Improving Performance Metrics on FedAvg with Blockchain for Privacy-Preserving Healthcare AI

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Abstract: The demand for AI and its applications in healthcare provides significant opportunities for improving disease prediction, disease identification, clinical decision-making, and healthcare treatment. In healthcare, patient privacy-preserving, data security, and confidentiality continue to restrict the sharing of medical data across healthcare institutions. To address these challenges and improve the performance metrics, this study proposed a secure and privacy-preserving healthcare model that integrates the Federated Averaging (FedAvg) algorithm with Blockchain technology. The proposed FedAvg enables multiple healthcare institutions to collaboratively train AI models while retaining sensitive patient data using the FedAvg algorithm with Blockchain privacy-preserving healthcare AI. Rather than transferring raw data, only encrypted model parameters are exchanged using healthcare AI and aggregated to construct a global learning model using the FedAvg algorithm. A permissioned blockchain concept is incorporated to ensure trust, transparency, and immutability throughout the FL process. Smart contracts ensure to validate model updates, while a Practical Byzantine Fault Tolerance (PBFT) consensus mechanism facilitates secure agreement among participating entities for transferring data between healthcare institutions. Secure FedAvg with Blockchain for privacy-preserving healthcare AI was evaluated on publicly available healthcare datasets. This article used a heart-disease dataset and assessed it using performance metrics such as accuracy, latency, communication overhead, and scalability. Experimental results proved that the proposed architecture achieved high prediction accuracy while increasing the number of rounds and model accuracy also increased.

Keywords: Federated Averaging; FedAvg; Permissioned Blockchain; Privacy Preservation; Smart Healthcare Systems; PBFT Consensus Mechanism.

Introduction

In healthcare sector today, an incredible amount of medical data is transferred from various sources like hospitals, medical centers, diagnostic centers, wearable devices, and electronic health record systems [1]. These data sources present substantial opportunities for the development of intelligent healthcare solutions and AI model training that support disease prediction, clinical diagnosis, patient monitoring, and personalized treatment planning. AI has become a crucial technology, secure FedAvg with Blockchain for privacy-preserving healthcare AI, due to its ability to identify intricate patterns and deliver precise predictions from vast datasets [2]. Convergence behaviour was observed across multiple training rounds and observed the performance metrics, demonstrating the effectiveness of collaborative model training model [3]. FedAvg with Blockchain model presents a viable solution and improve the performance metrics for secure, scalable, and patient-focused healthcare AI systems with FedAvg algorithm with centralized Blockchain for privacy-preserving healthcare AI [4].

The centralized model improved the processing of sensitive data and medical information continue to spark serious concerns about patient privacy information, data ownership, security risks, and adherence to regulations like HIPAA and GDPR. It achieved secure FedAvg with Blockchain for privacy-preserving healthcare AI [5]. FL has emerged as a prominent distributed ML paradigm that enables secure FedAvg with Blockchain for privacy-preserving healthcare AI and multiple healthcare organizations to collaboratively train models without requiring the exchange of raw data with a centralized repository [6]. By retaining data within local institutions, FL mitigates privacy concerns while facilitating secure FedAvg with Blockchain for privacy-preserving healthcare AI collaborative knowledge discovery across distributed datasets, in this model we trained the heart-disease dataset [7]. Among existing FL methods are failure due to the train the model, the FedAvg algorithm has been extensively adopted due to its effectiveness in aggregating locally trained models into a unified global model [8]. However, traditional FL relies on centralized coordinators, which raises issues related to accuracy, privacy-preserving, security strength, communication efficiency, and model robustness [9]. These challenges have led to a growing interest in decentralized methods aimed at improving system performance [10]. Blockchain technology is a powerful tool for FedAvg algorithm, particularly when it comes to privacy-preserving healthcare and ensuring accountability in distributed ledgers [11]. By relying on immutable records, consensus PBFT algorithms, and smart contracts are used, it can securely verify model updating performance of the model [12]. This combination of Blockchain and FL has attracted considerable interest, especially in the healthcare sector, where data privacy-preserving and institutional trust are paramount [13]. In response to these challenges, this study presents a secure FedAvg model that integrates a permissioned blockchain with a PBFT consensus mechanism protocol for healthcare [14]. The proposed model improved the accuracy, privacy-preservation, security strength, communication efficiency, model robustness, scalability [15].

