# A Decentralized and Efficient Crowdfunding Framework for Secure Transactions and User Engagement

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**Abstract.** *Crowdfunding has become essential for financing entrepreneurial projects, innovative projects, and social initiatives. However, existing platforms face critical challenges, including a lack of transparency, low user engagement, data privacy concerns, and ineffective personalization of user experiences. To address these limitations, this study introduces a novel decentralized crowdfunding framework that integrates Federated Learning (FL), blockchain technology, and Q-learning to enhance security, transparency, and user engagement. The framework leverages FL to collaboratively train models across distributed datasets while ensuring privacy preservation by eliminating the need to share raw user data. Blockchain technology is utilized to ensure tamper-proof transaction records and automate trustless interactions through smart contracts, effectively preventing fraud while increasing transparency. Additionally, a Q-learning-based incentive mechanism is incorporated to predict and stimulate user engagement, ensuring dynamic long-term engagement. The experimental evaluation illustrates that the designed framework attains state-of-the-art performance with an accuracy rate of 99.39%, surpassing existing methodologies. The results demonstrate the effectiveness of the framework in providing a secure, decentralized, and highly personalized crowdfunding system, raising trust and engagement among stakeholders and resolving long-standing issues in crowdfunding platforms.*

## Keywords

Bidirectional recurrent neural network, blockchain, crowdfunding, Federated Learning (FL), MetaMask wallet, Q-learning, smart contract

## 1. Introduction

Crowdfunding is an innovative digital business model that involves a campaign to raise a modest amount of money from a large number of people using the Internet as an intermediary. Researchers have reasoned that global connectivity through the Internet and web-based platforms is an effective way to reach investors and entrepreneurs, thereby raising capital [1], [2]. Crowdfunding primarily provides financial support for individuals, enterprises, and projects [3], [4]. The global crowdfunding market volume reached around USD 18 billion in 2022 and is projected to double by 2030. However, the motivations of backers in crowdfunding significantly varied from those of investors [5]. Several ethical concerns were also associated with crowdfunding across 100 campaigns conducted on behalf of individuals who disclosed their personal information to receive attention, as well as insufficient marketing efforts to attract investors and promoters [6]. Crowdfunding success can be uneven; as a digital platform, it does not facilitate direct interaction between campaigners and funders, leading to information asymmetry. Some platforms attempt to implement various strategies to sustain the crowdfunding industry [7]. Blockchain technology offers desirable features, including decentralization, integrity, verification, and fault tolerance. In a trustless environment, blockchain can help prevent fraud and ensure that credentials are genuine [8], [9]. To ensure this, hybrid Machine Learning (ML) techniques were studied between 2018 and 2023 to detect fraud on crowdfunding platforms and provide real-time alerts [10].

Emotions play a crucial role in charitable crowdfunding, influenced by both verbal and nonverbal cues, including facial expressions. These examinations were conducted by implementing regression and fuzzy-set qualitative analysis using data collected from 1 372 campaigns [11]. Numerous studies have been conducted using data from various crowdfunding campaigns to identify key factors and improve overall success rates. [12]. Existing crowdfunding platforms utilize decentralized ledgers and smart contracts [13] to enhance transparency and efficiency in educational donations within the context of sustainable development. This technology enables donors to track how their contributions

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are being utilized, ensuring that their funds reach the intended recipients. Similarly, predictive models for crowdfunding success using ML techniques [14] can be used to forecast campaign performance. These models integrate important theoretical features and utilize post-hoc explainability techniques like SHapley Additive exPlanations (SHAP) values and Accumulated Local Effects (ALE) plots to provide insights into the factors influencing fundraising success. Crowdfunding fraud detection has also been researched using feature selection techniques such as Correlation-based Feature Selection (CFS), Pearson Correlation Coefficient (PCC), and Information Gain (IG) on web and social media information [15]. These techniques apply publicly available data to identify and classify fraudulent crowdfunding campaigns. Despite their effectiveness, these approaches have several limitations. Privacy concerns remain a significant challenge, as many systems expose sensitive user information due to inadequate data protection mechanisms. Centralized data storage and processing create security vulnerabilities, increasing the risk of data breaches and unauthorized access. Fraud detection processes are based on static, rule-based approaches, which tend to be ineffective against adaptive fraud strategies and lack real-time detection capabilities. Existing engagement strategies are based on fixed incentive frameworks, thereby limiting their adaptability in the long-term context of user behavior. Additionally, inconsistencies in dataset quality impact the accuracy and reliability of predictive analytics and decision-making. Lastly, scalability challenges remain, as handling large-scale transactions can lead to performance bottlenecks. The proposed framework addresses these issues by leveraging Federated Learning (FL), blockchain, and Q-learning to enhance security, transparency, and user engagement. FL facilitates privacy-preserving crowdfunding by avoiding the exchange of raw data, ensuring user data protection while still allowing for model training. Blockchain technology enhances security and transparency through smart contracts, facilitating trustless and tamper-proof transactions that prevent fraud and ensure equitable fund distribution. Moreover, a Q-learning-based incentive mechanism dynamically optimizes engagement strategies, promoting long-term participation and creating a more interactive and sustainable crowdfunding environment.

### 1.1. Research Contributions

The key contributions of this study are as follows:

- This work presents an innovative crowdfunding platform that uses Federated Learning (FL) to maintain user privacy during model training. Unlike traditional systems that demand centralized data storage, FL facilitates decentralized training across user devices without sharing raw data. This ensures strong data privacy while still maintaining high performance.
- The proposed model incorporates blockchain technology and smart contracts to facilitate safe, transparent, and tamper-proof transactions. Through eliminating the need for centralized intermediaries and integrating MetaMask wallets, the system increases stakeholder trust levels. Smart contracts automate fund distribution and fraud detection, ensuring campaigns adhere to predefined terms.
- A reward system based on reinforcement learning using Q-learning is designed to predict user behavior and dynamically encourage participation. This system dynamically optimizes rewards from past interactions, ensuring long-term user engagement. It addresses the problems of static reward policies in existing platforms, making the crowdfunding environment more engaging and sustainable.

### 1.2. Research Paper Structure

The structure of the paper is as follows: Section 2 analyzes the related work on crowdfunding platforms. Section 3 describes the structure of the proposed crowdfunding platform. The results are depicted in Sec. 4, and Section 5 concludes the paper.

