A Blockchain-enabled Incentive Framework for Federated Learning Systems

Abstract—**In the rapidly evolving landscape of machine learning, Federated Learning (FL) has emerged as a pivotal methodology for training models across decentralized devices while maintaining data privacy. However, significant challenges in FL include how to practically evaluate the training data and fairly incentivize data owners. This paper introduces a novel framework that integrates blockchain technology into FL, leveraging a Bitcoin-like economic model to address these challenges. We propose a unique method to replace the traditional Shapley value calculation for dataset valuation, utilizing Bitcoin token prices as a dynamic, market-driven metric. This approach not only incentivizes people to participate in FL but also aligns with real-world token economics, ensuring a robust and scalable system. Our system is hosted on a blockchain platform, enhancing transparency, security, and trust among participants. We demonstrate the effectiveness of our model through simulations that integrate real-world Bitcoin price data, showing improved accuracy and participation in FL. This research not only contributes a new perspective to dataset valuation in FL but also opens avenues for integrating economic models with machine learning in a blockchain environment.**

Index Terms—**blockchain, federated learning, Bitcoin economics, data valuation, data privacy, decentralized systems**

I. Introduction

In the rapidly evolving landscape of machine learning, *Federated Learning (FL)* has emerged as a pivotal methodology, enabling model training across decentralized devices while preserving data privacy [1], [2]. A significant challenge in FL is incentivizing data contribution and accurately valuing datasets. This paper introduces a novel framework that integrates *blockchain technology* into FL, employing a Bitcoin-economic model to address these challenges [3], [4]. We propose replacing the traditional Shapley value calculation for dataset valuation with Bitcoin token prices, offering a dynamic, market-driven metric [5].

FL represents a paradigm shift in machine learning. It facilitates model training across decentralized devices, ensuring data privacy. However, it confronts substantial challenges in incentivizing data contribution and valuing datasets accurately [6]. Blockchain technology, with its decentralization, transparency, and security, offers a promising solution to these challenges in FL [7]. Its integration into FL systems can significantly enhance trust among participants in a decentralized environment, fostering greater collaboration and data sharing.

We propose a novel approach that integrates a Bitcoin-like economic model with FL. Our model employs Bitcoin token prices as a dynamic, market-driven metric for dataset valuation. This aligns with real-world economic fluctuations and incentivizes individual contributions [3]. The Bitcoin token economy, operating on a decentralized blockchain, marks a significant shift in digital currency and economic models [4]. We integrate this dynamic pricing mechanism into our FL framework, creating a reward system that aligns rewards with real-world economic values, thereby motivating participants.

The advancements in data valuation methods have introduced various approaches, most notably the Shapley Value. Originally from cooperative game theory, the Shapley Value $\phi(i)$ for a player i in a coalition is given by:

$$\phi(i) = \sum_{\mathcal{S} \subseteq \mathcal{N} \setminus \{i\}} \frac{|\mathcal{S}|!(|\mathcal{N}| - |\mathcal{S}| - 1)!}{|\mathcal{N}|!} \left(v(\mathcal{S} \cup \{i\}) - v(\mathcal{S})\right),$$

where $\mathcal{N}$ is the set of all players, $\mathcal{S}$ is any subset of players excluding i, and $v(\cdot)$ is the value function [5]. This concept has been adapted in federated learning, as seen in probabilistic classifiers [8], efficient dataset valuation methods like DU-Shapley [9], enhanced approaches for nearest neighbor algorithms [10], Data-OOB as an out-of-bag estimate [11], and reinforcement learning-based methods [12]. Aligning with these innovations, this paper integrates IPFS for model storage and distribution, ensuring data integrity and availability [2].

Our research contributes to the field in two primary ways. First, we propose a blockchain-based FL system that leverages Bitcoin-like economics for dataset valuation. This system is demonstrated through simulations with real-world Bitcoin price data, showcasing its practical applicability and effectiveness in a dynamic economic environment. Second, we introduce a new vector mathematics-based method for dataset valuation. This method offers scalability and computational efficiency, providing a robust and practical alternative to traditional valuation methods. Our approach not only addresses the current limitations in FL but also opens new avenues for integrating economic models with technological advancements, paving the way for more innovative and effective solutions in the realm of decentralized machine learning.

II. Methodology

This section describes our research's methodology, focusing on integrating blockchain technology with FL and applying a Bitcoin-like economic model to enhance data contribution, model accuracy, and dataset valuation.