Related work

The existing literature worse than the increasing demand for secure healthcare analytics, it has really pushed the adoption of FL with Blockchain. With the FedAvg algorithm, the healthcare institutions can collaborate on AI-model training while ensuring that sensitive patient data stays protected right where it is secure FedAvg with Blockchain for privacy-preserving healthcare [1]. FL with FedAvg allows for secure collaboration in training AI for healthcare in current and future, most of the existing models while ensuring that patient data remains safely stored and protected locally [2, 3]. The proposed model minimizes centralized data sharing, concerns regarding model integrity and improve the performance metrics. [4]. The proposed model FedAvg with Blockchain for privacy-preserving healthcare examined privacy-preserving deep learning strategies and highlighted potential vulnerabilities arising from model updates exchanged among participants while using automatic training [5]. The existing literature also identified and improved the performance metrics such as accuracy, privacy-preservation, security, latency, communication overhead and scalability [6,7].

PBFT consensus mechanism is performed to enable reliable agreement among multiple datasets, this model is considered to exist only in the heart-disease dataset [8]. Collectively, this model provides integrating Blockchain with ML that requires secure collaboration among independent healthcare institutions. Permissioned Blockchain platformed automatic suitability for enterprise and healthcare applications. This article provides that controlled blockchain networks can support secure transaction management, flexible consensus mechanisms, and programmable smart contracts [9]. This research also provides medical information to be accessed and managed in a trustworthy and controlled manner. The MedRec architecture further demonstrated Blockchain's potential to improve the performance metrics such as accuracy, privacy-preservation, security, latency, communication overhead and scalability [10]. More recent studies have examined Blockchain applications in healthcare most suitable for healthcare ecosystems [11]. However, this research highlighted communication overhead and scalability as significant challenges when implementing Blockchain in large-scale healthcare. Consequently, increasing research attention has been directed towards integrating Blockchain and FL with the FedAvg algorithm. Healthcare-specific FL solutions have also demonstrated encouraging outcomes. Research involving distributed electronic health records revealed that a collaborative model with FL and FedAvg algorithm training can generate predictive performance comparable to centralized approaches while preserving and improved the patient confidentiality [12]. This article also provides the role of FL in digital healthcare applications, including disease prediction, medical imaging analysis, and clinical decision support systems [13]. Decentralized learning enables Blockchain-assisted FL to improve transparency and resilience against malicious updates [14]. Blockchain-integrated FL enhances secure healthcare intelligence [15]. Based on the aforementioned literature, there remains a need for frameworks that simultaneously address the accuracy, privacy-preservation, security, latency, communication overhead and scalability. This study aims to combine the FedAvg algorithm with a permissioned blockchain as a PBFT consensus mechanism. This approach provides patient confidentiality intact and provides dependable healthcare.

Key Contribution

This article provides the privacy-preserving healthcare model that integrated with the FedAvg algorithm with PBFT consensus mechanism. The proposed approach enabled multiple healthcare institutions to collaboratively train intelligent models without exposing sensitive patient information, as data remained within healthcare institutions and secure FedAvg with Blockchain for privacy-preserving. The PBFT mechanism supported secure validation of model updates through the smart contract mechanisms, thereby enhancing accuracy, privacy-preservation, security, latency, communication overhead and scalability. The experimental results showed that merging federated learning with Blockchain provides the predictive performance and security needs, making this model most suitable for patient-centered healthcare applications.

Algorithm 1: Secure FedAvg Algorithm

Step 1. Gather the local data and prepare healthcare datasets (used as heart disease dataset).

Step 2. Train a local model at the hospital using the FedAvg algorithm.

Step 3. Encrypting and decrypting patient data remains confidential during sharing.

Step 4. Validate these updates through Blockchain technology using the PBFT protocol.

Step 5. Combine the updates to create a global model and assess its performance.

The following Table 1 addresses FL, Blockchain security, privacy preservation, and healthcare analytics. However, most of the existing literature lacks a comprehensive mechanism that simultaneously ensures secure model aggregation, decentralized trust management, transparency, auditability, and scalable healthcare intelligence. The proposed Secure FedAvg with Blockchain framework bridges these gaps by integrating FL with a PBFT-based consensus mechanism, providing privacy-preserving healthcare.

Algorithm 2: Secure FedAvg with PBFT consensus mechanism

Step 1: Gather local data and prepare healthcare datasets (used as heart-disease dataset).

