Proof of Federated Learning Contribution (PoFLC) for Secure Agri-Data Sharing and Collaborative Model Training

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***Abstract*—The proliferation of heterogeneous agricultural devices generates vast amounts of data, necessitating secure and efficient methods for decentralized training and data sharing. Traditional centralized approaches face significant challenges concerning data privacy, security, and scalability. This paper introduces a novel consensus mechanism called Proof of Federated Learning Contribution (PoFLC) within a secure multi-chain framework designed for agri-data sharing and collaborative model training. PoFLC quantifies the contributions of participating devices based on model update quality, reliability, and resources. Integrating federated learning with blockchain technology ensures data privacy while enhancing model performance in a decentralized environment. Extensive experiments on agricultural datasets demonstrate the effectiveness of PoFLC in maintaining data confidentiality, achieving consensus efficiently, and improving the accuracy of collaborative models trained on agri-data.**

***Index Terms*—Blockchain, Federated Learning, Consensus Mechanism, Decentralized Training, Agricultural Data, Proof of Federated Learning Contribution (PoFLC), Multi-chain Framework, Data Sharing.**

I. Introduction

The advent of the Internet of Things (IoT) in agriculture has led to an exponential increase in data generated by heterogeneous devices, including sensors, drones, and smart farming equipment [1], [2]. Managing and utilizing this agri-data efficiently and securely is a significant challenge. Traditional centralized approaches pose risks to data privacy, security, and scalability [2], [3]. Decentralized methods that incorporate blockchain technology and federated learning offer promising solutions to these challenges [4]–[6].

Blockchain provides a decentralized and immutable ledger for secure data transactions, ensuring transparency and trust among participants [8]. Its application in agriculture enhances data integrity and traceability [9], [10]. Federated learning enables collaborative model training without the need to share raw data, thus preserving data privacy [5], [11]. Combining these technologies, we propose a secure multi-chain framework for decentralized training and data sharing among heterogeneous agricultural devices.

This framework introduces a novel consensus mechanism called Proof of Federated Learning Contribution (PoFLC), which quantifies the contribution of each device based on model update quality, reliability, and resources. Devices with higher contributions have a greater impact on the global model and the consensus process. By integrating PoFLC within the blockchain-based federated learning framework, we address the unique challenges posed by heterogeneous agri-devices.

The main contributions of this paper are:

- Proposing a novel PoFLC consensus mechanism tailored for agricultural applications.
- Designing a secure multi-chain framework for decentralized agri-data sharing and collaborative model training.
- Implementing and evaluating the framework using real-world agricultural datasets, demonstrating significant improvements in model performance.

The rest of the paper is organized as follows: Section II reviews related work. Section III describes the proposed methodology and framework. Section IV details the experimental setup. Section V presents the results and discussion. Finally, Section VI concludes the paper and outlines future work.

II. Related Work

A. Blockchain in Agriculture

Blockchain technology has been increasingly applied in agriculture to enhance data security, transparency, and traceability [12], [13]. Tian [9] discussed how blockchain improves food supply chain traceability, ensuring food safety. Lin et al. [14] surveyed blockchain applications in agriculture, highlighting its potential to improve trust among stakeholders.

Blockchain's decentralized nature eliminates the need for a central authority, enhancing overall security and reliability [4]. Its immutability and transparency enable the creation of national or global data repositories while preserving data privacy [15].

B. Federated Learning Applications

Federated learning allows devices to collaboratively learn a shared model while keeping all training data on the device, decoupling the ability to do machine learning from the need to store the data in a central location [5], [11]. In agriculture, it helps in building models across different farms without compromising data privacy [16], [17].

Federated learning addresses data privacy and security issues inherent in traditional centralized machine learning approaches [18]. By keeping data localized during training, it reduces privacy risks associated with centralized models, making it attractive for applications involving sensitive data [19].

C. Consensus Mechanisms in Blockchain

Traditional consensus mechanisms like Proof of Work (PoW) [7] and Proof of Stake (PoS) [20] are not suitable for resource-constrained devices due to their high computational demands [21]. Alternative mechanisms, such as Proof of Contribution [22], have been proposed to address this issue by considering the contribution of participants in the consensus process.

