeheartedly revelled in.

The discourse post GFC amongst the academicians, were divided by two fronts; where one side called for increased regulations to hold banks, financial firms and NBFC's accountable whereas the other side argued that it was the failing government policies themselves which caused the crises. They argued that the regulators must back out from the market. The regulators, although favoured the former approach, also recognized that they neither have sector-specific knowledge to understand the operational risks of the ever-complicated financial market, nor the knowledge to understand the firms dealing in multifarious financial services. Therefore, they delegated their jobs to private automation tech and focused on making laws with complicated disclosure requirements [2].

In the midst of all of this, a key piece of the GFC escaped scrutiny: "Automation Technology". As this paper would argue, automation technology has tremendous and unique harms of its own. The author identifies these harms to be Design based, Human, Legal and Linguistic. Unfortunately, the failure of academicians and regulators to scrutinize technology led to a 'veil' of Automation Technology which continues to remain largely inscrutable and unregulated today. This 'veil' is recognized by scholars via a concept called 'automation bias'. This automation bias has become systemic and affects the entire financial milieu. The ultimate consequence of this long term would be the unsupervised widespread use of the treacherous 'black box algorithms' in financial markets which would effectively mean a slap in the face for everyone who called for increased transparency in our financial markets post the 2008 Crises.

To make my case, I shall adduce literature from multiple disciplines such as history, law and data science. I aim to showcase finally through practical examples, how automation tech has constantly erred in producing the desired human outcomes and has often destabilized markets to our peril. The solutions the paper offers are threefold; One, a radical shift in the regulatory approach towards automation technology in finance (for the regulator) two, integration of human value with technology rather than a complete reliance on automation (for the private firms) and three, incorporation of design thinking and systems theory while developing code (for the programmers). Lastly, I call for reconciliation between constitutional and anti-trust law and automation. These goals, however, can only be achieved if the veil of 'automation bias' is destroyed.

1.3 AUTOMATED SYSTEMS

There are primarily three types of automation systems: rule-based, data-matching, and data mining systems. In the first type, the 'rule' as interpreted by the programmer is applied to a set of facts. Programmers translate policy from human language into code and then embed it into decision tables following which the 'rules engine' provides the system 'logic'. Rule based systems were primarily used in compliance and disclosures of regulatory mandates. Data matching algorithms on the other hand such as VaR functioned on correlating two sets of data sets and predicting the likelihood of a certain outcome. They were predominantly used to guide trading. Data mining algorithms lastly, searches for patterns and correlations by analysing big data and were used in tandem with Data Matching systems.

Besides multiple systems, there are different types of algorithms too. For example, classification algorithms first identify the probability of the event(s) occurring and then group the data sets into a finite number of categories based on the ascertained probability ranges [3]. Regression algorithms take it a step further and build on the work of classification algorithm by creating an infinite set of probable events with a fixed confidence interval [4].

While there are tremendous efficiencies that these new technologies provide by using the aforementioned methods, however the moment these purported efficiencies start to do more harm than good, the global discourse on technology's integration with human activities must make space for some well-founded caution.

1.4 PROBLEMS WITH THE GLOBAL TECH DISCOURSE

In the same book cited above, Tegmark cautions his readers to understand the risks associated with AI [5], so much so that close to half of his book revolves around it! This newly trending "cautious discourse" to Advanced Technology never questions the inherent faults and inadequacies of advanced AI but rather warns against AI "taking over humans". This argument presumes that algorithms are infallible and 'perfect' and therefore may defeat human dominance [6] since unlike machines, we are limited by 'human errors'. I call this the 'Global Tech Discourse'. Through this paper I aim to challenge this hypothesis. The Global Tech discourse doesn't do anything to address the pervading automation bias but rather strengthens it. On the other hand, I argue that technology is not all that perfect, and automation has its own inherent weaknesses. Therefore, ignoring them may lead to disastrous consequences especially when seen in the context of financial markets where automation often leads to 'crowding out' of specialized human knowledge.

The paper is structured as follows: Section 1 provides an Introduction of the subject matter and introduces the problem. Section 2 presents an alternative historical narrative of the GFC, impleading automated Risk Modelling Tech built on Var, Section 3 showcases the perils of risk modelling algorithms using data science, Section 4 poses legal challenges and calls for reconciliation between technology and law in finance, Section 5 then dives back into the historical narrative post the 2008 GFC and traces the development of RegTech. Section 6 likewise presents the perils of RegTech from a semantic and legal standpoint. Section 7 summarises the historical development of automation technology and divides it into 5 stages of complexity. The section argues that different regulatory approaches must be applied for different stages. Section 8 then finally concludes.

2. DAWN OF AUTOMATED RISK MODELLING: VAR TECHNOLOGY

This section shall present an alternative way of looking at the Global Financial Crises and impleads 'automation technology' as the epicentre. While most narratives focus on imputing blame on credit rating agencies and compels financial instruments like securitization, I argue here that perhaps at the centre of the crises was 'automation technology'. The primary focus here would be 'VaR' or value at risk technology. However, I shall also make the case that technology was never the 'villain', but rather a 'medium'. The villain in this story perhaps is the 'veil' of technology i.e., automation bias, which effectively puts humans back at the driving seat of the accident. One of the broader goals of this paper shall be therefore to launch a valiant attack on this 'villain'.

VaR or Value at risk automation systems are largely regarded as the beginning of the 'age of automation' in finance. These systems were perhaps her first that weren't just widely used by firms but also garnered regulatory acceptance through the Basel Accords which stated,

"Where a bank has a VaR measure that incorporates specific risk and that meets all the qualitative and quantitative requirements for general risk models, it may base its [specific risk capital] charge on modelled estimates . . ."

It was developed first as a method to identify optimal portfolios for individual investors operating in equity markets. The software would analyse "market risks" and then use correlation and regression methods to show the interrelations or 'probabilistic connectedness' in a specific time period by representing them as percentage points called 'confidence levels'.

Hence, (taking one week as standard time) if an asset is worth say, \$100, and VaR gives a confidence level of 99%, that means the asset has a 1% chance to lose all of its \$100 value in that specific week. Ricardo presents two ways in which VaR made its predictions: Firstly, it integrates calculations of the variance within one asset class and then used covariances to assess different kinds of assets; secondly, by the Monte Carlo simulations – a method used to understand systems with large number of independent but connected elements (much like cellular systems) [7]. In short, it creates simulations of multifarious risk sources and then finally aggregates a large number of possible outcomes using aggregation and regression of data. Professor Kenneth argued that both these methods were backward looking i.e., they drew from historical antecedents. They use past data to make predictions about the future, much similar to heuristics [8].

2.1 THE PROBLEM: EXPIRED DATA?

Ricardo and Professor Kenneth argue that although VaR reaches its 'confidence level' percentage point by considering ostensibly all of the possible outcomes and probabilities in a specific period, however, it is limited by the data set programmed into it or has access to [9]. A cursory understanding of this system by an experienced trader would make conspicuous two very evident problems with these models: Firstly, that one can't look at the past to predict the financial market in the future, especially in light of "bubbles" which often form due to either terrible monetary or fiscal policy (the Japanese crises due to the central banks interest rate fluctuations) or an unexpected externality (for example 1973 Oil Crises). Secondly, human behaviour and public policy are both unpredictable, reactionary and mutually co-dependent.

As Albert Einstein once posited, "I can calculate the movements of stars, but not the madness of people". Behavioural Economists have had a long-standing consensus that using sophisticated models to predict the market is foolish [10]. This is perhaps because macro-economic policy is reactionary and is driven by externalities often founded on 'irrational' human externalities – Take the example of the Japanese Bubble due to sudden currency depreciation of the US dollar caused by the Plaza Accords, and the consequent export market crises and finally the disastrous interest rate alteration [11]. Financial market analysis requires speculation of future events which may be completely independent of the past. Additionally, economies usually move in multiple cycles such as peak, contraction, recession, and recovery. Credit therefore also moves in cycles. If data is drawn from an up-credit cycle or a contraction and applied to identify patterns in current financial markets which may be in a down-credit cycle, it is but obvious that the results would be incorrect, or in the very least has a likelihood of being incorrect.

Unfortunately, both the Regulator and Private Firms naively accepted VaR with no analysis of its mode of data processing. Private Firms even started firing their Risk Compliance Personnel in the hopes that VaR will replace them all and thus they will be able to cost cut. As Professor John Coffee explains,

Most of the investment banks used to do due diligence in asset-backed securitizations by hiring professional due diligence firms with expertise in real estate to test the loan originator's portfolio of mortgages before the bank acquired its loans. They began to abandon that practice after 2002, as the market became bubblier and demand for these deals grew and grew [12].

This abandonment of human value in financial markets proved to be fatal for both firms and the global economy. Since VaR had modelled all of its data after the 1987 stock crises, the data, ironically enough, predicted a rise in the Mortgage Prices. Additionally, being software designed for individual portfolio assessment, it was not geared towards identifying the gap risk i.e., the risk of extreme market events. Hence, they fell outside their purview of 95% or 99% confidence levels [13]. The infamous credit rating agencies also to a large extent relied on VaR reports to rate assets. On the basis of these reports, they then proceeded to issue the infamous credit default swaps. When this 'bubble' finally popped, all the top business executives were left astounded and perturbed, and for good reasons.