A. Blockchain with Federated Learning and IPFS

Leveraging the decentralized, immutable, and transparent nature of blockchain technology, our approach addresses critical challenges in FL, particularly in the areas of data privacy and participant incentivization. The blockchain framework ensures secure and transparent aggregation of model updates in FL, thereby enhancing data privacy and establishing a trustless environment [13], [14]. By avoiding centralized data storage, blockchain reduces vulnerabilities associated with data concentration and offers a robust solution for managing participant contributions [7], [15].

Smart contracts on the blockchain further automate and streamline the reward distribution process. These self-executing contracts with pre-defined rules provide an efficient, transparent, and unbiased mechanism for compensating participants based on their contributions [16], [17]. This automation not only reduces the administrative overhead but also eliminates potential biases in reward allocation, fostering a fair and equitable environment for all participants.

In conjunction with blockchain, we integrate the InterPlanetary File System (IPFS) for model storage and distribution within the FL framework [18], [19]. IPFS, a peer-to-peer hypermedia protocol, enhances the decentralization aspect by offering a distributed file system for storing and accessing model data. This integration allows for efficient and resilient access to model updates, ensuring high availability and redundancy. After each training round, the updated model's hash is stored on the blockchain, leveraging IPFS's capabilities for secure and decentralized data storage. This method not only guarantees the integrity and traceability of model updates but also optimizes data retrieval and distribution, reducing latency and bandwidth usage [20], [21].

Overall, the integration of blockchain technology with IPFS in the FL framework provides a solution for secure data handling, transparent contribution tracking, and efficient model update distribution. This innovative combination addresses challenges in FL and paves the way for more robust, scalable, and participant-friendly machine learning models. The architecture of our system is illustrated in Fig .

B. Token Economic for Learning Reward Distribution

Our FL framework adopts the economic principles of Bitcoin for valuing participant contributions and distributing rewards, leveraging a market-driven approach. We integrate Bitcoin's token-economic model to assign value to contributions made by participants in the FL process [22], [23].

In our model, a predetermined number of tokens, denoted as T, are allocated for each training round, with M representing the total number of participants. This allocation is inspired by Bitcoin's halving mechanism, where the total number of tokens designated for rewards is halved after every training round. This halving is a critical aspect of our model, mirroring the deflationary feature of Bitcoin's economy, where the reward for mining a block is reduced by half at regular intervals [24], [25]. This strategy creates a scarcity of tokens over time, potentially increasing their value and incentivizing participants to contribute early and consistently to the FL process.

The implementation of this halving mechanism aligns with the principles of supply and demand, where reduced supply can lead to increased value, assuming stable or growing demand. By reducing the token supply over time, we aim to create an environment where participants are motivated not only by immediate rewards but also by the potential future value of their earnings. This approach also helps in managing the token economy, preventing inflation, and ensuring a sustainable reward system that can adapt to the evolving scale and scope of the FL project.

Combining Bitcoin's market-driven valuation with its halving mechanism in our FL model offers a unique method for incentivizing data contributions. It provides a transparent, equitable, and economically sound system for rewarding contributions, aligning the interests of participants with the overall goals of the FL project.

C. Vector-Based Contribution Analysis and Evaluation

Our FL framework focuses on maximizing model accuracy by implementing vector-based methods for evaluating each participant's contribution. This technique quantifies the impact of individual data inputs on the overall model performance, providing a transparent and equitable basis for reward distribution [1], [16]. This approach aligns participant incentives intending to enhance model accuracy.

Central to this methodology is an algorithm that operationalizes vector-based assessments for contribution calculation and token reward distribution. This algorithm is crucial in ensuring fairness and transparency in participant incentivization.

Algorithm 1 Contribution Calculation and Reward Distribution

```
Require: Number of participants n, Total tokens T, Total
    participants in a round M
Initialize accuracy and contribution metrics.
for each training round do
    for each participant i = 1 to n do
        Compute contribution using vector-based method.
        Update model with participant i's data.
    end for
    Calculate total contributions.
    Distribute tokens based on contributions.
    Halve T for next round (Bitcoin-economic halving).
    Record updated model hash in IPFS and on blockchain.
end for
```

This algorithm ensures participants are rewarded in proportion to their contributions' impact on the model. The halving mechanism for token allocation aligns with the Bitcoin-economic model, promoting sustained engagement [24], [25]. The use of blockchain and IPFS for recording updates enhances the FL process's security and traceability, fostering a collaborative environment conducive to advancements in machine learning.