## 2. Related Work

Various studies were analyzed and developed for crowdfunding platforms, focusing on different aspects. The study by [16] employed Ordinary Least Squares (OLS) regression and conducted robustness checks to examine the impact of signals that mitigate information asymmetry in crowdfunding. However, it was only focused on reward-based platforms in China and the UK. Similarly, the authors of [17] used multiple regression analysis to predict funding levels for the donation-based crowdfunding campaigns. However, it was essential to note that it could not capture the donor's motivation and was only applicable to Indian platforms. To overcome this, the authors of [18] developed a crowdfunding platform for movies and web series that benefits all stakeholders in the film industry. This also offered monetary and non-monetary benefits to filmmakers, but it was primarily designed for reward-based funding. To improve other types of financing, the work of [19] utilized extensive data from 11 771 medical campaigns to predict the performance of fundraisers by employing an ensemble-based machine learning algorithm. This model showed high accuracy and provided valuable insights. Nevertheless, it was limited by the fact that the data relied upon a single platform. To mitigate this, the researchers [20] analyzed the largest crowdfunding platforms in Poland. They identified their role in financing business initiatives, providing quick fundraising, facilitating project implementations, enabling market entry for new products, and offering marketing benefits. However, the analyzed platform only focused on a donation-based model. To investigate patients' financial needs in online crowdfunding campaigns using automated software, the analysis of the investigators recognized the factors contributing to crowdfunding campaigns' success. However, the investigation was hindered by the lack of data on fundraisers [21]. To improve this, the authors of [22] developed a hypothetical model for analyzing the influence of transparency on crowdfunding. They provided new perspectives, but this analysis relies heavily on assumptions and cannot fully capture the complexities of the real world. The work of [23] investigated the influence of environmental, communal, and governance indicators on the achievement of sustainable crowdfunding platforms and developed a predictive model using machine learning (ML). It assisted crowdfunding platforms, backers, and creators. However, the work required further exploration of different crowdfunding platforms. Similarly, the authors of [24] examined the success aspects of globally supportable products in crowdfunding campaigns by collecting data from creators through a survey. This provided suggestions and highlighted the success, but it had a limited sample size. To address this, the researchers [25] utilized Kickstarter datasets and performed hyperparameter tuning to optimize their model. It was developed to recognize the accomplishment of crowdfunding and investigate the efficiency of wide-and-deep learning model in predicting success rates. This model achieved high accuracy and an F1-score for predicting success, but required further exploration of the factors that affected success. The authors of [26] utilized decentralized blockchain technology and FL to offer a crowd-computing model, which integrated an ElGamal-based re-encryption algorithm to protect users' privacy. While this model offered high security and better accuracy, it needed further optimization for complex real-world scenarios. In further studies, the researchers [27] suggested smart contracts on a blockchain platform to ensure control over invested money, security, and decentralization. However, blockchain in crowdfunding is still in the exploratory stage. The authors of [28] sought to identify the characteristics of fraudulent crowdfunding campaigns in order to accurately detect scams.

This study collected data from 100 fraudulent campaigns using Forward Stepwise Logistic Regression (FSLR). Though the model gave an accuracy of 87.3% in detecting scams, it missed some fraudulent activities. Authors of [29] proposed a system that integrates a crowdfunding platform with blockchain to provide a secure, transparent, and immutable framework for raising funds. This system utilized smart contracts on the Ethereum blockchain, ensuring transparency and security, and reducing the risk of fraudulent transactions; however, it had high implementation costs. To minimize this, the work of [30] used the modified Visual Analogue Scale Matrix for Criteria Weighting (VASMA-L) criteria weighting method to identify and rank the success rate that influenced the decision to fund blockchain-based campaigns. This method reduced the uncertainties in decision-making and aided investors in selecting promising blockchain-based crowdfunding campaigns. However, this study only analyzed the investor's perception. To further enhance this multi-level programming, a backward induction method was employed in blockchain technology for crowdfunding, thereby improving the supply chain value in marine ranching.

This model [31] enhanced the value of blockchain technology, but it focused only on two crowdfunding methods. Similarly, the Design Science Research (DSR) approach was employed to develop and evaluate a blockchain-based equity token prototype for crowdfunding, thereby enhancing early-stage funding processes. Although it improved efficiency, transparency, and interoperability in equity crowdfunding, its reliance on the Ethereum blockchain limited its applicability, and it was not considered for other crowdfunding models [32]. Similarly, the authors of [33] employed a qualitative research strategy to investigate the potential of blockchain technology in enhancing transparency and security on crowdfunding platforms. This platform offered improved security, transparency, efficiency, and lower transaction costs but was only used in the equity-based model. Crowdfunding has gained significant traction as an alternative funding mechanism for startups, social causes, and creative projects. Nevertheless, existing crowdfunding platforms exhibit several limitations that delay their effectiveness and adoption. Centralized platforms lack transparency in fund allocation and campaign management, leading to distrust between backers and campaign creators. Traditional platforms often require users to share sensitive personal and financial data, raising concerns about data breaches and misuse. Moreover, existing systems fail to provide personalized experiences for users, resulting in lower engagement and participation rates. Despite advancements in machine learning (ML) and blockchain technology, there is a lack of integrated solutions that leverage these technologies to address the challenges above. This study aims to bridge this gap by proposing a decentralized crowdfunding framework that integrates FL, Reinforcement Learning (RL), and blockchain technology.

## 3. Proposed Model

The study introduces a novel decentralized crowdfunding framework that combines advanced Deep Learning (DL) techniques and blockchain technology. The proposed framework is aimed at providing a secure, transparent, and personalized experience for all stakeholders, including individual backers, campaign creators, or organizations. The system ensures data privacy, fraud prevention, and intelligent reward mechanisms, fostering greater trust and participation in crowdfunding activities by leveraging FL, Q-learning, and blockchain-based smart contracts. At the core of the framework is FL, which enables the training of ML models across decentralized devices or servers without sharing raw data. This approach ensures that sensitive user data remains private while still allowing the system to learn from diverse datasets. The framework utilizes three local models in the federated learning (FL) setup. Each client model is independently trained on a BiRNN architecture for a classification task, while feature extraction is conducted via an AE.

The local models are periodically aggregated into a global model to ensure collaborative learning without compromising data privacy. The framework incorporates Q-learning to enhance user engagement and incentivize participation. This component predicts the contributions of individuals, campaigns, and organizations based on historical data and user behavior. By analyzing patterns and trends, the system dynamically allocates rewards, ensuring a fair and motivating experience for all participants. This intelligent reward mechanism not only encourages current contributions but also fosters long-term engagement. The framework integrates blockchain technology to secure transactions and avoid fraud. Smart contracts are used to route fund allocation, prevent fraud, and execute predefined rules without the need for trusted intermediaries. Additionally, the MetaMask wallet is integrated into the platform, enabling users to manage their cryptocurrency transactions seamlessly. This decentralized approach eliminates the risks associated with centralized control, such as biases and single points of failure, while enhancing trust and accountability.