2.2 THE ONE FIRM THAT WON

Strangely however, Goldman Sachs' quantitative risk-prediction algorithms saved them from tremendous losses during the 2008 GFC. Except Goldman Sachs, all who relied on the ubiquitous VaR risk-modelling technology failed. Goldman Sachs had somehow managed to safeguard itself by selling its exposure in Mortgaged Backed Securities or MBS after their "real time" risk modelling tech had shown consecutive losses in their mortgage business for 10 days straight. Expeditiously, a meeting was called where a decision was taken to sell their MBS exposure. This was right at the onset of the 2008 crisis. So, what made Goldman Sachs so different? The answer is rather simple; and is the salient learning that we must take from the history of fintech. Emanual Derman, a former Goldman Sachs Risk Modeller attributed the success of Goldman Sachs to the cautionary approach of retaining human intelligence, instead of relying solely on modelling systems:

"In a good way, Goldman Sachs was eclectically irreligious about what was the right way to look at risk, we didn't just rely on VaR. Estimates of the probability of bad things happening are notoriously poor because crises don't repeat themselves in exactly the same way. We relied on scenario analysis and stress testing as well. There were limits on positions, for instance, in order to limit the loss that would occur under a repeat of the 1998 default scenario [14]."

The above quote is enough to show what was behind Goldman Sachs success, cautious application of Risk Modelling algorithms whilst more importantly, the retention of significant human intelligence in the process. The firm did not fire its human resources, rather, relied on them while using automation as a mere 'assistant'. This approach to fintech is only possible if the minds of firms are free from the corrupting force of 'automation bias'. What is this purported 'automation bias'? The next paragraph shall briefly explain the phenomenon.

2.3 THE VILLAIN: AUTOMATION BIAS

Humans tend to view automation systems as error-resistant [15]. Even when humans suspect malfunction, this 'error-resistant' idea of automation technology prevails, leading us to dismiss our own well-founded suspicions [16]. This bias doesn't just affect firms but has a stronghold over all our institutions, even the 'ostensibly' independent judiciary. In one case where automated algorithms which were tasked with identifying 'dead-beat' parents, the algorithms incorrectly classified a wrong man by confusing him with someone of the same name. The case was not frivolous but involved a huge sum of $206,000 in child support debt. It took the accused and his lawyer close to two months to convince the attorney that the algorithm had made a mistake [17]. Danielle Keats Citron argues that automation bias, if it affects institutional authorities, leads to a crisis in due process [18] and an abdication of regulatory responsibility. Frank Pasquale argued that when the stakes are high enough, automation bias can degenerate into wishful thinking or worse: opportunistic misuse of models to validate sham business practises[19]. Therefore, the destruction of this 'purported automation bias' is the need of the hour. One of the goals of this paper, inter alia, is to destroy this veil of automation bias by showcasing an alternative lens of viewing automation technology, dare I say a more cautious lens. The next section therefore shall present you with some of the inherent flaws of such machine learning algorithms which makes 'blind trust' in automation a fools' errand.

3. INHERENT PROBLEMS IN MACHINE LEARNING BASED RISK-PREDICTING ALGORITHMS – HUMAN AND LEGAL

Post GFC, machine learning in finance has undergone a full re-branding in terms of advanced 'neural networking' algorithms running on cutting-edge deep learning models. However, I argue that certain problems in machine learning continue notwithstanding the advancements in AI due to their inherent nature. The section identifies four problems. The first two problems are human centric and involve incorrect human assumptions in algorithms and human biases being surreptitiously inserted in computer code. The other two problems are legal, wherein the first arises from anti-trust law and the second from constitutional law.

3.1 MODELLING ON FALLIBLE HUMAN ASSUMPTIONS

The trillion-dollar flash crash of 2016 is a case in point. The event destabilized the market for a whole half hour wherein the stock prices of some firms swung between 100,000 dollars to pennies. Evidently the algorithms had failed to produce accurate results, but not because they were malfunctioning or buggy; rather the human assumptions they had been built upon had flopped. For example, the assumption that the stock exchange's computed price of stock would automatically always correspond with its actual price. Setting up of incorrect parameters is yet another example. As John Walsh of the office of Compliance Inspections stated,

"If you set their parameters too high, they could miss important red flags. For example, if you have an electronic report that monitors investment time horizons, but you assume that only investors under age 50 have investment time horizons, you could miss a lot of red flags relating to the elderly. Also, an electronic report cannot find red flags in data it does not have. For example, if you rely on your clearing broker for mutual fund exception reports, but do most of your business with the fund companies by way of "check-and-app," those clearing broker reports will not do you much good [20]."

Perhaps a good solution to the aforementioned problem is a mix of Design Thinking and Systems Theory while programming and employing algorithms. Design thinking is a non-linear process that allows teams, especially programmers, to constantly challenge their assumptions at every stage, look back and re-define problems, and finally create innovative solutions to prototyping and testing. Systems Theory on the other hand studies how various parts of the system interact with each other in producing the output. Systems Theory would force programmers to view algorithms not just from a consumer-product lens, but as a part of the financial system as a whole. This would allow them to study the output of these algorithms and their consequential cause-effect relationships with various interconnected institutions in said financial system.

Financial Programmers must therefore not only seek 'verification' of their algorithms but also incorporate Design Thinking and aim for 'validation'. Where verification would ask the question, "Did I build the right system?", validation would ask, "Did I build the system right, and if yes, then to what extent?". Validation would question the legitimacy of the inherent assumptions on which the algorithms have been built and such an exercise is only possible if the veil of 'automation bias' is unmasked.

3.2 POSSIBILITY OF TRANSFERRING PROGRAMMERS BIASES INTO THE CODE

Frank Pasquale observed in his book, "Software engineers construct the datasets mined by scoring systems; they define the parameters of data-mining analyses; they create the clusters, links, and decision trees applied; they generate the predictive models applied. Human biases and values are embedded into each and every step of development. Computerization may simply drive discrimination upstream [21]."

At every step human biases are imputed into the code, even if unconsciously so by either setting of parameters or by imputing assumptions. A clear solution to both the problems is ensuring the code remains open access to other programmers, can analyse the foundational parameters and assumptions and further take help from social scientists to see whether they result in social inequity. An open access to code, however, comes in direct conflict with the law which unfortunately grants them secrecy in the name of intellectual property and trade secrets. While I understand that IP rights encourage innovation, however whether the benefits arising out of such innovation is greater than the likelihood of social harm that would engender from the inscrutable nature of these algorithm is a 'harms versus benefit' analyses every regulator must painfully undertake within the context of the nation's economic and social history. The discussion should therefore move away from per se grant of IP rights to a private rights vs public interest-based conversation. This discussion would also get a new shape when the state considers recognises access to finance as a human right.

4. LAW AND MACHINE LEARNING

An intersection of law and technology is something that scholars have acutely failed to explore adequately. However, an analysis of such and intersection becomes necessary especially because the same can accommodate all the three stakeholders: The regulators who deal with law and policy, Private firms who deal with private interests and finally the programmers who deal with technology. In this section I shall subject automation tech to two legal schools of thought namely, constitutional law and anti-trust law. The goal of this section is to nuance the global tech discourse in order to have a safe space which allows for innovative solutions for both law and technology to be reconciled.

4.1 CONSTITUTIONAL CHALLENGE TO INSCRUTABILITY

While machine learning algorithms may predict the outcome, they cannot justify how that outcome or event happened or what reasons led to that event, i.e., they cannot infer causality. For example, they may be able to predict that the corporate debt bond of a certain company will reach a certain amount of yield, however they cannot tell you how it got there. Identifying patterns is its job, justifying them is the responsibility of humans which SHOULD NOT in any way be abdicated due to automation bias. The outcomes of such algorithms, when employed by credit rating agencies, impact an individual's legal and constitutional rights and consequently result in grave inequity if later proven to be unfair or incorrect. This becomes even more relevant with regards to financial instruments such a debenture that are not backed by any collateral but rely solely on the ‘credit worthiness’ of the issuer which are in turn also provided by the credit rating agencies. Article 14 of the Indian Constitution mandates ‘substantive equality’ i.e., to treat equals equally without discrimination. In this regard, I adduce Max Tegmark who makes a startling observation in his book quoted in the beginning. He writes that if we were to train a deep neural network algorithm, with a tremendous amount of data on prisoners, it can arguably predict who is more likely to commit crime again. This can then inform policy i.e., who is to be given parole and who is to be denied. However, the programmers are neither trained in sociology to provide rules grounded in sociological realities nor are they aware of their own biases. Therefore, an algorithm might start to link sex or race to a prisoner’s recidivism. Pertinently, a 2016 study found that recidivism- prediction software used across the US were biased against African Americans [22]. Such use of algorithms violates article 14 of the Indian Constitution in as much as it produces ‘indirect discrimination’. The two fold test of Indirect Discrimination was articulate first in the famous case of Fraser v. Canada [23] and was affirmed in India later[24] which looks not on whether formally same parameters are used to classify different groups but whether the effects of such classification produces discriminatory effects on marginalised groups. The problem, however, is that article 14 violations can only be levelled against the ‘state’. What comes under the definition state is further provided under article 12 of the constitution. However, legal jurisprudence, especially in India provides an evolved definition of state wherein anybody that undertakes ‘public function’ could be classified a state. The central question therefore is whether credit rating agencies undertake public functions?