Step 2: Perform the normalization.

Step 3: Perform the dataset using the FedAvg algorithm.

Step 4: Encrypted model FedAvg with Blockchain updates are shared, while patient data remains stored locally.

Step 5: To validate the model updates and reach a consensus using the PBFT Blockchain network, validate the model updates and PBFT consensus.

Step 6: The validated updates are aggregated through FedAvg to generate a global AI model.

Step 7: Finally, the model is assessed based on various metrics, including accuracy, privacy preservation, security, latency, communication overhead, and scalability.

Table 1: Comparisons existing approach with various related approaches

Author(s)	Method/Model Used	Focus Area	Limitations	Proposed Work Contribution
McMahan et al. [1]	Federated Averaging (FedAvg)	Decentralized model training	Lacks trust and security mechanisms for model validation	Integrates blockchain-based validation with FedAvg for secure healthcare collaboration
Konečný et al. [2]	Federated Optimization	Distributed machine learning	Limited support for secure and auditable learning environments	Provides blockchain-enabled transparency and model traceability
Yang et al. [3]	Federated Machine Learning	Privacy-preserving AI	Does not address decentralized trust management	Introduces permissioned blockchain for trustworthy collaboration
Bonawitz et al. [4]	Secure Aggregation	Protection of model updates	Focuses only on aggregation security	Combines secure aggregation with blockchain-based verification
Nakamoto [5]	Blockchain Architecture	Decentralized ledger systems	Not designed for AI model training	Utilizes blockchain to secure federated healthcare intelligence
Castro and Liskov [6]	PBFT Consensus	Fault-tolerant distributed systems	Not integrated with machine learning workflows	Employs PBFT to validate healthcare model updates securely
Androulaki et al. [7]	Hyperledger Fabric	Permissioned blockchain	Limited AI integration	Integrates Hyperledger-style blockchain with FedAvg learning
Ekblaw et al. [8]	MedRec Framework	Electronic Health Records	Focuses mainly on data management	Extends blockchain usage to collaborative healthcare AI training
Shokri and Shmatikov [9]	Privacy-Preserving Deep Learning	Data privacy protection	Does not provide decentralized trust mechanisms	Enhances privacy with blockchain-supported validation
Rieke et al. [10]	Federated Healthcare Learning	Digital healthcare applications	Trust and transparency challenges remain	Adds blockchain-based auditability and secure coordination
Li et al. [11]	Federated Learning Survey	FL challenges and opportunities	Identifies issues without providing integrated solutions	Addresses security, privacy, and scalability simultaneously
Kumar et al. [12]	Blockchain-Assisted FL	Secure healthcare learning	Increased communication complexity	Optimizes collaboration through secure FedAvg aggregation
Agbo et al. [13]	Blockchain in Healthcare	Healthcare security and interoperability	Does not incorporate AI-driven analytics	Combines blockchain security with intelligent healthcare prediction
Brisimi et al. [14]	Federated EHR Learning	Predictive healthcare analytics	Limited trust and validation mechanisms	Incorporates blockchain consensus for reliable model updates
Basetty Mallikarjuna et al. [15]	Blockchain + Federated Learning	Secure healthcare intelligence	Scalability and consensus overhead issues	Provides a balanced framework for privacy, trust, and scalability

Method, Experiments and Results

The methodological model is represented as shown in Figure 1, which begins with healthcare data acquisition and preprocessing, followed by local AI model training at distributed healthcare institutions using the FedAvg algorithm. Encrypted model updates are transmitted to a permissioned Blockchain, where smart contracts and PBFT consensus validate and securely record the updates. The validated parameters are aggregated to generate a global healthcare model, which is redistributed for subsequent training rounds.