III. Implementation

The implementation of our FL framework integrates blockchain technology with the InterPlanetary File System (IPFS) to address key challenges in data privacy and incentivization. This practical execution involved setting up a test

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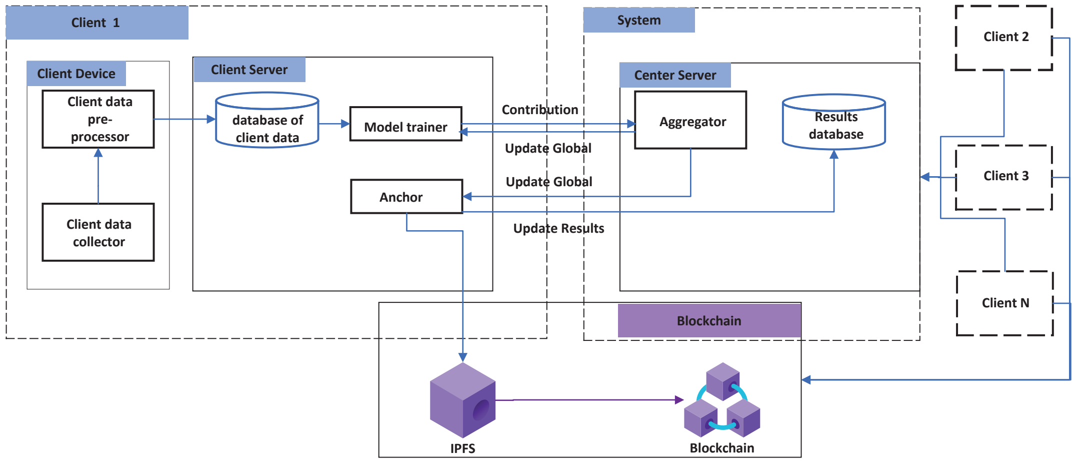

Fig. 1. The system architecture combining blockchain and IPFS for FL.

environment, deploying smart contracts for reward distribution, and establishing a protocol for data exchanges.

Test Environment Setup: Our FL system was deployed on a cluster of virtual machines, each simulating a client node with data collection and local model training capabilities. The central server, responsible for model aggregation, ran on a high-capacity server with adequate processing power to handle the computational load.

Blockchain and Smart Contracts: We utilized a private Ethereum blockchain to manage the reward distribution process. Smart contracts, written in Solidity, were employed to automate the validation of model updates and to log contributions from each node. The contracts were designed to distribute tokens based on the quantity and quality of data contributions, following the halving mechanism previously described.

IPFS for Data Integrity: IPFS nodes were established corresponding to each client and the central server to enable decentralized storage. Model updates, identified by unique hashes, were stored on IPFS, ensuring data integrity and eliminating the need for a central repository.

Operational Workflow: The implementation follows these steps for each round of FL:

1) The central server disseminates the global model to each client.
2) Clients perform local data collection, preprocessing, and training.
3) Each client publishes the updated model's hash to IPFS and records the transaction on the blockchain.
4) The central server retrieves the updates, verifies them using smart contracts, and performs aggregation.
5) After aggregation, the updated global model is redistributed to clients for the next round.
6) Rewards in the form of tokens are distributed as per the smart contract conditions.

Security and Reward Mechanism: Additional security measures included cryptographic signatures for model updates and access control in IPFS. The reward mechanism, driven by the smart contract, calculated and distributed tokens automatically, using the halving principle to regulate the token supply and incentivize participation.

This end-to-end implementation showcased the feasibility of using blockchain and IPFS in an FL context, marking a step forward in secure, decentralized machine learning applications.

IV. Results

A. *Correlation Between SHAP and Vector Contributions*

Our study leveraged the `breast_cancer()` and `iris()` datasets to analyze SHAP (SHapley Additive exPlanations) values, a modern interpretation of the Shapley value tailored for machine learning models.

Instead of employing the complex, direct computation of Shapley values, we utilized the SHAP library, which provides an efficient and scalable approach suitable for high-dimensional data typical in machine learning. This method allowed us to explore the relationship between SHAP values and vector contributions across different model types. As illustrated in Fig. 2 and Fig. 3, both linear and tree-based models exhibited a strong positive correlation between these metrics, reinforcing the validity and fairness of our vector-based contribution assessment.

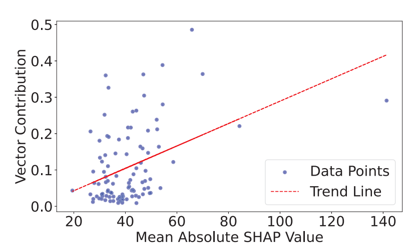

Fig. 2. Linear model using `breast_cancer()` dataset.

This adaptability of the SHAP library in handling different model architectures underlines the robustness of our contribution calculation method, ensuring a fair and transparent reward system in FL.