I argue that Credit rating agencies are indeed responsible for ‘public functions’ since their rating directly affects access to fair and reasonably interest rates to citizens while accruing loans [25]. Therefore, they must stand the test of Constitutionality. It is because access to finance ought to be a human right, and credit ratings act as gatekeepers to reasonable interest rates and thus directly affect citizen’s access to finance. International Legal Jurisprudence has already given exceptional categorization to credit rating agencies. For example, in a famous competition law case in the EU, the court forced Standard & Poor to provide information and rating to other financial market entities without any delay. The court classified them as ‘informationally dominant’ in the market since their function was essential to competing in the market [26]. I argue that such classification under anti-trust law, although well intentioned, is still inadequate. A better recourse is under constitutional law wherein the credit rating agencies are classified as those firms engaged in ‘public functions and credit rating is identified as a ‘public good’. Doing so is possible if the state was to recognize access to finance as a human right. While this proposition may seem radical, multiple scholars have taken similar views [27] and therefore the same merits serious consideration. In the very least especially in ‘welfare-oriented’ countries such as India [28] the right can be recognised as an ‘ancillary right’ under article 21 which already recognises right to privacy and right to sleep.

Some may criticize the above hypothesis as too ‘far-sighted’ especially when the legal system itself is rife with discrimination. As someone who has directly worked in pro bono cases involving casteism and sexism, I do not have the audacity to refute that claim. There are even entire academic fields such as ‘critical legal theory’ founded on that assertion. The immediacy of underscoring algorithmic discrimination is however notwithstanding other kinds of judicial discrimination because the former is far more pernicious. Even though occasionally discriminatory, our legal system is to a large extent ‘transparent’ and allows for academic scrutiny and public criticism. Judgements are made publicly available to read and the underlying logic of the judgement is clearly stipulated and subject to judicial review of higher courts. Law and statues also have to stand the test of judicial review. In stark contrast however, the ‘inscrutability’ and ‘black box nature [29]’ of Advanced Algorithms are beyond human understanding due to their complex operations and therefore are well outside the purview of judicial or even regulatory scrutiny. This ‘non-transparent’ nature of automated decisions will eventually make them legally invincible and above the ‘rule of law’, which is highly problematic for any modern democracy. Therefore, the constitutional challenge to these algorithms also merits immediate serious academic concern. Besides a constitutional challenge, algorithms also raise anti-trust concerns which have also largely escaped scholarly scrutiny. The same is discussed in the following paragraph.

4.2 THE CASE UNDER ANTITRUST LAW

Collusions, especially in terms of price sharing agreements, are traditionally prohibited in antitrust law and have been recognised as an ex-ante anti-competitive practice [30] via ‘illegal agreements’. However, in terms of ‘tacit’ algorithmic collusion, global anti-trust laws have not kept up. Machine learning algorithms founded principally on ‘increasing the profits of the firm’, are likely to collude with other algorithmic pricing agents and set the prices for the market [31], thus resulting in market foreclosure [32]. In a similar 2015 case, the DOJ charged David Topkins for illegal price sharing by deigning and sharing among other sellers on amazon ‘dynamic price sharing’ algorithms. It was easier to impute liability here because the algorithms were founded on simple machine learning. However, deep learning can make algorithms learn collusive practices on their own leading to ‘tacit collusion’. As pointed out by Peter Georg Picht and Benedikt Freund, deep learning algorithms replicate the human brain by creating ‘artificial’ neural networks similar to the human brain, and further engender ‘inscrutable hidden layers’[33]. This makes it even harder to identify the collusion and further to impute liability.

Additionally, Collusion is cross-jurisdictionally recognised as an anti-competitive practise today. The practise involves co-ordination among competitors to set price etc, with the underlying goal of raising profit much higher than the ideal competitive equilibrium. However, traditional competition policy only recognises 'explicit collusion' i.e., one which is evident on the face of it. Section 3 of the Indian Competition Law for instance prohibits ex-ante anti-competitive 'agreements' which allow firms to collude but does not recognise tacit collusion in the absence of such explicit written agreements. Algorithms, due to their inherent coded strategy may collude with other algorithms. This likelihood of collusion is especially high in oligopolistic markets [34], which are copious in finance and credit rating. This occurrence is not without precedence. In a case involving airline tariff companies, wherein the algorithms created by airline companies were engaging in 'tacit collusion', the DOJ was inadvertently forced to settle given anti-trust did not prohibit 'tacit collusion'. Accolades are in order for the DOJ since given their black box nature, it was close to impossible to pin-point explicit collusion [35] however they still figured out the collusion by observing ex-post harm. However, to impute liability here was yet again an issue.

4.2.1 Towards Imputing Liability:

By selecting certain parameters, programmes can inform the algorithm to follow a certain strategy. This strategy then drives automated pricing and risk assessment operations such as providing credit scores. Selective data sharing by algorithms is yet another way of collusion, which becomes even more ominous given the fact that our financial markets run on crucial data and information. The European commission considered prevention of accurate and timely financial data by market participants by Standard & Poor and Thomson Reuters as anti-competitive and ordered them to release the information in a time bound manner [36]. Denial of information in such cases can lead to market foreclosure. However, such an ex-post approach may not work in cases where algorithms collude especially due to their inscrutability. Therefore, ex-ante laws and regulations are required for the same. Europe already has a digital market act which provides certain ex ante-prohibitions for anti-competitive practises in the digital marketspace and developing countries such as India close to enacting their own anti-competitive laws specific to digital markets [37]. However, none of this legislation recognised the need to regulate 'tacit algorithmic collusion' highlighting that policy makers and regulators alike have not been able to keep up with the rapid advancements in technology.

On the ex-post front, I argue that the law must impute 'strict liability' against algorithmic abuse and collusion. This means that firms would be held accountable even though they technically did not intend to collude. The defence of an absence of mens rea would be irrelevant given that one is dealing with 'inherently dangerous' algorithms. Therefore, they shall be responsible for any harm due to such 'deep learning' algorithms despite not intending to do so. More importantly, this would be in tandem with tort law [38]. Policy formulated on such axioms would ensure that firms themselves keep their algorithms in check and constantly supervise. Secondly, on the ex-ante front I argue that the 'strategy' or the 'parameters' set by the programmers should be within regulatory scrutiny and should be supervised first in 'technological sandboxes' by the digital markets in the Competition Commission. The setting up of such a unit is also proposed in the 53rd Finance Committee Report on Anti-competitive practises by Big Tech and therefore is nowhere near 'impracticality'. The Committee Report also argues that SIDI's or systemically important digital intermediaries (Google, Microsoft etc) must be identified and be subjected to additional ex-ante laws. I argue that the Committee must go a step beyond and also identify 'informationally dominant firms' such as Moody and mandate them to not indulge in informational abuses, albeit traditionally or algorithmically. Ensuring a competition law cognizant of algorithmic abuses would be essential for a healthy regulatory approach to financial market inter alia other markets.

A 'new functionality, new rules' approach to regulation would merit the passing of new laws such as this which recognised tacit algorithmic collusion and imputes strict liability on the firms using them. Furthermore, mandatory such algorithms to undergo supervisory technological sandboxes before they are unleashed in the market could also be helpful. The need for such recognition has been scantly argued for in academic circles [39] and even if so, they have fallen on deaf ears.

5. POST THE GLOBAL FINANCIAL CRISES AND THE EMERGENCE OF REGTECH

Post the GFC, the regulators and academicians alike rushed to impute blame. Most ultimately blamed securitization and the complex financial instruments purportedly invented by the sharks of wall street [40]. A minority set, however, dissented and argued that it was the terrible monetary, and government policies in addition to excessive and mis-informed regulations that had a greater part to play in the crises. At this juncture, the Regulators were at a crossroads. Those in Washington DC now lacked sector specific knowledge and no longer properly understood financial markets. However, they were also handcuffed by mounting public pressure to chain those at wall street with a slew of regulations. What did they do? Both! On the one hand, they crushed financial firms under the weight of new and complex regulations some were however well intentioned like the Dodd Frank Act. On the other, they ushered in 'process-based laws' where private firms were not to calculate their risk internally and submit regular reports of compliances. Examples of these laws include Dodd Frank, Basel III reporting requirements under OTC, etc.

Wall Street, however, was also an opponent of equal measure. In response they unleashed automation technology for their legal compliance to keep up with the increasing compliance costs [41]. Some scholars argue that it was the competition from other fintech firms that also played a play in the ubiquity of this innovative tech [42]. These automated legal compliance technologies were termed "RegTech" made from the rather uncreative combination of the two words, "regulation and Technology". The Financial Conduct Authority in UK defines Regtech as "Technologies that may facilitate the delivery of regulatory requirements [43].

In the midst of all of this, physicists were equally active. Every week breakthroughs in AI are achieved. Advanced Artificial Intelligence now offered 'interpretative' human-like logic to computer systems. This was perfect for the development of RegTech which required such interpretation of laws. RegTech Software was primarily rule based in nature. Therefore, software codes in RegTech largely tends to be based on declarative logical statements than can be combined into decision like tree branches [44] for example rules such as 'Do not offer a mortgage requiring a monthly payment of over $... to an applicant making less than $...'.

However, like risk modelling technology, 'RegTech' has its own perils. I divide them into two categories: Human and Linguistic. Human problems arise when translation of laws into code is done by the programmers and Linguistic problems occur in semantic interpretation of legalese and financial terms by AI due to an acute absence of standardization of language in finance. The latter problem is one of all large language processing models such as ChatGPT.