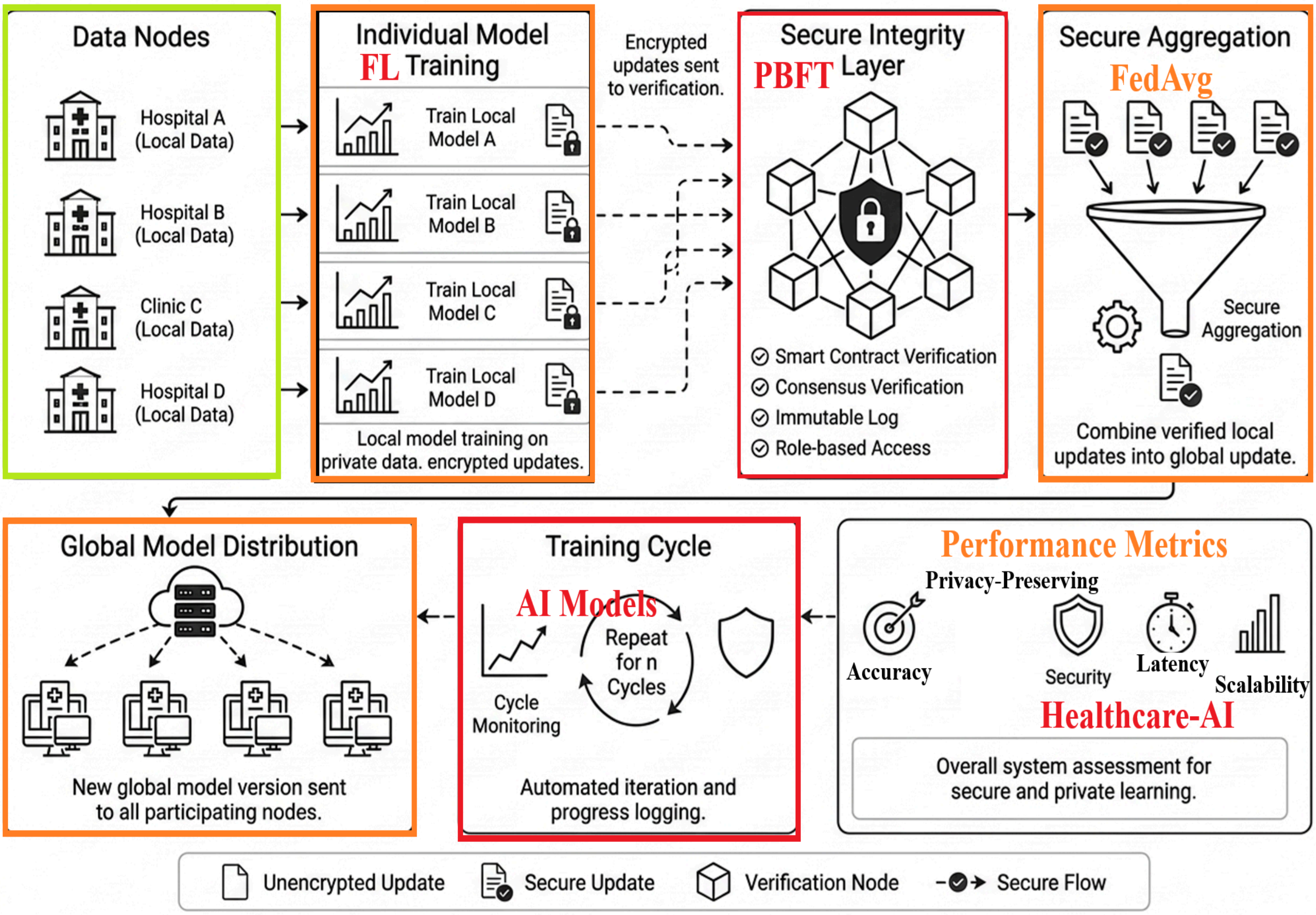

Figure 1. Methodological Framework of Secure FedAvg with Blockchain for Privacy-Preserving Healthcare AI.

Finally, the framework is evaluated using accuracy, privacy preservation, security, latency, communication overhead, and scalability metrics to assess its effectiveness in privacy-preserving healthcare intelligence.

Data Nodes: The process starts with decentralized entities like hospital A, hospital B, clinic C and hospital D with all of their local data needs for training.

Individual Model FL Training: Each participating node takes the initiative to train the local data and its own local model, and the encrypted update for verification.

Secure Integrity Layer with PBFT: These encrypted local models performed the smart contract verification updates, which are then securely transmitted for consensus verification to a blockchain-based verification and provided an immutable log network, which is overseen by smart contracts and consensus protocols, providing role-based access.

Secure Aggregation with FL: Performed secure aggregation, once verified through the immutable log, the individual local updates are filtered and combined into a singular global model version.

Global Model Distribution: Performed through the PBFT mechanism, and the aggregated global model is then synchronized and pushed back down to all participating client nodes.
Training Cycle with PBFT Consensus: This entire decentralized training loop automatically repeats for end-to-end designated while automated iteration and progress logging.
Performance Metrics Evaluation: Finally, the performance of the secure system is evaluated based on Accuracy, privacy-preservation, security, latency, communication overhead and scalability.