## 3.1. Data Collection

The datasets are collected to train and test models within the FL framework, aiming to improve model performance.

This is achieved by utilizing Beautiful Soup and Selenium to extract data from crowdfunding platforms such as Kickstarter, CrunchBase, Indiegogo, and others. These datasets include information about campaigns [34], organizational backers [35], and individual backers [36]. Three types of local models are trained to correspond to the individual investor, crowdfunding campaign, and organization-based investor. Client-1 includes data collected from each individual who is a backer in crowdfunding.

It consists of 21 313 data points, including the backer's name, mobile number, email ID, ID card, and state. Out of the total data, there are 12 680 genuine cases and 8635 fraudulent cases. Similarly, there are 7 584 cases of regular backers and 5 097 instances of irregular backers. Client-2 contains data collected from various campaigns conducted by each crowdfunding platform. It contains 45 887 campaign details, such as name and ID, target amount, currency format, duration, backers count in each campaign, and category. Out of the total data, there are 24 463 real campaigns, 21 425 fake campaigns, 12 681 regular campaigns, 11 783 irregular campaigns, 21 286 successful campaigns, and 24 602 unsuccessful campaigns. Client-3 comprises data from various organizations, including the organization name, founding year, headquarters location, industry sector, company net worth, and website. Of the 30 102 data points, 17 576 were genuine companies, 12 527 were scams, 9 156 were regular backers, and 8 421 were irregular backers. These datasets were available in data.world, which requires a user sign-in for access. The dataset distribution was given in Tab. 1.

## 3.2. Data Preprocessing

This phase includes cleaning the data to remove noise, outliers, and inconsistencies. To ensure data quality and readiness for the following step, the dataset undergoes standardization, normalization, treatment of missing data, and other necessary processes. Initially, ordinal integers are created by using the ordinal encoder to encode categorical data. The MinMax scaler is then used to scale numerical features so that their values fall within a predetermined range from 0 to 1.

| Dataset Split | Train (80%) | Test (20%) | Total (100%) |
|---|---|---|---|
| **Campaign** | 36 708 | 9 178 | 45 886 |
| **Organization** | 24 080 | 6 021 | 30 101 |
| **Individual** | 14 919 | 6 394 | 21 313 |

**Tab. 1.** Distribution of the dataset.

## 3.3. Federated Learning Setup

The proposed framework employs a multi-client federated learning (FL) architecture, in which three distinct local models —Client-1 for individual backers, Client-2 for campaigns, and Client-3 for organizations —are trained on separate datasets corresponding to various stakeholders.

Each client model is trained separately on its own preprocessed data, ensuring both security and localization of sensitive data, including backers' personal information or an organization's private data. In both local and global models, AE is used for feature extraction and dimensionality reduction to extract significant features from the data. This stage maximizes the prediction accuracy of the models by ensuring that they focus on the most relevant patterns.

BiRNN is utilized for classification tasks, as it can extract contextual information and temporal dependencies from sequential data, such as campaign timelines or contribution histories. In the proposed structure, powerful and accurate modeling is ensured by the effective pipeline developed through the combination of AE for feature extraction and BiRNNs for classification. These elements work together to enable the system to manage diverse and complex data while protecting user privacy and delivering personalized services. The following subsections give elaborate information on the two techniques as applicable to the FL setup. The pipeline of the proposed framework is shown in Fig. 1.

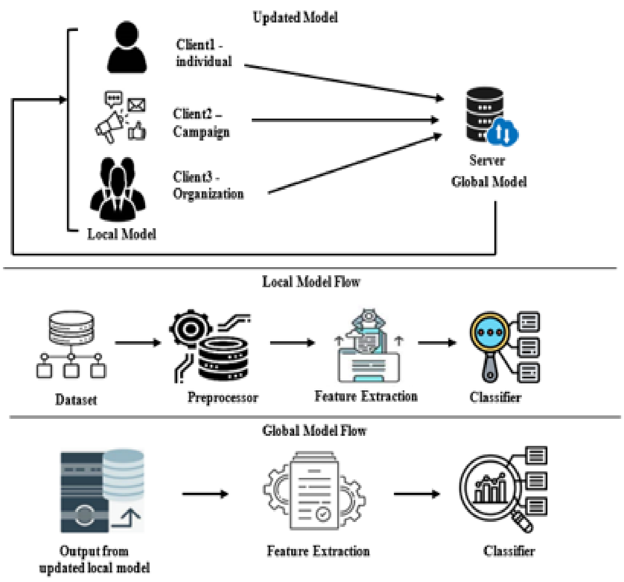


**Fig. 1.** Federated learning flow.

### 3.4. Feature Extraction using AE for Local and Global Models

AE is used for feature extraction in the proposed crowdfunding architecture due to its ability to minimize dimensionality and extract significant features from intricate datasets. AE is used for feature extraction in both local and global models. It is a type of neural network that learns a comprehensive depiction of the input data to reconstruct the original input. AE comprises an encoder network, multiple hidden layers, and a decoder network [37].

For the encoder phase for training, initialize the weight matrix $\mathbf{Weight}_\mathrm{x}$ and bias vector $\mathbf{bias}_\mathrm{x}$ and update the weight matrix and bias vector based on the error value $E$ as shown in (1) and (2):

$$\mathbf{Weight}_\mathrm{x} = \mathbf{Weight}_\mathrm{x} + E\,, \tag{1}$$

$$\mathbf{bias}_\mathrm{x} = \mathbf{bias}_\mathrm{x} + E\,. \tag{2}$$

For the decoder phase, make the decoder layer weight matrix $\mathbf{Weight}_\mathrm{y}$ and bias vector $\mathbf{bias}_\mathrm{y}$ to be the transpose of the $n$ encoder $\mathbf{Weight}_\mathrm{x}$ and $\mathbf{bias}_\mathrm{x}$ as shown in (3) and (4).

$$\mathbf{Weight}_\mathrm{y} = \mathbf{Weight}_\mathrm{n}^\mathrm{T}\,, \tag{3}$$

$$\mathbf{bias}_\mathrm{y} = \mathbf{bias}_\mathrm{n}^\mathrm{T}\,. \tag{4}$$

Equations (5) and (6) can be used to represent AE with only one hidden layer in the encoder and decoder.

$$\mathbf{h} = \delta\left(\mathbf{Weight}_\mathrm{e}\,\mathbf{i} + \mathbf{bias}_\mathrm{e}\right), \tag{5}$$

$$\hat{\mathbf{i}} = \delta\left(\mathbf{Weight}_\mathrm{d}\;\mathbf{h} + \mathbf{bias}_\mathrm{d}\right) \tag{6}$$

where $\mathbf{i}$ represents the input data, $\mathbf{h}$ represents the minimum spatial feature space, $\delta$ represents the stimulation performance, e is the encoder, and d is the decoder.