In the context of federated learning, new consensus mechanisms are needed to accommodate the unique challenges of decentralized training [23].

D. Integration of Blockchain and Federated Learning

Recent studies have explored integrating blockchain with federated learning to enhance security and decentralization [26], [27]. Lu et al. [28] proposed a blockchain-based federated learning scheme for IoT devices. However, these works do not specifically address the challenges in agricultural data sharing and collaborative model training. Kim et al. [43] proposed a blockchain-enabled federated learning framework for secure on-device AI, focusing on data privacy. Similarly, Lu et al. [44] integrated blockchain with federated learning for IoT devices but did not specifically address agricultural applications. Our work extends these studies by tailoring the consensus mechanism to handle the heterogeneity of agricultural devices and data types, demonstrating effectiveness in real-world agri-data scenarios.

E. Our Contribution

Our work extends the existing literature by introducing the PoFLC consensus mechanism within a secure multi-chain framework tailored for agricultural applications. We focus on handling heterogeneous devices and data types in agriculture, ensuring efficient and secure collaboration.

III. Methodology

A. Framework Overview

The proposed framework integrates federated learning with blockchain technology using the PoFLC consensus mechanism. It consists of the following components:

1) **Heterogeneous Devices:** Agricultural devices (sensors, drones, farm equipment) with varying computational capabilities and data types.
2) **Federated Learning Process:** Devices train local models on their private data and share encrypted model updates.
3) **Blockchain Network:** A multi-chain architecture where each chain represents a specific group of devices or data types, improving scalability and adaptability [29].
4) **Smart Contracts:** Automate the execution of predefined rules for data sharing, model updates, and reward mechanisms [30].

B. Proof of Federated Learning Contribution (PoFLC)

PoFLC quantifies the contributions of participating devices based on three factors:

$$CS_i = w_q \cdot Q_i + w_r \cdot R_i + w_s \cdot S_i \tag{1}$$

where:

- CS_i is the Contribution Score of device i.
- Q_i is the model update quality, inversely proportional to the local model's loss [31].
- R_i is the device reliability, based on historical participation and consistency.
- S_i is the device's available computational resources.
- w_q, w_r, and w_s are weighting factors summing to 1.

Devices with higher CS_i values have greater influence during the consensus process and model aggregation.

C. Consensus Algorithm

The consensus algorithm operates as follows:

Algorithm 1 PoFLC Consensus Algorithm

Input: Online devices D, Contribution Scores CS
Output: Aggregated global model M_g
for each round **do**
  Calculate total contribution: $TCS = \sum_{i \in D} CS_i$
  Calculate selection probabilities: $P_i = CS_i / TCS$
  Elect leader device L based on P_i
  Leader proposes model update
  Devices validate and agree if $CS_i \geq \theta \cdot CS_L$
  if Consensus achieved **then**
    Aggregate updates weighted by CS_i
    Update global model M_g
  else
    Skip update for this round
  end if
end for

D. Federated Learning Process

1) **Local Training:** Each device trains a local model M_i on its private data.
2) **Model Update Submission:** Devices compute model updates ΔM_i and submit them along with CS_i.
3) **Aggregation:** Model updates are aggregated using weighted averaging based on CS_i.
4) **Global Model Update:** The aggregated model becomes the new global model M_g.
5) **Broadcast:** The updated global model is distributed to all devices.

E. Security and Privacy Considerations

- **Data Privacy:** Raw data remains on local devices, ensuring data privacy [18].
- **Model Security:** Model updates are encrypted during transmission using secure cryptographic methods [32].
- **Immutable Ledger:** Blockchain ensures an immutable record of transactions and model updates.

IV. Experimental Setup

A. Dataset

We used the *Plant Pathology 2020 - FGVC7* dataset from Kaggle [33], which contains 3,651 images of apple leaves classified into four categories: healthy, multiple diseases, rust, and scab. This dataset is representative of real-world agricultural data and is suitable for evaluating our framework.

B. Data Partitioning

The dataset was partitioned among 10 initial devices, simulating heterogeneous devices with varying data distributions. Each device received approximately 290-300 samples. Devices could join or leave the network with certain probabilities to mimic real-world scenarios. The data distribution is shown in Table I.