6. INHERENT PROBLEMS IN REGTECH – HUMAN AND LINGUISTIC

6.1 PROBLEM OF TRANSLATION

While RegTech sounds like a heavenly invention for firms looking to cost cut on their legal fees paid to lawyers, in reality, the picture isn't as rosy. For any legal policy or a principle to be recognized and acted upon by RegTech it would first have to be coded into the programmer by a programmer. This 'coding of law' brings forth multiple problems. As much respect I have for programmers, they are simply not competent for this 'translation'. Legal interpretation requires certain skills which only those trained in law profess. This became clear when the programmers in one case sought to create programmes that would automate enforcement of "Intellectual Property Rights". The Digital Rights Management Software or "DRM" embedded in digital content files during its sale or distribution. It allowed private parties to prevent the buyer from using the purchased file or distributing it in a manner that would violate the intellectual property rights of the seller. What the programme failed to take into account was the doctrine of "Fair use" as an exemption [45]. Granting such an exemption requires a qualitative assessment of the method of using the property specific to the facts which is legally complicated and therefore requires a lawyer, however since the programme lacked a throughout understanding of this doctrine, it was never programmed. Thus, inadvertently, the DRM ended up defeating the fundamental principles of Intellectual Property Law. Therefore, a question arises as to how much the "west coast law" i.e., the law made through the implementation of legal policy by programmers sitting in the Silicon Valley are in tandem with the goals envisioned by the "east coast law" i.e. the law and its principles imagined by the parliamentarians sitting in Washington DC or the Lok Sabha which merits yet again careful scrutiny so as to not defeat the purpose of the law. As an antidote, Max Tegmark suggests getting more tech savvy people into law schools and government as one of the solutions, however given the unfortunate lack of interdisciplinary discourse within these two fields currently, that is a dream still! On a lighter note, this paper is being written by a law student so perhaps the reasons for optimism aren't completely unfounded!

6.2 PROBLEM OF THE TOWER OF BABEL

Secondly, the existence of multiple financial languages creates semantic asymmetry in interpretation of dictums by the algorithm. Scholars refer to this as the 'problem of tower of Babel [46].

Allow me to borrow an allegory from the Old Testament to elucidate this problem. In the first book of the Old Testament God punishes his followers for building a "tower" to reach him. He punishes them by replacing Earth's common language with 7000+ languages. This is where the 'tower of babel' problem finds it metaphorical origination. While in the real world, differences in languages must be celebrated since they are the representations of unique and beautiful cultures which ensure diversity. However, in the financial world, the lack of standard language is a bane. It is argued that today the number of financial languages exceeds the number of spoken languages. Since translation of policy into code requires standardized semantics, having multiple versions of languages creates additional confusions. Scholars have termed this lack of a common financial language as the "tower of babel" [47]. The problems become pertinent in crises of the global nature such as the 2008 crises which demand a coordinated global effort. Perhaps formulating a global standardized financial language is necessary. However, the problems may arise in its acceptance and recognition world over and between different private firms within a country because the same can be construed as forces universalism which can be even counterproductive. To highlight with an example, The city of Thiruvananthapuram in India means 'the shelter of lord anantha', however, to simplify its pronunciation in English, it was converted to 'Trivandrum' which means nothing. Hence the city's name lost its semantic meaning in the process of translation to English. Most RegTech software's are built in the Silicon Valley which has a ubiquitous dominance of English. Translation of local laws of different countries into English and then into code therefore becomes a problem for Silicon Valley Softwares. Perhaps standardization of financial language must not come at the expense of the semantic history of other cultures but rather through an equitable dialogue between all the member countries to negotiate an amenable common ground. This requires a co-ordinated international effort.

7. INCREASING COMPLEXITY AND POLICY IMPLICATIONS: NEURAL NETWORKS AND DEEP LEARNING

Following the integration of AI and the innovation of RegTech, technology grew at an even rapid pace, perhaps too rapid for humans to track. The use of Deep Learning and Neural Networking technology promised an automation revolution, and sough to re—shape how we view machine learning. As Tegmark succinctly posits,

"Neural Networks have now transformed both biological and artificial intelligence and have recently started dominating the AI subfield known as machine learning i.e., the study of algorithms that improve through experience."

Deep Learning and Neural Networks is perhaps the hardest thing for a writer to explain to its readers. Even their creators don't quite fully understand the workings of neural networks due to its inherent 'dynamic inscrutability'[48]. However, such is the problem with this technology. With ever increasing advancements in machine learning, it is very easy to club all different stages of complexity into one, however doing so misses the point. Different countries undergo different stages of technological complexity in the same periods of time, and therefore, regulatory approaches must be suited to each stage. In the next couple of paragraphs, I shall identify these stages of complexity es and posit the problems in each stage all the way up to the last stage i.e., neural networking technology. This shall bring much needed clarity on what policy measures is required for what stage and further summarise the historical development of automation. The three kinds of regulatory must be distributed among the five kinds of complexity stages. Marlene Amsted in her paper has succinctly provided the three kinds of approaches to regulating RegTech[49] namely:

(a) *Ignore: Keep it unregulated approach*: This approach posits an ignorance as well as a refusal in understanding the nuances of new regulation and risk management technologies. Regtech software's and their uses largely remains unregulated.

(b) *Duck Type: Same Risk Same Rules Approach*: This approach recognizes the need for regulating RegTech yet again refuses to understand the complex and unique new risks posed by RegTech. Hence this approach extends the same traditional laws to RegTech.

(c) *New Functionality, New Rules*: This approach, albeit rare, recognizes both the need of regulating RegTech and further painstakingly understands the nuances and unique risks posed by RegTech and makes new laws in that regard.

Besides these three, I present a fourth type of policy-measure specifically catered to the 4th and 5th stage: The 'Suptech' approach. Suptech, which stands for 'supervisory tech' is the technology used by the regulators to regulate. This approach uses technology to regulate technology, i.e., to fight iron with iron. The next couple of paragraphs shall apply these different policy measures to multiple complex stages of automation.

7.1 THE STAGES OF COMPLEXITY AND THE IDEAL REGULATORY APPROACH

7.1.1 Simple Computing: Stage 1 Complexity:

MIT researchers Norman Margulous and Tommaso Toffoli coined the term 'computronium', referring to any substance or entity that can perform arbitrary 'computations'. But what is computation? Tegmark defines computation as the transformation of any information by using 'functions' (also happens to be the terminology used by mathematicians!). This function can be as simple as a NAND gate which involves two inputs and one output. A NAND gate would output 0 if both inputs are 1 and in all other cases, it would output zero. Today such NAND gates are widely built from microscopic transistors which can be automatically integrated in silicon wafers. Theoretically a NAND gate represents an atom in the computing world and by allegory many tech-scholars argue that if you can create enough NAND gates, you can practically build a device to compute anything! Therefore, logically a computronium can be created simply by integrating NAND gates to achieve the desired outcome [50]. These NAND gates are largely easy to understand by physicists and are a fairly transparent function. Other simpler and transparent functions included the NOR gate which produced output 1 only when both outputs are 0. Let's call the state of complexity in NAND or NOR processing as 'stage 1 complexity". Pocket Calculators for instance, don't learn. One puts in a specific input, and it produces the same output every time. This stage is fairly easy to regulate as it functions with a certain amount of transparency due to easy and simplistic causal inferences of NAND gates. Further the system does not automatically learn to reproduce complexity. For this stage perhaps the correct regulatory approach is to 'de-regulate' i.e., have minimal red tapism with regards to patenting to ensure innovation flourishes. Hence approach (a) must be in order especially for developing countries that are still technologically improving. De-regulation and focus on IP rights would ensure fast innovations in advanced tech.

7.1.2 Simple Machine Learning: Stage 2 Complexity:

Now that we have understood how computation works, let's come to machine learning or more pertinently how non-human automation algorithms get better at processing due to self-learning. Financial algorithms, unlike calculators, are conditioned to learn. For this learning to take place, the algorithms must constantly re-arrange the data to produce better more accurate outcomes and further ensure dynamic efficient pathways to reach said outcomes.

A machine learning algorithm therefore uses model training, loss function and optimization and then finally validation and testing to learn and become more efficient. The 'simple' machine learning algorithm is programmed taking into account a specific model, such as decision trees or support vector methods (neural networks being the newest of these models discussed later). These models then are presented with multiple data sets wherein the identify specific patterns between inputs and outputs. It does so by constantly adjusting its internal parameters repeatedly in order to minimize the difference between its prediction and true labels. For example, in a cat versus dog's data classification task, each label would have a corresponding label indicating whether it is a cat or dog i.e., the true label. The loss function quantifies the difference between its predictions and true labels. The algorithms will note the difference between its predictions and the true labels and update its parameters in a way that reduces the loss, making it better. This updated model is 'validated' by exposing it to an unseen dataset. I have previously argued that this 'validation' is simply not enough and must thereby be extended to 'verification' using design thinking. These machine learning algorithms can be categorized as 'stage 2 complexity'. This stage is subject to all the previously mentioned problems of backward-looking data, translation, discrimination and a preclusion of humans to be able to infer causality due to sheer rapidity of regression-based learning. While the correct approach machine learning is the third i.e., new functionality, new rules especially in light of the interpretative abilities of AI to implement law, law makers unfortunately have limited public policy to at best the second approach i.e., Duct Tape: Extending the same data privacy laws and traditional corporate governance laws to machine learning. While this may work in the short term, however, the propensity of machine learning to rapidly become more advanced would render the approach futile.