Equation (5) is an encoder network that transforms the low-dimensional features with input features, and Equation (6) shows the decoder network reconstructs the original input from the minimum spatial feature space.

Equation (7) illustrates how the reconstruction error function, which represents the difference between the AE model's input and output, is minimized using the AE model:

$$L\left(\mathbf{i},\hat{\mathbf{i}}\right) = \left|\mathbf{i} - \hat{\mathbf{i}}\right|_2^2 \tag{7}$$

where $|\;|^2$ denotes the Euclidean norm and $\hat{\mathbf{i}}$ is the output data. After the AE model is attained from the training dataset, a threshold value is verified.

Equation (8) calculates the mean square error (MSE) between the original and predicted data:

$$\mathrm{MSE}_\mathrm{value} = \frac{1}{n}\sum_{n}\left(\mathbf{i}_\mathrm{value} - \hat{\mathbf{i}}_\mathrm{value}\right)^2 \tag{8}$$

where $n$ denotes the number of validation data. A threshold value determines the variation in normal data compared to attack data, and it is calculated from the sample mean and standard deviation, as shown in (9)

$$\mathrm{Threshold} = \mathrm{mean}\left(\mathrm{MSE}_\mathrm{value}\right) + \mathrm{std}\left(\mathrm{MSE}_\mathrm{value}\right). \tag{9}$$

### 3.5. Classification using BiRNN Classifier for Local and Global Models

Classification plays a crucial role in the proposed crowdfunding architecture, as it enables the system to classify and forecast results based on the retrieved data. In both local and global models, BiRNN is used as the classifier for classification. It comprises two distinct Recurrent Neural Networks (RNNs), one for the forward-order input sequence and the other for the backward-order [38].

At each step, the outputs of both orders of RNN are combined to create the final output, which represents the combined sequence of both directions as depicted in Fig. 2.

Initially, the vectorized depiction of the text is the input layer. Each sample word can be expressed after the extension as shown in (10):

$$\mathbf{a} = \left\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \ldots\ldots, \mathbf{v}_n\right\} \tag{10}$$

where $\mathbf{a}$ is the input layer, and $\mathbf{v}$ is the sample words with $n$ number of elements.

The forward and backward RNNs, as expressed in (11), are used to obtain deep-level text samples from the input text vector:

$$\mathbf{K}_{q,r,s} = \mathrm{BiRNN}\left(\mathbf{w}_{q,r,s}\right),\; s \in [1,n] \tag{11}$$

where $\mathbf{w}_{q,r,s}$ is the word vector of $s$-th word ranges from 1 to $n$, the $r$-th input sentence at the $q$-th instant, and $\mathbf{K}_{q,r,s}$ is the word after encoding the samples.

The probability weight of each word vector is calculated as shown in (12), (13), and (14):

$$\mathbf{x}_{q,r,s} = \tanh\left(\mathbf{Weight}_\mathrm{v}\,\mathbf{K}_{q,r,s} + \mathbf{biases}_\mathrm{v}\right), \tag{12}$$

$$\mathbf{y}_{q,r,s} = \frac{\exp\left(\mathbf{x}_{q,r,s}^\mathrm{T}\,\mathbf{x}_\mathrm{v}\right)}{\sum_s \exp\left(\mathbf{x}_{q,r,s}^\mathrm{T}\,\mathbf{x}_\mathrm{v}\right)}, \tag{13}$$

$$\mathbf{z}_{q,r,s} = \sum_{q=1}^{n} \mathbf{y}_{q,r,s}\,\mathbf{K}_{q,r,s} \tag{14}$$

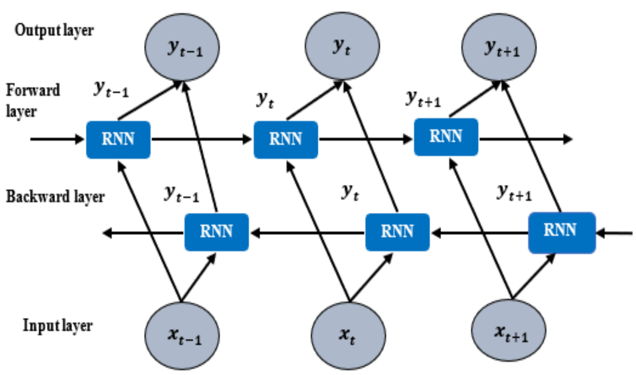


**Fig. 2.** BiRNN architecture.

where $\mathbf{x}_{q,r,s}$ represents the parameter learned by the attention mechanism, and $\mathbf{Weight}_v$ and $\mathbf{biases}_v$ are the weights and biases of feature conversion, respectively. After incorporating the self-attention mechanism, the feature representation is represented by $\mathbf{z}_{q,r,s}$, the $\mathbf{x}^T{}_{q,r,s}$ represents the transpose of a vector-matrix $\mathbf{x}_{q,r,s}$, and the attention weight matrix is represented by $\mathbf{y}_{q,r,s}$. Equation (15) expresses how the gating layer transforms the input feature representation into a new feature space **L**:

$$\mathbf{L} = \pi\left(Vx\mathbf{F} + c\right) * \mathbf{F} \tag{15}$$

where **F** is the output of BiRNN, π is the activation function, * represent the element's dot product, and $V$ and $c$ are the learnable parameters.

Finally, the output is calculated using the SoftMax function. Thus, the classification can be performed using the trained **Weight** and **bias** parameter as shown in (16):

$$p_r = \mathrm{SoftMax}\left(\mathbf{Weight}\, z_r + \mathbf{bias}\right) \tag{16}$$

where $p_r$ and $z_r$ are the predicted label and feature representation of the output layer.