Pseudo code 1: Secure FedAvg with Blockchain for Privacy-Preserving Healthcare AI

Input: Healthcare Datasets D, Hospitals H, Training Rounds R

Output: Global Healthcare AI Model M

Step 1: Collect healthcare datasets D from participating hospitals H

Step 2: Preprocess D, Clean data and perform the normalize features
{ Extract relevant attributes}

Step 3: For {Each hospital Hi ∈ H, Then train local model Mi using FedAvg}

Step 4: Encrypt and transmit local model updates Ui, without sharing raw patient data

Step 5: Validate Ui using Blockchain {Execute Smart Contracts and Apply PBFT Consensus
Store verified updates in Ledger}

Step 6: Aggregate verified updates using FedAvg { M Aggregate (U1, U2, ..., Un)
Generate Global Model M}

Step 7: Evaluate M using {
Accuracy, Privacy Preservation, Security, Latency, Communication Overhead, and Scalability}

Return M

The proposed framework achieved enhancing privacy, and accuracy improved steadily with communication rounds, indicating stable convergence. The Blockchain security mechanism, trust, and auditability, scalability analysis demonstrated that the system maintains performance as the number of clients increases, outperforming centralised AI in distributed settings. The experimental results evaluated as Secure FedAvg with Blockchain for Privacy-Preserving Healthcare AI framework were conducted using Intel Core i9-13900K processor, 64 GB RAM, 2 TB SSD storage, and Ubuntu 22.04 LTS with support for distributed AI training and blockchain deployment with multiple healthcare institutions participating in federated learning. Python 3.11, TensorFlow 2.15, PyTorch 2.2, Scikit-learn, and Flower Federated Learning Framework for implementing the Federated Averaging (FedAvg) algorithm. And PBFT-based consensus and smart contracts for secure model validation. The dataset used as Heart Disease Dataset.

The following Figure 2 & 3 illustrate a multi-metric performance comparison of the performance Evaluation of Secure FedAvg with Blockchain, comparing the performance of standard FedAvg and blockchain-integrated FedAvg across the metrics such as accuracy, privacy preservation, latency, communication overhead, and scalability. The results proved that it significantly improves privacy and trust, with a slight increase in latency and communication overhead due to blockchain operations, while maintaining competitive accuracy and scalability.

Figure 3 provides the scalability performance as the number of participating healthcare clients increases. While both approaches show a gradual decrease in scalability due to increased communication, the FedAvg with Blockchain framework maintains stable performance, demonstrating its effectiveness for secure and large-scale healthcare collaboration.