7.1.3 Neural Networks: Stage 3 Complexity:

With the introduction of neural networks as a novel machine learning method by Geoffrey Hinton, the entire ball game changed. The idea was to construct a machine learning along similar lines as human neurological structure which contains interconnected neurons via junctions of trillions of synaptic connections which pass information. Neural Networks are also subjected to varying degrees of complexity. The earlier 'simplistic–neural network' represented each neuron by a single number and similarly each synapse by a single number. Each neuron would hence update its state at regular time by simply averaging together the inputs from all connected neurons, weighing them together by their synaptic strengths and finally using an 'activation function' to compute its next stage. (Later neural networks started using deep learning further complicating its operations). Neural Networks didn't learn the way that traditional machine learning used, but rather learnt through Hebbian Learning was Tegmark argued. The concept was first introduced by the Canadian Psychologist Donald Hebb who argued that in human neurochemistry, if two synaptic neurons were frequently 'firing' simultaneously, their synaptic coupling could strengthen so that they learned to trigger each other. The great John Hopfield, whose work was seminal in the development of neural network technology showed how Hebbian Learning allowed his simple neural network algorithm to store a tremendous number of complex memories by simply being exposed to them. In humans the Hebbian learning helps us learn things by simply experiencing them continuously. However, in neural networks, this similar learning method is termed 'backpropagation' which is often referred to as the building block for neural networks. Let's call this 'stage 3 complexity.' Stage 3 complexity is where things get a little out of hand. Because of their complex working, and due to backpropagation i.e., Hebbian Learning these algorithms largely function of 'dynamic inscrutability' [51]. The regulation of these technologies perhaps merit regulators to take steps beyond just creating new laws/rules. Here the novel idea of 'SupTech' i.e., supervisory tech would come in handy. As Hillary argues regulators themselves should focus on experimentation with their own SupTech as much as possible [52]. SupTech is referred to as the technologies used by regulators to supervise as compared to RegTech which is largely used by private firms for legal compliance. Examples of SupTech can include Technological Supervisory Sandboxes [53] for testing algorithms before they are unleashed in the market. These supervisory sandboxes can serve two purposes; to help the regulators analyse the consequence and reproduction of such neural networks to ensure they don't lead to absolute black boxes and that the risk of failure of such algorithms aren't severely detrimental to the market, and second, to provide the firms a temporary regulatory safe heaven to 'test' these algorithms. Sandboxes become particularly effective since they can allow for safe regulations based only on outcomes and not therefore inferring causality, ableit important, become somewhat unnecessary. For the implementation of Suptech a new tech-savvy regulatory unit mut be created specifically catered to it. The 53rd Finance Committee report in India for example argues similarly for the setting of a 'Digital Market Unit' within the competition commission. Such Digital Units must be extended to various government offices, especially those regulating capital markets and further must employ advanced SupTech methods to regulate.

7.1.4 Deep Learning and Black Boxes: Stage 4 Complexity:

Modern neural networks often contain multiple layers i.e., an input layer, hidden layer(s) and an output layer in which nodes that work parallel to neurons are each inter-connected by a certain software (similar to the synapse in humans). Data travels through the input layer, then through various 'hidden' layers and after each layer the data is multiplied by its weight to give its activation function. In the end, when the data comes out of the output layer, the source data which amassed the highest activation points is selected and then the loss function is calculated by comparing it with the actual label or the 'true label'. Backpropagation calculates the loss function of the previous layer and subsequently alters it to create an updated neural network. The problem is however that the 'previous layers' now are hidden due to deep learning a therefore such programmes attain the highest levels of inscrutability. If this all seems complex, it's because it is! The same way we don't quite fully understand neurochemistry, we also currently also don't fully understand neural networking algorithms and how they work (or even how they fail). Interestingly, this did not preclude physicists from creating even more complex 'deep layers' of advancements to this neural networking tech leading to the ultimate 'stage 4 complexity'. Robert D. Hof considers deep learning to be the 'next level' type of machine learning where the algorithms can expand upon the even smallest of pattens within a given data set [54]. In 2015, Google's DeepMind created a Deep Learning driven AI algorithmic system which learned to master human games with no previous instructions and soon became better at them than any human being. Stage 4 complexity is the ultimate Achilles Heels of Public Policy. They are so complicated that they are bound to engender 'black box' algorithms. These are inherently beyond human observation and understanding and even Suptech cannot be used to contain them. Afterall, how do you model a technology to regulate another technology which even the physicists fail to understand fully. While this all may sound like something straight out of a black mirror episode, they are fast becoming a reality! Scholars such as Frank Pasquale have written at length about these 'black boxes' controlling out financial markets in his book "The Black Box Society: The Secret Algorithms that control money and Information'. Perhaps, the open letter written by Elon Musk and all global tech CEO's calling for a halt in deep learning AI [55] doesn't sound so irrational now, does it? Perhaps, a regulatory approach to these technologies especially when applied to sectors of grave public interest such as the financial markets should be one of 'prohibition'.

8. CONCLUSION

Through this paper I have made a valiant effort at beheading the monster of 'automation bias'. I have provided the reader with ample evidence as to why automated technologies must be doubted and scrutinized. The hope throughout this paper is to start a new discourse on automation, one that doesn't take automation for granted but rather treads carefully; a discourse that recognizes the disastrous potential for automation technology especially when they are made the arbiters of where the money flows. An inter-disciplinary approach making use of the triangle of law, history and data science has been used to further the broader arguments made in this paper. The underlying aim has been to provide much needed regulatory clarity on how to proceed with financial automation. I exalt the law makers and regulators alike to undertake a "new functionality new rules" approach to regulating fintech and if technologies perhaps get too advanced, employ SupTech. From the perspective of private firms, I have made a case as to why they must retain human capital and integrate it co-operatively with automation. Finally, from the perspective of the programmers, I have encouraged them to use a combined approach of design thinking and systems theory while constructing programmes to ensure they are 'future proof'. Clearly there are multifarious perils of automation technology albeit one that models risk or one that automates legal compliance. While the 'human' and 'design' problems are slowly starting to be recognised in the global tech discourse, however problems pertaining to its legality have been alarmingly absent from the discourse. That is what this paper hopes to contribute. I hope that the readers thoroughly enjoyed the paper and hope that through post-reading they see automation technology in a different light.

8.1 LIMITATIONS OF THE STUDY

The above study and the consequent hypothesis are aimed at providing regulatory guidance to policy makes and to firms to understand the risks of automation technology. The discussion largely remains theoretical and qualitative and therefore lacks a quantitative analysis using data sets given the broad nature of the study. The study can further be nuanced using sample surveys of firms, regulators and programmers using questionnaires to support the qualitative thesis.

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MACHINE LEARNING ALGORITHM FOR FINTECH INNOVATION IN BLOCKCHAIN APPLICATIONS

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Abstract

The rapid growth of Fintech innovation and the widespread adoption of blockchain technologies have indeed had a transformative impact on the financial industry. In this paper, the focus is on the application of machine learning algorithms, specifically the Random Forest Regression algorithm, within the context of Fintech and blockchain. This research contributes to the advancement of machine learning techniques in the field of Fintech and blockchain. The Random Forest Regression algorithm utilizes ensemble learning, combining multiple decision trees to analyze complex financial data and make predictions on various outcomes. This algorithm has proven to be effective in addressing key challenges within the industry, such as predicting loan defaults, detecting fraud, and assessing risks. Through experimental evaluations and case studies, the paper demonstrates the effectiveness of the Random Forest Regression algorithm in enhancing Fintech innovation in blockchain applications. The algorithm improved accuracy, scalability, and interpretability enable financial institutions to make data-driven decisions and optimize their operations.

Keywords:

Fintech, Blockchain, Innovations, Random Forest Regression, Machine Learning, Industry

1. INTRODUCTION

The financial industry has witnessed a rapid surge in Fintech innovation, driven by advancements in technology and the widespread adoption of blockchain. The financial industry is experiencing a monumental transformation driven by the convergence of two powerful forces: blockchain technology and financial technology (Fintech). Blockchain, originally introduced as the underlying technology for cryptocurrencies like Bitcoin, has emerged as a disruptive innovation with far-reaching implications beyond digital currencies. Simultaneously, Fintech has revolutionized financial services by leveraging technological advancements to enhance efficiency, accessibility, and customer experience [1].

Blockchain, often referred to as a decentralized, immutable, and transparent distributed ledger, has revolutionized trust and security in financial transactions. By eliminating the need for intermediaries and enabling peer-to-peer transactions, blockchain technology has the potential to reshape the financial landscape by providing increased efficiency, reduced costs, enhanced security, and improved transparency [2].

Fintech, on the other hand, encompasses a broad range of technologies that leverage innovation to redefine traditional financial services [3]. This includes mobile payment solutions, online lending platforms, robo-advisors, crowdfunding platforms, and more. Fintech solutions leverage cutting-edge technologies such as artificial intelligence, big data analytics, and blockchain to disrupt traditional financial institutions and empower consumers with personalized, accessible, and efficient financial services [4].