## 3.6. Model Training Aggregation

The FL aggregation [39] process generally includes the following steps:

***(i) Local training:*** Each client trains a local model on its private dataset.

***(ii) Model update sharing:*** A central server receives the most recent local model updates from clients.

***(iii)*** **Model aggregation:** A new global model is created by combining the updates on a central server. The simplest core aggregation method is Federated Averaging (FedAvg), where the central server averages model updates. This is usually closely tied to the number of data points that each client has. FedAvg can be expressed mathematically as (17):

$$M_g = \frac{1}{K}\sum_{i=1}^{K} n_i m_i \tag{17}$$

where $n_i$ is the number of data points in the data of the $i$-th client, $m_i$ denotes the model update from the $i$-th client, $K$ represents the total number of clients, and $M_g$ is the global model.

***(iv) Model distribution across the globe:*** Clients utilize the updated global model for training on local data.

Given a convergent series, the global model might be gradually enhanced at each aggregation round over a series of iterations.

## 3.7. Contribution Prediction using Q-Learning Algorithm

In the proposed crowdfunding framework, predicting the contributions of individuals, campaigns, and organizations is essential for designing an effective reward system that incentivizes participation and fosters long-term engagement. In this study, Q-learning is employed as an adaptive approach for contribution prediction. Q-learning is an RL algorithm that enables the agent to learn the optimal action to take in the environment, thereby maximizing its total reward over time. The initializations are made to the replay buffer, Q-network, target neural network, and greedy policy. After $N$ number of episodes and $T$ number of steps, the setting is reset. Transitions included in the replay buffer are chosen by the action the policy selects. Lastly, the batch transition loss is calculated, and gradient descent is performed in the Q-network to update the parameters and policy [40]. The primary objective of this algorithm is to ensure that the action performance will not vary the attained reward. Hence, knowing the action value at every time step is not required.

In general, the value of the action is defined as shown in (18):

$$P^{\theta}\left(a_t, b_t\right) = D_{\pi}\left[\sum_{l=t}^{T}\alpha^{l-t} G_t \mid \left(a_t, b_t\right)\right] \tag{18}$$

where $P^{\theta}(a_t, b_t)$ represents the function that depends on the action $a_t$ and $b_t$ at time $t$, and $D_{\pi}$ is the expectation under the policy π.

The state value is defined as expressed in (19):

$$W^{\theta}\left(a_t\right) = D_{\pi}\left[\sum_{l=t}^{T}\alpha^{l-t} G_t \mid a_t\right] \tag{19}$$

where $W^{\theta}(a_t)$ is a function that depends only on action $a_t$ at time $t$.

The gain value displays the advantages of choosing an action relation with another action in the given state. The gain function $S^{\theta}(a_t, b_t)$ is attained by deducting the state value from the action value expressed in (20):

$$S^{\theta}\left(a_t, b_t\right) = P^{\theta}\left(a_t, b_t\right) - W^{\theta}\left(a_t\right). \tag{20}$$

By combining (19) and (20) into (21), the contesting design learns the state value without knowing the consequences of each action on each state.

$$P^{\theta}\left(a_t, b_t; \alpha, \beta, \gamma\right) = W^{\theta}\left(a_t; \alpha, \gamma\right) + \left(S^{\theta}\left(a_t, b_t; \alpha, \beta\right) - \frac{1}{\left|S^{\theta}\right|}\sum_{\theta'} S^{\theta}\left(a_t, b_t; \alpha, \beta\right)\right) \tag{21}$$

where $\alpha$, $\beta$, $\gamma$ are discount, weighting, and scaling factors, respectively.

The algorithm's basic idea is to arrange the transitions in a replay buffer that is more effective for learning. It measures the importance of each transition time difference error, and an offset value is added to preserve the position from becoming zero, as in (22):

$$M_i = \left|\sigma_i\right| + \varepsilon \tag{22}$$

where $M_i$ is the function of the absolute value of $\sigma_i$ and the constant value ε to avoid becoming zero. Using the precedence, the probability of choosing each transition is expressed in (23):

$$M_i = \frac{(M_i)^\theta}{\sum_{i=1}^{N}(M_i)^\theta} \tag{23}$$

where $\theta$ is the factor that determines the prioritization.

Prioritized replay creates a bias during training due to its selection of some frequent transitions. To avert this, the neural network updates the steps as shown in (24):

$$v_i = \left(\frac{1}{N}\cdot\frac{1}{M_i}\right)^b \tag{24}$$

where $b$ represents the bias correction.

## 3.8. Blockchain Integration

Blockchain technology has revolutionized the way transactions are carried out by providing a transparent, secure, and decentralized platform for handling data. Blockchain technology is integrated into the crowdfunding framework to address key issues, including fraud prevention, transparent fund allocation, and transaction security. Smart contracts are essential for automating and securing transactions, as they are self-executing agreements with preset rules encoded on the blockchain. Additionally, consumers can easily manage their finances while maintaining complete control over their assets by using MetaMask wallets. This decentralized strategy not only enhances platform security but also aligns with the broader objective of creating an open and user-centric crowdfunding environment.

### 3.8.1. Smart Contracts for Secure Transactions

Smart contracts on blockchain are used to automate and enforce regulations for crowdfunding campaigns. These contracts specify the terms and conditions for allocating funds, ensuring that money is only disbursed upon the achievement of specified benchmarks. For instance, if the campaign financing target is met, the smart contract will automatically transfer funds to the campaign founder. On the other hand, if the target is not met, money is returned to backers. Thus, these contracts reduce the need for intermediary involvement, thereby minimizing the risk of fraud or mismanagement. The blockchain creates immutable audits of each transaction executed across the network, resulting in a trustless environment where all are welcome to audit the transactions. This transparency ensures that all stakeholders can verify the flow of funds and hold each other accountable. The decentralized nature of blockchain eliminates single points of failure, making the platform more resilient to attacks and ensuring the integrity of the data.

### 3.8.2. MetaMask Wallet for Cryptocurrency Management

The proposed framework integrates the MetaMask wallet as a means for users to securely manage their digital assets. MetaMask allows users to store, send, and receive cryptocurrencies directly within the application, providing a seamless and user-friendly experience. Through MetaMask, users maintain full control over their private keys, safeguarding their funds, which are accessible only to them. The proposed framework utilizes blockchain technology to decentralize the process of allocating funds, ensuring that no single organization has complete control over them. This decentralization ensures that the platform operates impartially and fairly, while also fostering confidence among stakeholders. The blockchain provides a permanent and impenetrable record of all contributions, transactions, and campaign information. This immutability further improves confidence and accountability by guaranteeing that the platform's history is transparent and traceable. The crowdfunding platform provides a high level of security, transparency, and decentralization by incorporating blockchain technology. This is because the new mode will address all the problems that can be found in traditional crowdfunding systems and further provide a fairer and more reliable environment for everyone involved.