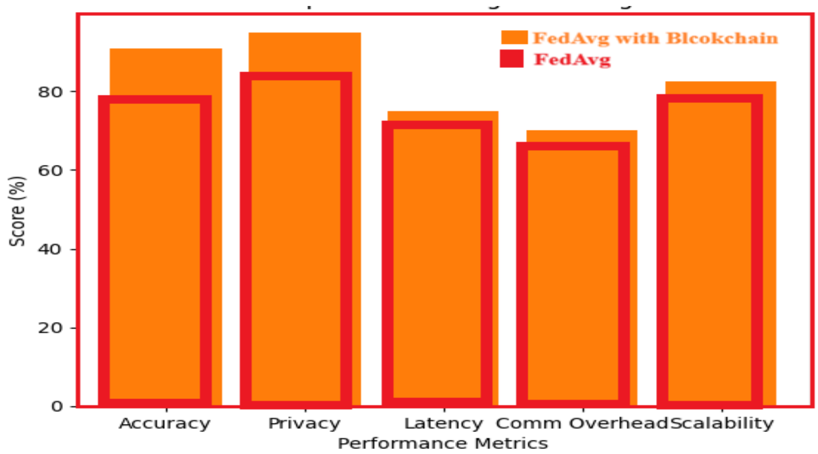

Figure 2. Performance FedAvg versus FedAvg with Blockchain

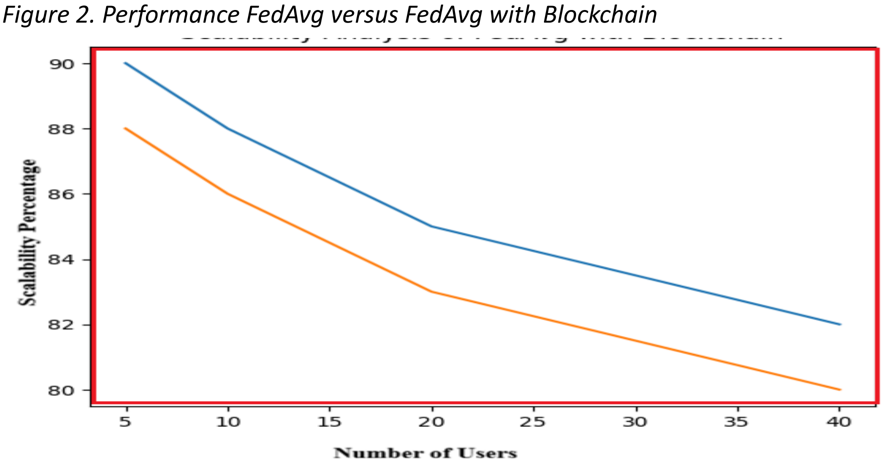

Figure 3. Scalability Analysis of FedAvg with Blockchain in Distributed Healthcare Systems.

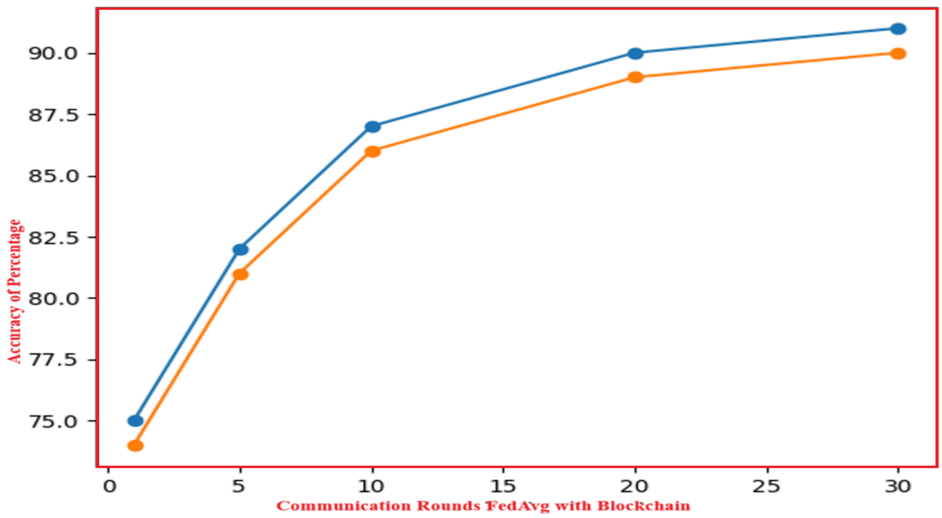

Figure 4. Convergence Analysis Accuracy with Communication Rounds.

Convergence Analysis Accuracy with communication rounds proved that secure FedAvg with Blockchain framework over multiple communication rounds. It demonstrates stable learning and effective collaboration among distributed healthcare institutions. The results confirm that blockchain integration preserves model performance while ensuring security, privacy, and trustworthiness.