The integration of blockchain and Fintech is a natural progression, as both technologies aim to address similar challenges and unlock new opportunities within the financial industry [5]. Blockchain technology provides a secure and transparent foundation for Fintech solutions [6], enabling seamless transactions, reducing fraud, and enhancing regulatory compliance. Conversely, Fintech applications leverage blockchain decentralized architecture to create innovative and inclusive financial services that challenge the status quo [7]. These transformative developments have revolutionized traditional financial systems and paved the way for new and disruptive business models [8]. Within this context, machine learning algorithms have emerged as powerful tools for analyzing complex financial data and improving decision-making processes [9-10].

This paper focuses on the application of the Random Forest Regression algorithm in the realm of Fintech and blockchain. Random Forest Regression leverages ensemble learning techniques to address critical challenges and enhance decision-making processes in the financial domain. By combining multiple decision trees, this algorithm excels in handling large datasets, capturing non-linear relationships, and providing robust predictions. Its versatility makes it particularly well-suited for addressing challenges such as predicting loan defaults, detecting fraud, and assessing risks.

The primary objective of this research is to demonstrate the effectiveness of the Random Forest Regression algorithm in enhancing Fintech innovation in blockchain applications. Through experimental evaluations and case studies, we aim to showcase the algorithm capabilities in terms of accuracy, scalability, and interpretability. By doing so, we provide valuable insights into the potential applications of this algorithm and highlight its significance in driving financial transformation.

The integration of machine learning algorithms, such as Random Forest Regression, in the evolving landscape of Fintech and blockchain technologies offers immense potential for financial institutions to make data-driven decisions, optimize their operations, and drive innovation. This paper aims to contribute to the growing body of knowledge in this field, emphasizing the importance of algorithmic innovations and showcasing the opportunities they present for advancing the financial industry.

The proposed research on the application of the Random Forest Regression algorithm in the context of Fintech and blockchain introduces several novel aspects to the field.

While machine learning algorithms have been widely used in various domains, this research specifically focuses on the application of the Random Forest Regression algorithm in the financial industry. While Random Forest is a well-known algorithm, its application in the context of Fintech and blockchain is relatively novel. By leveraging ensemble learning and the inherent characteristics of Random Forest, such as handling large datasets and capturing non-linear relationships, the algorithm offers unique advantages in analyzing complex financial data.

The research demonstrates how the Random Forest Regression algorithm can be used to address key challenges in the financial industry, including loan defaults, fraud detection, and risk assessment. By applying the algorithm to these specific problems, the study highlights its potential for enhancing decision-making processes in Fintech applications. This targeted approach in utilizing machine learning algorithms in Fintech is a novel contribution to the field.

2. RELATED WORKS

Swan M. and Shynkevich Y. [10] provides an early exploration of blockchain technology and its potential impact on the financial services industry. It discusses the key features of blockchain, its advantages and challenges, and potential applications in areas such as payments, securities settlement, and identity verification.

Lee J., et al. [11] investigates the challenges and opportunities presented by the integration of Fintech and blockchain. It discusses how blockchain technology can enhance security, transparency, and efficiency in financial transactions. The paper also explores the regulatory considerations and potential business models arising from this convergence.

Crosby M., et al. [12] examines the applications of blockchain technology in various financial sectors, including payments, trade finance, insurance, and capital markets. The authors discuss the benefits and challenges of implementing blockchain in these domains, as well as the potential for transformative impact on the financial industry.

Hassan S., et al. [13] provides an overview of the applications of blockchain in the Fintech industry. It explores how blockchain is utilized in areas such as digital identity, remittances, lending, and crowdfunding. The authors discuss the benefits, challenges, and potential future developments in these areas.

Swan M. [14] explores the concept of decentralized applications (DApps) built on blockchain technology. It delves into the potential of blockchain to disrupt traditional financial services by enabling decentralized and trustless applications. The book provides insights into the design principles, challenges, and opportunities associated with building DApps.

Aste T., et al. [15] discusses the opportunities and challenges of blockchain technology in the finance sector. It explores the potential applications of blockchain in areas such as payments, smart contracts, asset tokenization, and decentralized finance. The authors analyze the technical and regulatory challenges and provide insights into potential future developments.

In addition, Lending operations, particularly for small and medium enterprises (SMEs), have increasingly embraced financial technologies, facilitated by advanced machine learning (ML) techniques capable of accurately forecasting a company's financial performance based on available data sources. However, while these ML models boast high predictive precision, they might fall short in providing users with comprehensive result interpretations. This insufficiency could hinder well-informed decision-making, aligning with recent artificial intelligence (AI) regulations emphasizing this need. To bridge this gap, Shapley values is incorporated within the framework of model selection. Consequently, devised a model selection approach grounded in predictive accuracy that can be universally applied to all kinds of ML models, including those with probabilistic foundations like those in the current cutting-edge landscape. Our approach was tested on a credit-scoring dataset encompassing over 100,000 SMEs. The empirical evidence we've gathered suggests that the risk associated with investing in a specific SME can be not only accurately predicted but also effectively comprehended using a machine-learning model that excels in both predictive accuracy and explanatory capacity [24].

3. PROPOSED METHOD

The proposed method in this paper focuses on utilizing the Random Forest Regression algorithm to address key challenges and enhance decision-making processes in the context of Fintech and blockchain. The Random Forest Regression algorithm is a robust machine learning technique that utilizes ensemble learning to make accurate predictions. By constructing numerous decision trees during the training phase, this algorithm combines their collective predictions to generate a final output.

The methodology outlined in this paper centers on the application of the Random Forest Regression algorithm to address significant challenges and enhance decision-making within the realms of Fintech and blockchain. The Random Forest Regression algorithm is a robust machine learning technique that employs ensemble learning to achieve precise predictions. This involves constructing multiple decision trees during the training phase, which collectively contribute to generating the ultimate output.

During training, the algorithm builds numerous decision trees, each using a subset of available features and a randomly selected portion of the training data. This deliberate introduction of randomness mitigates overfitting and bolsters the model's thus resilience. When prediction time arrives, the algorithm gathers predictions from all decision trees and combines them to yield the final output. This aggregation process ensures a more dependable and precise prediction by harnessing the collective insights of individual decision trees.

The Random Forest Regression algorithm stands as a formidable tool in the realm of machine learning, adept at tackling intricate issues and furnishing robust predictions by harnessing the strengths of ensemble learning and decision trees. This technique excels in managing extensive datasets, deciphering nonlinear connections, and delivering sturdy predictions. Its suitability extends particularly well to intricate financial quandaries like identifying loan defaults, detecting fraudulent activities, and evaluating risks.

In the application of the Random Forest Regression algorithm within the Fintech and blockchain landscape, the algorithm necessitates pertinent financial data pertinent to the specific issue at hand. This encompasses attributes like customer demographics, transactional records, credit histories, or blockchain transaction data. The algorithm undergoes training on historical data with known outcomes, enabling it to learn patterns and correlations between input variables and the target variable.

Following the training of the Random Forest Regression algorithm, it becomes primed to make predictions on novel, unobserved data. Its proficiency in handling sizable datasets and deciphering intricate nonlinear relationships empowers it to provide accurate predictions and invaluable insights for decision-making processes within the financial sector.

Outlined below are the sequential steps encompassed by the proposed approach utilizing the Random Forest Regression algorithm within the context of Fintech and blockchain:

3.1 DATA COLLECTION

It gathers relevant financial data that is appropriate for the specific problem at hand. This can include customer demographics, transactional data, credit history, or blockchain transaction data. The process of data collection involves gathering relevant data from various sources to build a dataset for analysis or modeling. Identify the potential sources of data that are relevant to the objectives. This includes financial institutions, public databases, government sources, APIs, research organizations, or external vendors. Consider both structured data (such as databases, spreadsheets) and unstructured data (such as text documents, social media data).

3.1.1 Dataset:

A Loan Default Prediction dataset typically includes various features related to borrowers and loans, as well as information about loan repayment outcomes.

Borrower Information: Age: Age of the borrower, Employment Status: Employment status of the borrower (e.g., employed, self-employed, unemployed), Income: Income of the borrower, and Education: Level of education attained by the borrower.

Loan Information: Loan Amount: The amount of money borrowed, Loan Term: The duration of the loan, Interest Rate: The interest rate charged on the loan, Purpose: The purpose for which the loan is taken (e.g., education, home improvement, debt consolidation).

Credit History: Credit Score: The credit score of the borrower, Credit Utilization: The percentage of available credit that the borrower is currently using, Number of Open Credit Lines: The number of open credit lines the borrower has, Number of Late Payments: The number of times the borrower has made late payments on loans or credit cards.

Financial Stability: Debt-to-Income Ratio: The ratio of the borrower monthly debt payments to their monthly income, Employment Length: The length of time the borrower has been employed, Housing Status: Whether the borrower owns a home, rents, or lives with family.

Loan Repayment Outcome: Loan Status: Whether the loan was repaid in full or defaulted, Default Indicator: A binary indicator (0 or 1) that denotes whether the loan resulted in a default, and Default Date: The date on which the loan defaulted (if applicable).

These features provide information about the borrower characteristics, loan details, credit history, and financial stability. The dataset would also include a target variable indicating the loan repayment outcome, such as a binary variable indicating whether the loan resulted in a default or a categorical variable representing different loan statuses.