# 4. Results and Discussion

In this section, we analyze the performance of the proposed model and discuss how FL and blockchain bring security and a decentralized system for crowdfunding. The proposed model has been executed following the hardware and software requirements in Tab. 2. The system parameters of the FL framework and Bi-RNN model are explained in Tab. 3 and 4.

| Parameter | Value |
|---|---|
| Processor | Intel(R) Xeon(R) CPU E5-2680 v4 @ 2.40GHz 2.40 GHz |
| RAM | 16 GB DDR4 |
| GPU | NVIDIA Quadro M2000 (2 GB) |
| Storage | 1 TB SSD |
| Operating System | Windows 10 Pro |
| System Type | 64-bit operating system, x64-based processor |
| Programming Language | Python 3.10 |
| Software | PyCharm 2024.3.5 |
| Deep Learning Framework | TensorFlow 2.9, PyTorch 1.13 |
| Blockchain Framework | Hyperledger Fabric 2.5 |

**Tab. 2.** Hardware and software components.

| Parameters | Value |
|---|---|
| Number of Clients | 10 |
| Communication Rounds | 10 |
| Learning Rate | 0.001 |
| Loss Function | Categorical Crossentropy |
| Local Training Epochs | 10 |
| Dropout Rate | 0.5 |
| Optimizer | Adam |

**Tab. 3.** Federated Learning hyperparameter.

| Parameters | Value |
|---|---|
| First Bidirectional LSTM | 128 units |
| Second LSTM layer | 64 units |
| Dropout Rate | 0.5 |
| Activation Function | Softmax (Output layer) |
| Epochs | 100 |
| Batch Size | 320 |
| Learning Rate | 0.001 |
| Loss Function | Categorical Crossentropy |
| Optimizer | Adam |

**Tab. 4.** Bi-RNN model hyperparameter.

## 4.1. Performance Analysis of the Proposed Model

Accuracy measures the percentage of accurate estimations among all values predicted using local models 1, 2, and 3, which are 97.39%, 99.52%, and 98.82%, respectively. The precision is the ratio of definite optimistic incidence to the total number of adequately predicted occurrences of local models 1, 2, and 3 at 98.35%, 98.52%, and 99.21%, respectively. The F1-scores for local models 1, 2, and 3 are 98.59%, 98.55%, and 99.31%, respectively, indicating the proposed model's balanced performance. The recall (sensitivity) for local models 1, 2, and 3 is 98.53%, 98.67%, and 98.22%, respectively, and the specificity is 99.59%, 99.63%, and 99.61%, respectively, reflecting the capability to identify almost all positive and negative instances of the proposed model. Additionally, the proposed model has a low tendency for mistakes, as indicated by its False Positive Rate (FPR) and False Negative Rate (FNR) for local models 1, 2, and 3, which are 0.0124, 0.0049, and 0.0056, respectively. Correspondingly, the FPRs are 0.0101 and 0.0104.

Figure 3 illustrates the accuracy and loss curves of the global model using federated learning (FL). These curves are a tool for estimating the model's improvement and adaptation to the dataset used. The accuracy curve illustrates the effectiveness of the FL, indicating that the model's classification ability improves progressively over the training epochs. The loss curve, on the other hand, shows a reduction in prediction errors, thereby enhancing the classification performance. The smooth nature of the curves suggests that the FL-based global model generalizes well without significant overfitting.

Figure 4 demonstrates the accuracy and loss curves of the global model using BiRNN. These curves are tools for assessing the model's learning progress and adaptation to the dataset. The accuracy curve shows a steady improvement, indicating that the BiRNN model effectively enhances classification performance throughout the training epochs. Meanwhile, the loss curve decreases sharply in the initial epochs, stabilizing at a lower value, signifying superior optimization. The minimal fluctuation of both curves suggests that the BiRNN model generalizes well to unseen data without significant overfitting, highlighting its effectiveness in handling sequential dependencies.

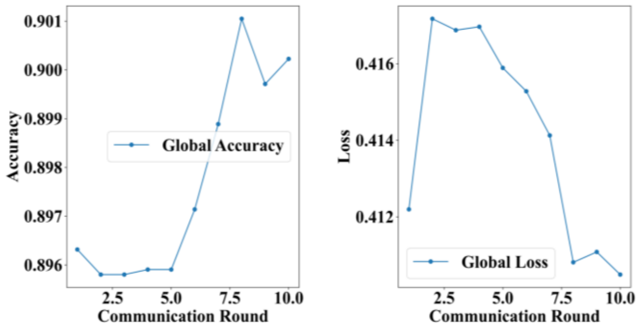


**Fig. 3.** Accuracy and loss curve for global model using FL.

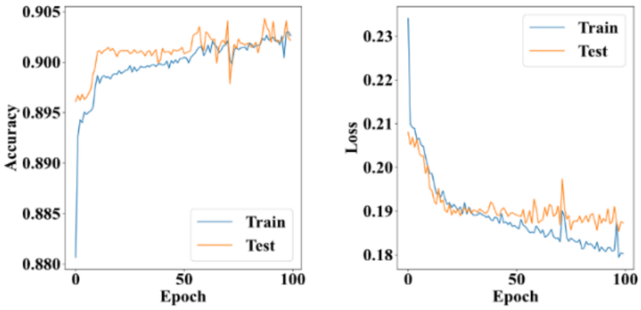


**Fig. 4.** Accuracy and loss curve for global model using BiRNN.

## 4.2. Rewards-based Mechanism for Donors

This section outlines the rewards available to organizations, individuals, and backers in return for their contributions to crowdfunding. Frequent contributors receive rewards from the platform based on their accumulated reward points. The points are categorized into three levels: frequent donors with more than six points (> 6), moderately frequent donors with three to six points (3–6), and infrequent donors with fewer than three points (< 3).

Figure 5 represents donors categorized as "Not a Frequent Donor," meaning they have irregular or infrequent transaction histories. The distribution of donations in this category exhibits large gaps between donation events, indicating irregular engagement with the platform. The system identifies these users based on their inactivity patterns, allowing targeted strategies to encourage future participation. A possible cause for infrequent donations could be a lack of incentives, insufficient platform engagement, or donor disinterest. By recognizing this group, the platform can deploy personalized marketing strategies such as targeted donation appeals or incentives to increase their engagement.