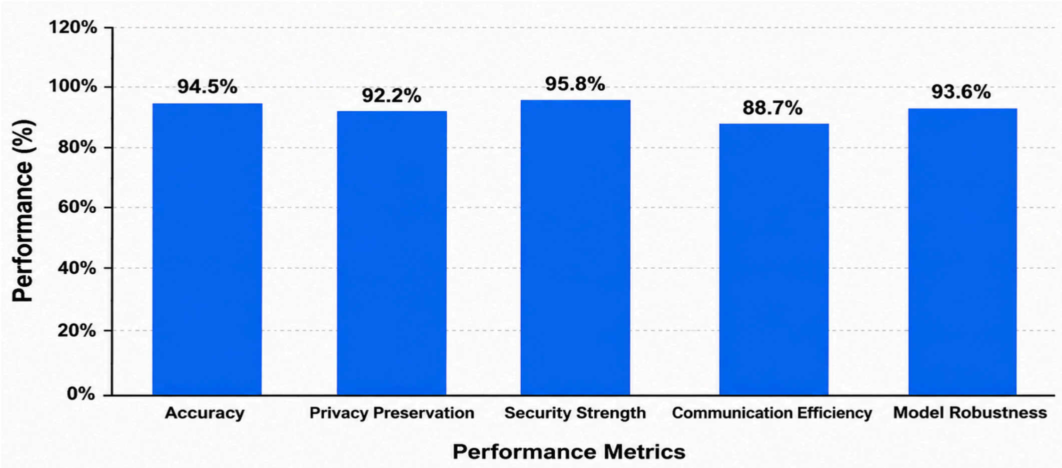

Figure 5. Performance metrics evaluation of FedAvg

Figure 5 illustrated as FedAvg with a Blockchain framework solved the metrics as accuracy, privacy preservation, security strength, communication efficiency and model robustness. The results obtained as accuracy 94.5%. privacy preservation 92.2%, security strength 95.8%, communication efficiency 88.7% and model robustness 93.6%. These findings proved that integrating blockchain with federated learning enables secure, trustworthy, and patient-centric healthcare intelligence.

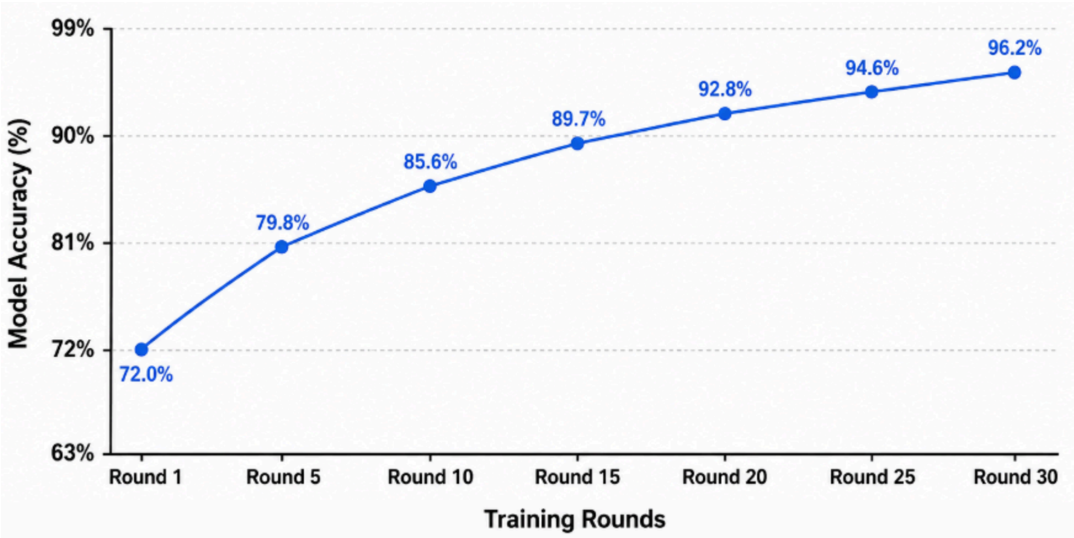

Figure 6. Accuracy Convergence of Secure FedAvg with Blockchain

Performance evaluation of secure FedAvg with Blockchain for privacy-preserving healthcare AI represented to increase to number of rounds model accuracy also increased, as shown in the line graph, represented as the effectiveness of the proposed Secure FedAvg with Blockchain framework across key performance metrics.

Discussions

Experimental results proved that integrating FedAvg with Blockchain improved privacy-preserving and model training, while blockchain-based mechanisms provided secure validation and permanent record keeping through this model. It was also observed that the proposed model achieved accuracy and improved scalability, even though it introduced a moderate increase in communication overhead and latency. The proposed model also proved that many communication rounds and model performance increased, which can secure FedAvg with a Blockchain model, offering a practical and dependable solution for privacy-preserving AI applications in healthcare.

Conclusions

This study proved that a secure FedAvg algorithm provides a privacy-preserving healthcare intelligence framework. Through the incorporation of a permissioned blockchain and PBFT consensus mechanism, the FedAvg algorithm, with Blockchain technology collaborative AI model, trains across the healthcare heart disease dataset. Secure FedAvg with Blockchain for privacy-preserving healthcare achieved secure validation, communication efficiency, latency, and scalability. It also observed that Blockchain-assisted validation increased the number of rounds the performance of the model also increased, and reduced the risks associated with unauthorized modifications and improved the reliability. Future work may be focused on integrating differential privacy techniques, lightweight

Blockchain protocols and real-world clinical deployments with a secure FedAvg algorithm.

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