TABLE I: Data Distribution Among Devices

Device	Number of Samples	Classes
Device 0	300	All
Device 1	280	All
Device 2	290	All
Device 3	295	All
Device 4	285	All
Device 5	300	All
Device 6	275	All
Device 7	290	All
Device 8	280	All
Device 9	275	All

C. Model Architecture

We designed a custom Convolutional Neural Network (CNN) with enhanced capacity to handle the complexity of the dataset. The architecture includes:

- **Input Layer**: Accepts images resized to $128 \times 128 \times 3$.
- **Convolutional Blocks**: Multiple blocks with increasing filter sizes (32, 64, 128) and batch normalization [34].
- **Pooling Layers**: Max pooling after each convolutional block to reduce spatial dimensions.
- **Dropout Layers**: Applied to reduce overfitting [35].
- **Fully Connected Layers**: Dense layers leading to the output.
- **Output Layer**: Softmax activation for four classes.

D. Training Parameters and Optimization Choices

- **Local Training Epochs**: 10 epochs per device per round.
- **Learning Rate**: Set to 1×10^{-4} with Adam optimizer .
- **Batch Size**: 32 images.
- **Data Augmentation**: Applied random flips, rotations, zooms, and contrast adjustments [37].
- **Global Rounds**: 35 federated learning rounds.

Optimizer and Activation Functions: We utilized the *Adam* optimizer [42] due to its computational efficiency and adaptive learning rate capabilities, which are particularly beneficial for handling the varying data distributions and resource constraints of heterogeneous devices in our network. In preliminary experiments, we compared *Adam* with Stochastic Gradient Descent (SGD) and observed that *Adam* achieved higher accuracy in fewer epochs. SGD required careful tuning of learning rate and momentum parameters, which was challenging given the limitations of resource-constrained devices.

For activation functions, we employed the Rectified Linear Unit (ReLU) activation function in hidden layers to introduce non-linearity and mitigate the vanishing gradient problem. The output layer uses the softmax activation function to produce probability distributions over the four classes. We considered other activation functions like sigmoid and tanh, but ReLU provided better performance in terms of training speed and accuracy.

E. Simulation of Device Behavior

To simulate realistic device behavior:

- **Online Probability**: Each device has a 90% chance of being online in each round.
- **Joining/Leaving**: Devices may join or leave the network with specified probabilities.
- **Resource Constraints**: Simulated by varying the computational capacity during local training.

F. Evaluation Metrics

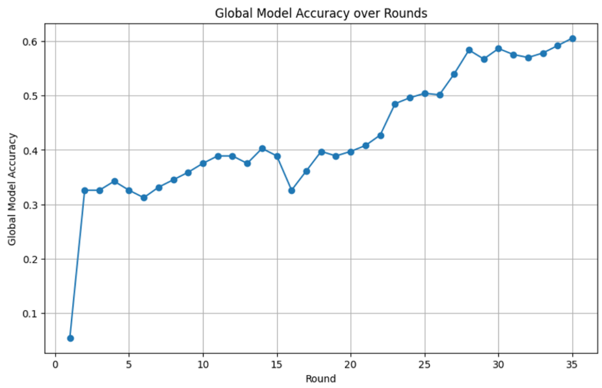
- **Global Model Accuracy**: Overall classification accuracy on the validation set over rounds.
- **Global Model Loss**: Cross-entropy loss on the validation set over rounds.
- **Computation Time per Round**: Total time taken for each global round.
- **Devices per Round**: Number of participating devices in each round.
- **Precision, Recall, F1-Score**: For detailed class-wise performance.