Figure 6 presents the "Moderately Frequent Donor" category, which comprises users who contribute at regular intervals but occasionally experience gaps in their donation activity. The transaction pattern in this figure shows periodic donations, indicating that these donors may be influenced by specific campaigns or external triggers such as fundraising events. These users engage more than occasional donors but are not yet consistently regular contributors. Understanding this group's behavior enables the system to optimize engagement strategies, such as sending personalized reminders or highlighting donation impact stories to encourage sustained contributions.

Figure 7 displays the "Frequent Donor" category, indicating users who contribute repeatedly to crowdfunding campaigns. The transaction pattern in this figure demonstrates a consistent and continuous trend of donations, suggesting a strong commitment from donors and platform activity. This group is crucial to the success of crowdfunding

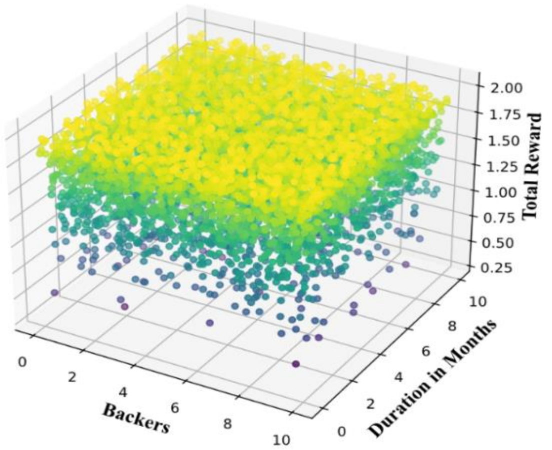


**Fig. 5.** Not a frequent donor.

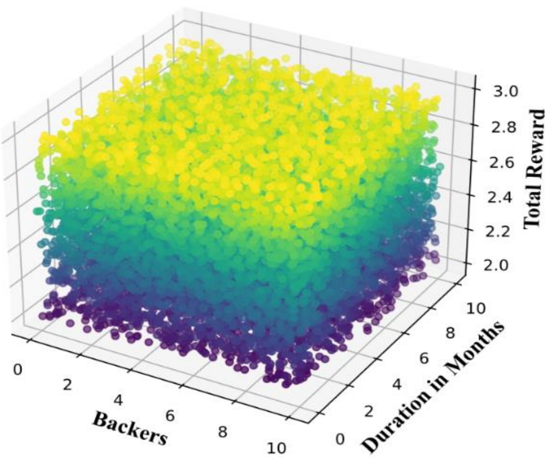


**Fig. 6.** Moderately frequent donor.

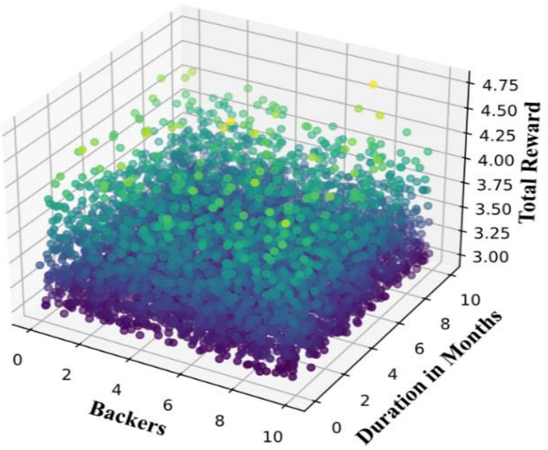


**Fig. 7.** Frequent donator.

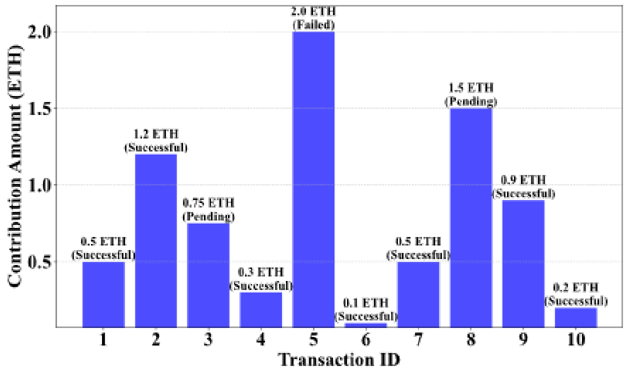


**Fig. 8.** Transaction history.

initiatives, as they provide financial stability and long-term support. Identification of such users allows the platform to implement reward-based incentives, VIP donor programs, or special participation programs to build loyalty. Additionally, understanding the behavior of repeat donors can enable the development of predictive models that help identify potential high-value donors in other categories.

Figure 8 illustrates the transaction history of the donation patterns over time in crowdfunding. It shows the amount of each transaction and its status, offering insights into user engagement levels. The visualization highlights fluctuations in donation frequencies, showing peaks that may correspond to specific fundraising campaigns or seasonal trends. A declining pattern in donations may indicate donor fatigue or reduced trust in the platform, requiring interventions such as personalized engagement or transparency initiatives. On the other hand, steady or increasing transactions suggest high donor retention. This analysis is crucial in optimizing fundraising strategies, as it helps identify key factors influencing donation behavior and enables the implementation of targeted donor engagement techniques.

## 4.3. K-fold Cross-validation

To evaluate the proposed model's robustness, 10-fold cross-validation is used. The results in Tab. 5 clearly indicate

| Models | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| Fold-1 | 89.75 | 88.5 | 90.2 | 89.34 |
| Fold-2 | 91.1 | 90.3 | 91.8 | 91.04 |
| Fold-3 | 90.25 | 89.8 | 90.5 | 90.15 |
| Fold-4 | 89.5 | 89.4 | 90.1 | 89.74 |
| Fold-5 | 90.5 | 90.1 | 90.8 | 90.45 |
| Fold-6 | 91 | 90.6 | 91.2 | 90.9 |
| Fold-7 | 90.15 | 89.7 | 90.4 | 90.04 |
| Fold-8 | 90.75 | 90.4 | 91 | 90.69 |
| Fold-9 | 89.85 | 89.3 | 90 | 89.64 |
| Fold-10 | 90.39 | 90 | 90.6 | 90.29 |
| Average | 90.369 | 89.81 | 90.66 | 90.228 |

**Tab. 5.** 10-fold cross-validation performance of the proposed model.

that the model exhibits a low standard deviation, demonstrating stable and reliable performance across different data splits. These results confirm the model's strong and stable performance, emphasizing its robustness and dependability.

These results indicate that the proposed model is not overly dependent on any specific subset of data, mitigating concerns about data homogeneity and overfitting. The minimal variations across folds further validate the model's ability to generalize well to unseen data, making it a dependable and scalable solution.