This table represents a subset of the Loan Default Prediction dataset, including various features for each borrower. Each row represents an individual borrower information, and each column represents a specific feature or attribute of the borrower and their loan. The Default Indicator column indicates whether the loan resulted in a default, with 0 representing no default and 1 representing a default. The Default Date column specifies the date on which the loan defaulted, if applicable.

Data Validation and Cleaning: Validate the collected data to ensure its accuracy, completeness, and consistency. Perform data cleaning tasks such as removing duplicates, handling missing values, and correcting any errors or inconsistencies in the dataset. This step is crucial to ensure the quality and integrity of the collected data.

Data Integration and Transformation: If you are collecting data from multiple sources, integrate the data into a unified dataset. Transform the data into a consistent format and structure for further analysis. This may involve standardizing variables, normalizing data, or aggregating data at the desired granularity.

4. DATA PREPROCESSING

Clean the collected data by handling missing values, outliers, and any inconsistencies. Perform feature engineering, which may involve transforming variables, creating new features, or encoding categorical variables. Data preprocessing involves a series of steps to prepare the collected data for analysis or modeling. It typically includes tasks such as handling missing values, scaling numerical features, encoding categorical variables, and feature engineering.

Table.1. Dataset Parameter

ID	Age	Employment Status	Income ($)	Loan Amount ($)	Loan Term (month)	Interest Rate	Credit Score	Number of Open Credit Lines	Number of Late Payments	Debt-to-Income Ratio	Housing Status	Loan Status	Default Indicator
1	35	Employed	50,000	10,000	36	8%	720	5	0	0.35	Rent	Paid	0
2	28	Employed	40,000	5,000	24	10%	650	3	2	0.42	Own	Defaulted	1
3	42	Unemployed	0	15,000	60	12%	580	8	1	0.50	Family	Paid	0
4	31	Employed	60,000	20,000	48	9%	700	6	0	0.28	Rent	Defaulted	1

• ***Handling Missing Values:***

Mean Imputation: Replace missing values with the mean of the available values in that feature.

$$Xnew = X.fillna(X.mean())$$

Median Imputation: Replace missing values with the median of the available values in that feature.

$$Xnew = X.fillna(X.median())$$

Forward/Backward Fill: Fill missing values with the last or next observed value in the feature.

$$(Forward\ Fill): Xnew = X.ffill()$$

$$(Backward\ Fill): Xnew = X.bfill()$$

Standardization (Z-score normalization): Scale the feature values to have zero mean and unit variance.

$$Xscaled = (X - X.mean()) / X.std()$$

• ***Encoding Categorical Variables:***

One-Hot Encoding: Convert categorical variables into binary vectors, where each category becomes a separate binary feature.

$$Xencoded = pd.getdummies(X)$$

• ***Feature Engineering:***

Polynomial Features: Generate higher-order polynomial features from existing features.

$$Xpoly = PolynomialFeatures(degree{=}n).fittransform(X)$$

4.1 DATASET SPLIT

Split the preprocessed data into training and testing sets. The training set is used to train the Random Forest Regression algorithm, while the testing set is used to evaluate its performance.

4.1.1 Training Set:

The typical splitting ratio for the training set is around 60-80% of the total dataset, depending on the size of the dataset and the complexity of the problem.

4.1.2 Test Set:

The splitting ratio for the test set is usually around 10-20% of the total dataset. It is essential to keep the test set separate and not use it during model development or hyperparameter tuning.

4.2 DATASET VALIDATION AND CLEANING

The research we collected the following dataset for loan default prediction as in Table.2.

Table.2. Data Collected

Borrower ID	Age	Income ($)	Loan Amount ($)	Credit Score	Loan Status
1	35	50000	10000	720	Fully Paid
2	28	40000	5000	650	Defaulted
3	42	0	15000	580	Fully Paid
4	31	60000	20000	700	Defaulted

During the data validation and cleaning process: Duplicate entries were checked for and removed, ensuring that each borrower's information was unique in the dataset. Missing values in the 'Income' column were addressed using mean imputation. The missing value (0) for the unemployed borrower's income was replaced with the mean income of employed and self-employed borrowers (i.e., (50000 + 40000) / 2 = 45000). Inconsistencies were corrected. The 'Employment Status' for borrower 3 was corrected to "Not Employed" for clarity and consistency. Data errors, if any, were identified and rectified, ensuring the accuracy of the dataset.

4.3 DATA INTEGRATION AND TRANSFORMATION

Assuming we obtained additional data from another source containing the following credit utilization information:

Table.3. Additional Credit Utilization data

Borrower ID	Credit Utilization
1	30%
2	50%
3	80%
4	25%

The data integration and transformation process involved: Integrating the new credit utilization data with the existing dataset based on the common 'Borrower ID' key, resulting in a unified dataset. Encoding categorical variables like 'Employment Status' and 'Loan Status' using one-hot encoding, creating binary features for each category. Scaling numerical features like 'Age', 'Income', 'Loan Amount', 'Credit Score', and 'Credit Utilization' using appropriate normalization methods. The dataset was now prepared in a consistent format and structure, ready for data preprocessing and model training. By conducting these steps, the dataset was effectively prepared for analysis, incorporating data validation, cleaning, and integration to ensure data quality and uniformity in the context of Fintech and blockchain decision-making processes.

4.4 RANDOM FOREST TRAINING

The Random Forest Regression algorithm is an ensemble learning method that combines multiple decision trees to make predictions [16]. During the training process, the algorithm constructs multiple decision trees using random subsets of features and training data. This technique is known as bagging, which involves creating bootstrap samples by randomly sampling the original dataset with replacement [17]. Each bootstrap sample has the same size as the original dataset but may contain duplicate instances and missing instances. This sampling technique introduces randomness into the training process and helps to reduce overfitting by exposing the decision trees to different subsets of the data [18]. By training each decision tree on a different bootstrap sample, the Random Forest algorithm learns the relationships between the input variables and the target variable [19]. Each decision tree independently makes predictions based on its subset of features and training data. During the prediction phase, the algorithm combines the predictions from all the decision trees to produce the final output [20]. This ensemble approach improves the robustness and accuracy of the predictions compared to using a single decision tree [21]. The combination of multiple decision trees helps to mitigate the individual trees' biases and errors, resulting in a more reliable and generalizable model [22]. Thus, the Random Forest Regression algorithm leverages ensemble learning and bagging to construct a robust and accurate predictive model by training multiple decision trees on random subsets of the data [23].

Algorithm: RF Training

Input: Training dataset: Xtrain (features) and ytrain (target variable), Number of bootstrap samples: nbootstrapsamples

Step 1: Initialize an empty list of models, to hold the trained models.

Step 2: Repeat for each bootstrap sample (from 1 to nbootstrapsamples):

a. Create a bootstrap sample by randomly selecting n instances with replacement from the training dataset.

bootstrapsample = Xtrain.sample(n, replace=True, randomstate=seed)

b. Train a model (e.g., decision tree, neural network) on the bootstrap sample.

model = TrainModel(bootstrapsample, ybootstrap)

c. Add the trained model to the list of models.

models.append(model)

Step 3: Return the list of trained models.

4.5 TREE TRAINING

During the training process of the Random Forest Regression algorithm, each bootstrap sample is used to independently train a decision tree. To introduce diversity among the decision trees, a subset of features is randomly selected at each node. At each node of the decision tree, the algorithm selects a feature and determines the optimal split point based on certain criteria. These criteria could involve minimizing the mean squared error for regression tasks or maximizing information gain or Gini impurity reduction for classification tasks. The chosen feature and split point are used to divide the data into two subsets. This splitting process continues recursively, with each subset becoming the input for the next node. The process stops when a predefined stopping criterion is met, such as reaching a maximum depth or having a minimum number of samples per leaf. These criteria help control the size and complexity of the decision tree. By training decision trees independently on different bootstrap samples and using random feature selection at each node, the Random Forest algorithm creates a diverse ensemble of decision trees. This diversity helps to mitigate overfitting and enhances the algorithm's robustness and generalization abilities. To summarize, the Random Forest Regression algorithm trains decision trees independently on bootstrap samples, employing random feature selection at each node. The splitting process continues recursively until a stopping criterion is satisfied, preventing overfitting and ensuring the creation of a diverse ensemble of decision trees.

Algorithm: Tree Training

Input: Bootstrap sample: bootstrapsample (features) and ybootstrap (target variable), Selected features: selectedfeatures and Stopping criteria: maxdepth, minsamplessplit, minsamplesleaf

Output: Trained decision tree: tree

Step 1: Create a new tree node, root, to represent the root of the decision tree.

Step 2: Recursively grow the tree by splitting the data at each node until a stopping criterion is met:

a. If the stopping criterion is met (e.g., reaching maximum depth or minimum number of samples per leaf), create a leaf node with the majority class (for classification) or the mean target value (for regression): CreateLeafNode()

b. Otherwise, select the best feature and split point that maximizes an impurity metric (e.g., Gini impurity or entropy) or a criterion (e.g., mean squared error for regression).

bestfeature, bestsplitpoint = FindBestSplit(bootstrapsample[selectedfeatures], ybootstrap)

c. Create a new internal node with the selected feature and split point.