V. Results and Discussion

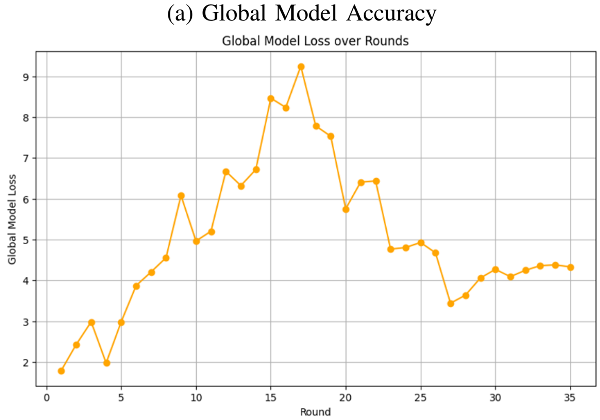
A. Global Model Performance

The global model's performance improved over the rounds. Figures 1 and 2 depict the global model accuracy, loss, computation time, and devices per round.
Figure 1a illustrates the global model accuracy over 35 rounds. The accuracy improves from 5.48% to 60.55

Figure 1b displays the global model loss, which decreases overall, indicating effective model training. The fluctuations in loss correspond to the varying number of participating devices and data quality in each round.



(a) Global Model Accuracy



(b) Global Model Loss

Fig. 1: Global Model Performance Over Rounds

B. Devices Participation and Computation Time

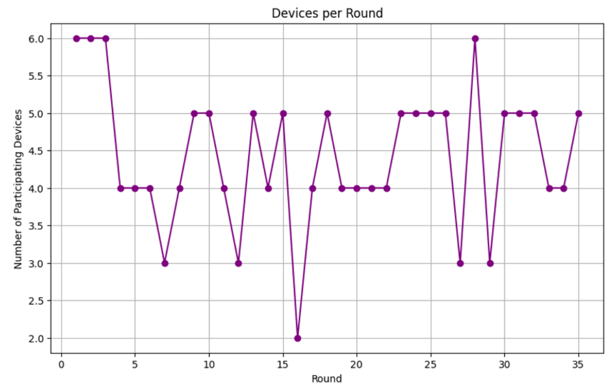
Figure 2 illustrates the number of participating devices and the computation time per round.
Figure 2a illustrates the number of participating devices per round, which fluctuates due to simulated network conditions. The number ranges from 2 to 6 devices, reflecting realistic scenarios in agricultural networks.

Figure 2 shows the computation time per round, which is impacted by the number of devices and their computational capacities. Optimal computation times are crucial for real-time agricultural applications.

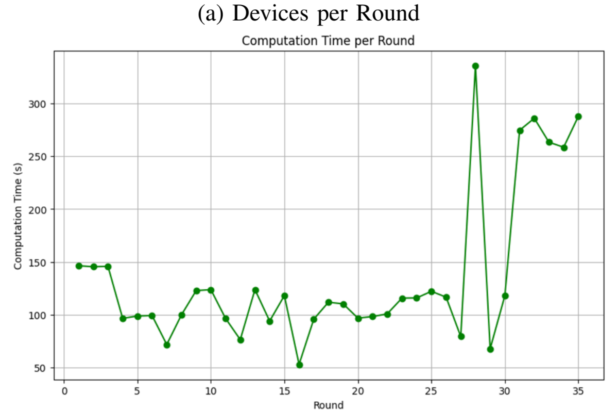
C. Consensus Algorithm Performance

The PoFLC consensus mechanism effectively prioritized devices based on their contributions. Table II shows the leader selection and consensus achievement across rounds.

As shown in Table II, Device 7 was frequently selected as the leader across multiple rounds due to its consistently high Contribution Score (CS_i). This high CS_i was a result of Device 7's reliable participation, high-quality model updates (indicated by low local loss), and sufficient computational resources. The consistent leadership of Device 7 contributed to the stability and convergence of the global model.



(a) Devices per Round



(b) Computation Time per Round

Fig. 2: Devices Participation and Computation Time

TABLE II: Leader Selection Across Rounds

Round	Online Devices	Leader Device	Consensus Achieved
1	[0, 2, 3, 4, 7, 9]	3	Yes
2	[0, 1, 2, 3, 7, 9]	9	Yes
3	[0, 1, 2, 3, 7, 8]	7	Yes
4	[1, 3, 7, 8]	7	Yes
5	[0, 1, 7, 8]	0	Yes
⋮	⋮	⋮	⋮
35	[0, 3, 7, 8, 10]	7	Yes

D. Classification Report

After the final round, the model was evaluated on the validation set. Table III presents the detailed classification report.