## 4.4. Comparative Analysis of BiRNN Classifier with Other Models in the Proposed Framework

Table 6 presents the performance metrics of the BiRNN model on the proposed crowdfunding framework compared with four models, including Bidirectional Long Short-Term Memory Network (BiLSTM), Stochastic Gradient Descent (SGD), and Support Vector Machine (SVM). The metrics include Accuracy, Precision, Recall, Specificity, F1-score, FPR, and FNR.

The BiRNN model employed in the proposed framework achieves the best overall performance, with an accuracy of 99.39%, a precision of 98.35%, a recall of 98.53%, a specificity of 99.59%, and an F1-score of 98.59%. Additionally, BiRNN has the lowest FPR (0.0124) and FNR (0.0013), signifying its superior ability to classify both positive and negative instances with minimal errors correctly. This exceptional performance can be attributed to BiRNN's ability to capture bidirectional temporal dependencies in sequential data, making it highly effective for tasks such as contribution prediction and campaign success classification in the crowdfunding framework.

Improved BiRNN accuracy exemplifies the significance of utilizing strong neural network architectures, particularly those that can process sequential data, in developing effective and efficient crowdfunding systems. Thus, these results validate the ability of the proposed framework to provide safe and personalized experiences to all individuals participating.

| Model | BiRNN (Ours) | BiLSTM | SGD | SVM |
|---|---|---|---|---|
| **Accuracy (%)** | **99.39** | 97.92 | 72.82 | 70.54 |
| **Precision (%)** | 98.35 | 97.82 | 70.21 | 70.01 |
| **Recall (%)** | 98.53 | 98.47 | 78.22 | 70.11 |
| **Specificity (%)** | 99.59 | 98.03 | 79.51 | 69.57 |
| **F1-score (%)** | 98.59 | 97.45 | 73.31 | 67.84 |
| **FPR** | 0.0124 | 0.0521 | 0.0234 | 0.0341 |
| **FNR** | 0.0013 | 0.0213 | 0.0412 | 0.0414 |

**Tab. 6.** Comparative analysis of the proposed model with existing models.

## 4.5. Accuracy Analysis of the Proposed Framework with Other Crowdfunding Platforms

Table 7 compares the accuracy of various methodologies proposed in prior studies with the accuracy achieved by the proposed crowdfunding platform. The proposed crowdfunding platform outperforms current approaches, achieving the greatest accuracy of 99.39%. The combination of blockchain technology for safe and transparent transactions, FL for collaborative model training and privacy protection, and a reward-based algorithm for encouraging participation is responsible for this outstanding result. Furthermore, the platform's prediction skills are further enhanced using BiRNN, which enables it to identify complex patterns and temporal relationships within the data.

The aforementioned evaluation results confirm that the proposed architecture is effective in addressing the shortcomings of current crowdfunding platforms. The proposed platform ensures data privacy, openness, and user engagement through the integration of blockchain, FL, and advanced DL techniques, which not only guarantees high levels of accuracy but also provides a viable solution to the crowdfunding platform scenario.

## 4.6. Discussion

The proposed architecture of the crowdfunding system represents a significant advancement in addressing the drawbacks of conventional crowdfunding platforms, including issues with data privacy, a lack of transparency, and ineffective incentive systems. The framework provides a secure, decentralized, and customizable platform that fosters confidence and participation among stakeholders by integrating blockchain technology, FL, and Q-learning. FL enables collaborative model training across decentralized devices while ensuring the privacy of sensitive user data. Because models can be customized for specific supporters, campaigns, and organizations, this method not only improves data security but also enables individualized user experiences. The platform is further strengthened by blockchain technology, which

| References | Methodology | Accuracy (%) | F1-score (%) |
|---|---|---|---|
| Feng et al. [12] | Hybrid ML algorithms | 82.46 | 82.64 |
| Petchhan et al. [25] | Wide and Deep Learning | 98.84 | 99.03 |
| Li et al. [26] | Blockchain and FL, integrated with a new re-encryption algorithm based on ElGamal | 93.94 | - |
| Lee et al. [28] | FSLR | 87.3 | 84.28 |
| Proposed crowdfunding platform | Blockchain integrated with FL and a reward-based algorithm | 99.39 | 98.59 |

**Tab. 7.** Comparative analysis of the proposed and existing crowdfunding works.

provides an immutable and transparent ledger for all transactions, keeping them safe from fraud while also deploying smart contracts for automated fund allocation. Customers have complete control over their funds through MetaMask wallets, ensuring seamless management. An important factor in encouraging involvement and promoting sustained engagement is the reward-based algorithm, which is strengthened by Q-learning. The platform guarantees a fair and inspiring experience for all stakeholders by anticipating contributions and dynamically allocating incentives. The BiRNN model's outstanding performance highlights the importance of utilizing cutting-edge neural network architectures to detect intricate patterns and temporal relationships in crowdfunding data. The proposed framework offers a comprehensive solution that addresses the practical and technical challenges of crowdfunding, in contrast to current approaches. Although earlier research has considered individual components, such as blockchain or FL, the proposed framework differs in that it combines these technologies with advanced methods. The evaluation results confirm the efficacy of this integrated approach, clearly highlighting its potential to transform the entire crowdfunding industry.

## 5. Conclusion

This study introduced an innovative crowdfunding framework that combines FL, RL, and blockchain technology to provide a safe, open, and customized platform for participants. The architecture provides a decentralized alternative to conventional crowdfunding platforms, addressing key issues such as user engagement, fraud protection, and data privacy. The proposed approach ensures data privacy and enables cooperative model training without exchanging raw data by leveraging FL. Blockchain technology provides a visible and immutable ledger for secure transactions, while smart contracts automate the distribution of funds while protecting against fraud. The Q-learning reward-based model encourages involvement and sustains engagement over time. The proposed approach outperforms current approaches with an accuracy of 99.39%, demonstrating the state-of-the-art performance of the proposed framework. Such superior performance highlights how well FL can be combined with cutting-edge machine learning techniques, with potential applications in blockchain technology. The framework fosters a more accessible and equitable environment by enhancing the technological capabilities of crowdfunding platforms and promoting transparency and trust among stakeholders. Future work could include testing the scalability of this framework on larger datasets and potentially on a broader range of applications, as well as integrating it with other technologies such as edge computing or zero-knowledge proofs to enhance privacy. Overall, this study demonstrates how blockchain, FL, and RL can be combined to transform crowdfunding and pave the way for a future that is more user-centric, transparent, and secure.

**Source code**:
https://github.com/Project007-MA/CF-0304.git

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