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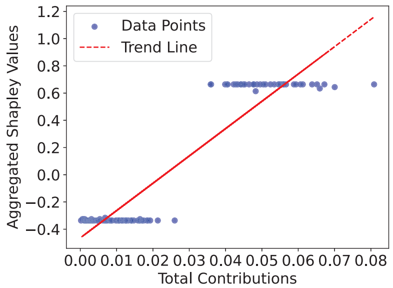

Fig. 3. Tree-based model using `iris()` dataset..

B. Model Performance and Economic Incentive Analysis

The sigmoidal growth pattern of our system's model accuracy mirrors established learning curve phenomena, illustrating the principle of diminishing returns, as shown in Fig. 4. This pattern, supported by insights from Goodfellow *et al.* [26] and Bishop [27], is reflected in our economic incentives design. Rewards in our system thus should be aligned with model maturation and contributor efforts.

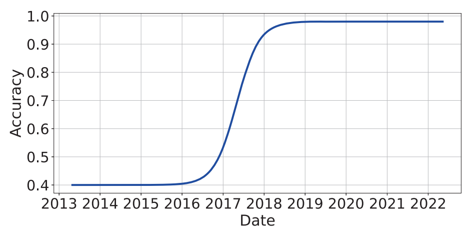

Fig. 4. Sigmoidal growth pattern in model accuracy.

Our analysis validates the use of the sigmoid curve for modeling accuracy progression and cryptocurrency-based rewards (*i.e.*, tokens) for maintaining a balanced incentive system such that the market value of the rewarding tokens in each round should be similar across all rounds.

C. Token Economics in FL

Our simulations addressed the token economics within our FL system by replicating the Bitcoin halving mechanism. Our system is not yet commercialized and our token has not been launched, we use the Bitcoin price shown in Fig. 5 for simulation purposes.

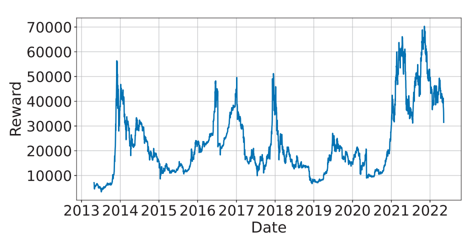

Fig. 5. The Bitcoin price used for our trace-driven simulation.

Fig. 6 illustrates the token distribution for three rounds, showing a clear deflationary pattern in the number of tokens distributed. Despite this, as shown in Fig. 7, the overall value of the tokens, when adjusted to the real Bitcoin's market price, exhibited stability across all rounds.

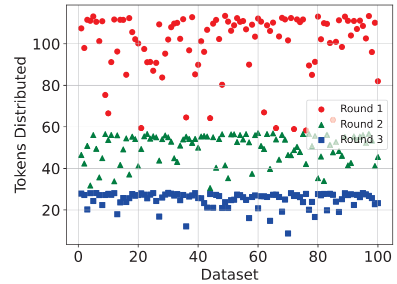

Fig. 6. Deflationary token distribution.

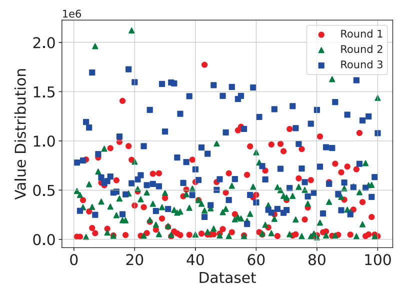

Fig. 7. Token value stability across rounds.

The simulation results underscore the effectiveness of our reward mechanism, ensuring that contributors are equitably compensated, even as the system emulates the halving approach seen in Bitcoin economics. With all results above, we show that the system ensures a fair and equitable reward distribution that is responsive to both individual contribution significance and market-driven token valuation.

V. Discussion and Future Work

In this study, we have demonstrated a consistent positive correlation between SHAP values and vector contributions across different datasets and model architectures. The implications of these findings are significant for the development of fair and transparent FL systems. The robustness of the correlation across both linear and tree-based models suggests that our contribution calculation method can be generalized across a variety of machine-learning tasks.

Our approach aligns well with the principles of interpretability and equity in machine learning, as it ensures that contributors whose data has a more significant impact on the model's performance are rewarded accordingly. This has the potential to motivate participants to provide high-quality data, ultimately leading to the development of more accurate and reliable models.

Future work will focus on expanding the diversity of datasets and model architectures to further validate the generalizability of our method. Additionally, exploring the integration of this reward mechanism in real-world FL applications will be a crucial step toward operationalizing our findings.

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