TABLE III: Classification Report

Class	Precision	Recall	F1-Score	Support
Healthy	0.60	0.51	0.55	103
Multiple Diseases	0.00	0.00	0.00	18
Rust	0.64	0.60	0.62	125
Scab	0.58	0.78	0.67	119
Accuracy		0.61		365
Macro Avg	0.46	0.47	0.46	365
Weighted Avg	0.58	0.61	0.59	365

Table III presents the classification report after the final round. The model achieved higher precision and recall for the 'Rust' and 'Scab' classes, which had more samples in the dataset. The 'Multiple Diseases' class, with significantly fewer samples, showed poor performance with zero precision and recall. This imbalance in the dataset affected the model's ability to learn representations for underrepresented classes.

The dataset used exhibits class imbalance, particularly with the 'Multiple Diseases' class having significantly fewer samples. To address this, we applied data augmentation techniques such as rotations, flips, and zooms to artificially increase the number of samples for the minority classes. While this helped to some extent, the model still struggled with the underrepresented class, as seen in Table III.

In future work, we plan to implement advanced methods like Synthetic Minority Over-sampling Technique (SMOTE) [47] and adjusted class weighting in the loss function to further mitigate the effects of class imbalance.

E. Analysis of PoFLC Contributions

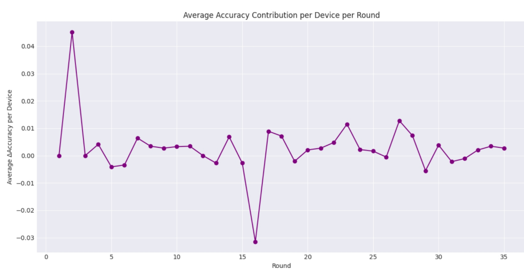


Fig. 3: Contribution Scores of Devices Over Rounds

Figure 3 illustrates the Contribution Scores (CS_i) of selected devices over the rounds. Devices with consistent participation and high-quality updates, such as Device 7, maintained high CS_i values. This directly influenced their likelihood of being selected as leaders, impacting the overall model convergence.

F. Discussion

Our experimental results align with previous studies that integrate federated learning and blockchain technology to enhance data security and privacy [43], [44]. However, our framework specifically addresses the challenges in agriculture by considering heterogeneous devices and applying the PoFLC mechanism.

During the experiments, we observed that devices with higher computational resources and consistent participation had a more significant impact on the global model's performance. This finding suggests that incentivizing devices to participate reliably can enhance model convergence.

Compared to traditional federated learning approaches, our framework improves scalability and security through the multi-chain architecture, which can be crucial for large-scale agricultural deployments.

However, there are areas for improvement:

- **Model Accuracy**: The overall accuracy is moderate. Incorporating more advanced architectures or transfer learning could enhance performance [38].
- **Class Imbalance**: Implementing techniques like class weighting or resampling could address the imbalance [39].
- **Scalability**: Testing the framework with more devices and larger datasets is necessary to evaluate scalability.

VI. Conclusion

We presented a secure multi-chain framework leveraging PoFLC for decentralized training and data sharing among heterogeneous agricultural devices. The proposed consensus mechanism effectively quantifies device contributions, ensuring efficient model aggregation and consensus achievement. Experimental results demonstrate the framework's capability to improve model performance over time while maintaining data privacy and security. The study contributes to the field by experimentally validating the proposed framework in a realistic agricultural setting. Future work could explore integrating incentive mechanisms to encourage device participation, investigating the impact of different data distributions on model performance, and applying transfer learning techniques [45] to improve accuracy.

Additionally, evaluating the framework's performance in other agricultural contexts, such as crop yield prediction or livestock monitoring, could demonstrate its versatility and broader applicability.

VII. Future Research

Future research directions include:

- **Improving Model Accuracy**: Incorporate advanced models or transfer learning techniques [38].
- **Handling Class Imbalance**: Implement strategies like weighted loss functions or data augmentation .
- **Scalability Testing**: Deploy the framework in larger networks with more devices and test scalability.
- **Security Enhancements**: Incorporate differential privacy and secure multi-party computation to further protect model updates [41].

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