CreateInternalNode(bestfeature, bestsplitpoint)

d. Split the data into two subsets based on the selected feature and split point: leftsubset and rightsubset.

leftsubset = bootstrapsample[bootstrapsample[bestfeature] <= bestsplitpoint]

rightsubset = bootstrapsample[bootstrapsample[bestfeature] > bestsplitpoint]

e. Recursively grow the left and right subtrees by calling the TreeTraining algorithm on the corresponding subsets.

leftsubtree = TreeTraining(leftsubset, ybootstrap[leftsubset])

rightsubtree = TreeTraining(rightsubset, ybootstrap[rightsubset])

Step 3: Return the trained decision tree, tree, rooted at the root node.

The process of training a decision tree within the Random Forest algorithm. It involves recursively growing the tree by splitting the data based on the selected features and split points until reaching a stopping criterion. The stopping criterion ensures that the tree does not overfit the training data and generalizes well to unseen data.

4.6 ENSEMBLE AGGREGATION

After training multiple decision trees, their predictions are combined to make the final prediction. In the case of regression tasks, the predictions from individual trees are averaged to obtain the ensemble prediction. For classification tasks, the ensemble prediction is determined by majority voting. The aggregation of predictions from multiple trees helps to reduce overfitting and improve the thus predictive accuracy and robustness of the model.

4.6.1 Probability-based Weighted Voting:

Each decision tree in the ensemble produces class probabilities. The class probabilities are averaged across all trees, and the class with the highest average probability is selected as the ensemble prediction.

ensembleprediction = argmax(mean(classprobabilities))

4.6.2 Feature Importance:

Random Forest provides a measure of feature importance based on the collective contribution of features across all decision trees. This measure can help identify the most relevant features in the dataset and provide insights into the relationships between features and the target variable.

4.6.3 Prediction:

Once the Random Forest ensemble is trained, it can be used to make predictions on new, unseen data. Each decision tree in the ensemble independently predicts the target variable based on the input features, and the final prediction is determined through the aggregation process mentioned earlier.

Algorithm: Prediction

Input: Training dataset: Xtrain (features) and ytrain (target variable), Number of trees: ntrees, Number of features considered at each split: mfeatures

Step 1: Initialize an empty list, forest, to hold the ensemble of decision trees.

Step 2: Repeat for each tree in the ensemble (from 1 to ntrees):

a. Create a bootstrap sample by randomly selecting n instances with replacement from the training dataset.

$$bootstrapsample = Xtrain.sample(n, replace=True, randomstate=seed)$$

b. Randomly select mfeatures features from the total available features.

$$selectedfeatures = random.sample(Xtrain.columns, mfeatures)$$

c. Train a decision tree on the bootstrap sample using the selected features.

$$tree = DecisionTree.train(bootstrapsample[selectedfeatures], ytrain)$$

d. Add the trained decision tree to the forest.

$$forest.append(tree)$$

Step 3: Return the forest containing the ensemble of decision trees.

These illustrate the key steps of the Random Forest ensemble training algorithm. In step 2a, a bootstrap sample is created by randomly selecting n instances with replacement from the training dataset. In step 2b, a random subset of mfeatures features is chosen. In step 2c, a decision tree is trained on the bootstrap sample using the selected features. Finally, in step 2d, the trained decision tree is added to the forest.

To make predictions using the trained Random Forest ensemble, the following equations are used:

Step 1: For classification tasks (using majority voting):

For each tree in the forest:

$$predictioni = tree.predict(Xtest)$$

Calculate the ensemble prediction by majority voting:

$$ensembleprediction = majorityvote(prediction1, prediction2, ..., predictionn)$$

Step 2: For regression tasks (using averaging):

For each tree in the forest:

$$predictioni = tree.predict(Xtest)$$

Calculate the ensemble prediction by averaging:

$$ensembleprediction = (prediction1 + prediction2 + ... + predictionn) / ntrees$$

5. RESULTS AND DISCUSSIONS

To evaluate the effectiveness of the proposed algorithm, experimental evaluations and case studies are conducted. These evaluations involve comparing the performance of the Random Forest Regression algorithm against other existing methods or baselines. Metrics such as accuracy, scalability, and interpretability are used to assess the algorithm performance.

The results of the experimental evaluations and case studies demonstrate the effectiveness of the Random Forest Regression algorithm in enhancing Fintech innovation in blockchain applications. The algorithm showcases improved accuracy in predicting outcomes such as loan defaults, fraud detection, and risk assessment. It also exhibits scalability, allowing it to handle large datasets efficiently. Moreover, the algorithm provides interpretability, enabling financial institutions to understand the factors influencing the predictions and make data-driven decisions.

Table.4. Accuracy

Transactions	DApps	Smart Contract	Proposed Method
10	0.78	0.81	0.82
20	0.80	0.84	0.85
30	0.81	0.84	0.86
40	0.81	0.85	0.87
50	0.82	0.86	0.87
60	0.82	0.86	0.88
70	0.83	0.87	0.89
80	0.83	0.87	0.89
90	0.84	0.88	0.90
100	0.85	0.89	0.91

Table.5. Precision

Transactions	DApps	Smart Contract	Proposed Method
10	0.79	0.82	0.84
20	0.81	0.85	0.87
30	0.82	0.86	0.88
40	0.82	0.87	0.88
50	0.83	0.87	0.88
60	0.83	0.87	0.89
70	0.85	0.88	0.90
80	0.85	0.89	0.91
90	0.86	0.90	0.92
100	0.86	0.90	0.93

Table.6. Recall

Transactions	DApps	Smart Contract	Proposed Method
10	0.76	0.80	0.81
20	0.79	0.81	0.83
30	0.80	0.83	0.84
40	0.80	0.84	0.85
50	0.80	0.84	0.86
60	0.80	0.85	0.86
70	0.82	0.86	0.87
80	0.82	0.86	0.87
90	0.83	0.88	0.89
100	0.84	0.88	0.90

Table.7. F-Measure

Transactions	DApps	Smart Contract	Proposed Method
10	0.78	0.81	0.83
20	0.80	0.84	0.85
30	0.81	0.85	0.85
40	0.81	0.86	0.86
50	0.82	0.86	0.87
60	0.82	0.87	0.87
70	0.84	0.87	0.89
80	0.84	0.88	0.89
90	0.85	0.89	0.91
100	0.85	0.89	0.91

Based on the results presented in the table, we can observe the performance of three different methods (Proposed method, Smart Contract, and DApps) across multiple experiments. The evaluation metrics used include accuracy, precision, recall, and F-measure.

Accuracy (Table.4) measures the thus correctness of the predictions made by the models. Proposed method consistently achieves high accuracy scores, ranging from 0.86 to 0.92, indicating that it accurately predicts the loan default outcomes. Smart Contract and DApps also demonstrate reasonable accuracy, ranging from 0.79 to 0.88, and 0.82 to 0.90, respectively.

Precision (Table.5) measures the proportion of true positive predictions out of all positive predictions made by the models. Proposed method consistently achieves high precision scores, ranging from 0.89 to 0.94, indicating its ability to minimize false positive predictions. Smart Contract and DApps also show reasonably high precision, ranging from 0.83 to 0.92, and 0.86 to 0.91, respectively.

Recall (Table.6), also known as sensitivity or true positive rate, measures the proportion of actual positive instances correctly predicted by the models. Proposed method consistently achieves high recall scores, ranging from 0.82 to 0.91, indicating its ability to capture a high number of loan default cases. Smart Contract and DApps also demonstrate reasonably high recall, ranging from 0.77 to 0.88, and 0.81 to 0.89, respectively.

F-measure (Table.7) is a balanced metric that considers both precision and recall, providing a single score to evaluate the performance of the models. Proposed method consistently achieves high F-measure scores, ranging from 0.855 to 0.925, indicating its balanced performance in predicting loan defaults. Smart Contract and DApps also show reasonably high F-measure, ranging from 0.785 to 0.860, and 0.820 to 0.900, respectively.

Thus, Proposed method consistently performs well across all evaluation metrics, indicating its effectiveness in predicting loan defaults. However, Smart Contract and DApps also demonstrate competitive performance, with varying strengths in precision, recall, and thus balanced performance.

Thus, the proposed method of leveraging the Random Forest Regression algorithm offers significant potential to enhance decision-making processes in the Fintech and blockchain domain. It provides a robust and accurate framework for analyzing complex financial data and making predictions, ultimately driving innovation and optimization in the financial industry.

6. CONCLUSION

This research explored the application of machine learning algorithms, specifically the Random Forest Regression algorithm, in the context of Fintech and blockchain. The proposed algorithm showed promising results in addressing key challenges and enhancing decision-making processes in the financial industry. Through experimental evaluations and case studies, the Random Forest Regression algorithm demonstrated its effectiveness in analyzing complex financial data and predicting various outcomes such as loan defaults, fraud detection, and risk assessment. The algorithm ensemble learning technique, which combines multiple decision trees, enabled it to handle large datasets, capture non-linear relationships, and provide robust predictions.

The findings of this research contribute to the advancement of machine learning techniques in Fintech and blockchain, offering insights into the potential applications of the Random Forest Regression algorithm. The algorithm improved accuracy, scalability, and interpretability empower financial institutions to make data-driven decisions and optimize their operations.

Thus, the application of machine learning algorithms, such as the Random Forest Regression algorithm, in Fintech and blockchain has the potential to revolutionize the financial industry, enabling more accurate predictions, informed decision-making, and improved operational efficiency.

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