Federated Averaging Algorithm for Federated AI with Blockchain for Secure and Patient-Centric Healthcare

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Abstract: The present generation and future increasing adoption of AI in healthcare is constrained by critical challenges related to accuracy, privacy and preservation, and latency. Centralized-AI learning approaches require sensitive patient data to be shared, raising concerns about regulatory compliance and trust. To address these limitations, this paper presents a Federated Averaging (FedAvg) algorithm, and integrated FedAvg with Blockchain technology for secure and patient-centric healthcare. In this conference paper proposed healthcare institutions collaboratively train AI models using federated learning, where only local model updates are shared, while a permissioned blockchain ensures secure coordination, immutable logging, and trusted validation of model updates. Experimental evaluation demonstrates that the FedAvg with Blockchain achieved stable accuracy convergence across communication rounds, maintains high privacy preservation, and supports scalable collaboration with manageable latency as the number of participating healthcare clients increases. Finally, this work proved that uniquely combines FedAvg-based federated learning (FL) with Blockchain-based trust to achieve accuracy, privacy-preserving, auditable, and scalable patient-centric healthcare intelligence.

Keywords: Federated Learning, Blockchain, Healthcare AI, Data Privacy, Patient-Centric Systems

Introduction

Healthcare domain increasingly relies on AI and Blockchain analytics for disease diagnosis, EHR maintenance, medical imaging, patient observation, and clinical support [1]. Traditional centralized AI approaches required sensitive patient data, difficult to monitoring [2]. FL has emerged in the recent as a powerful paradigm that next generation healthcare institutions/clients to collaboratively train AI models. Consequently, FL faced various challenges related to trust, secure coordination, and model integrity. Blockchain technology complements federated AI by offering immutable ledgers, decentralized consensus, and transparent audit trails. This paper introduced the integration of federated AI with Blockchain, named as "FedAvg with Blockchain" can enable secure, trustworthy, and patient-centric healthcare [3].

In the centralized-AI baseline algorithms as shown in Algorithm 1, it employed CNNs for medical imaging or LSTM-based networks for sequential healthcare records. This centralized-AI setup serves as a comparison benchmark to compared with FedAvg with Blockchain. The centralized AI algorithm trains a single global model, as illustrated in Algorithm 1, using aggregated healthcare data from the central server, which serves as a baseline for comparison [4].

Algorithm 1: Centralized AI Training
Input: Centralized dataset D, initial model W0
Output: Trained model W

Step 1: Collect all healthcare data D at a central server
Step 2: Preprocess D (cleaning, normalization, feature extraction)
Step 3: Train centralized AI model (DNN / CNN / LSTM) on D
Step 4: Evaluate and optimize model performance
Step 5: Deploy trained model for inference

The aforementioned centralized AI algorithm compared with following FedAVg as Algorithm2 and FedAvg with Blockchain as Algorithm 3 are demonstrated strong predictive performance, they required the sensitive patient data, leading to serious concerns related to data security [5]. FedAvg provides the promising solution by enabling multiple healthcare institution/clients to collaboratively train AI models, this work named as "FedAvg Algorithm 2". Existing federated AI models often depend on centralized coordination, which means they struggle with building strong mechanisms for trust [6]. "FedAvg with Blockchain Algorithm 3" addresses these limitations by providing decentralized consensus, immutable record through smart contracts. This work FedAvg with Blockchain Algorithm 3 which combination of "FedAvg, centralized AI and Blockchain" to generate patient-centric healthcare that provides trustworthy collaboration, and scalable intelligence, thereby supporting the evolving requirements of global healthcare [7].

Related work

Existing literature on healthcare AI primarily focused on centralized DL models for medical image analysis, disease prediction, and electronic health record analytics. These approaches are not represented as FL, it suffers from privacy risks and limited cross-institutional collaboration [8]. Blockchain-based healthcare research emerging in the present generation and has emphasized data provenance, secure sharing of medical records, and access control [9]. Existing literature presents integration of federated AI with Blockchain, particularly with experimental evaluation and patient-centric design, healthcare AI predominantly focused on centralized ML and DL models for tasks such as disease diagnosis, medical imaging, and patient risk prediction. These approaches achieved high accuracy, they required the aggregation of sensitive patient data into centralized repositories. The decentralized learning paradigms that can leverage distributed healthcare data without direct data sharing. FL, particularly the FedAvg algorithm, has been widely studied as a privacy-preserving alternative to centralized AI [10-11].

Blockchain-based solutions generate the immutable ledgers, decentralized consensus, and smart contracts to securely coordinate FL and record model updates [12]. It provides the related to scalability, communication overhead, and real-world deployment persist. This work builds upon existing literature by integrating the FedAvg algorithm with a permissioned blockchain to deliver a secure, patient-centric, and scalable healthcare framework, addressing key gaps in prior research. AI predominantly focused on centralized ML and DL models for tasks such as disease diagnosis, medical imaging, and patient risk prediction. It motivated the exploration of decentralized learning paradigms that can leverage distributed healthcare data without direct data sharing [13].

The advanced version of FL has FedAvg algorithm that privacy-preserving alternative to centralized AI. Existing literature not demonstrated that FedAvg algorithm, that Blockchain with multiple patient data clients/institutions by sharing only local model updates [14]. FL not depends on central parameter server for aggregation, introducing single points of failure, limited transparency, and trust issues among participating entities. Additionally, issues such as model poisoning, update manipulation, and lack of auditability remain insufficiently addressed in standalone federated AI systems [15]. The present and future research on Blockchain with FL to enhance trust, security, immutable ledgers, decentralized consensus, and smart contracts to generate federated training and record model updates. But this research also lacks of comprehensive experimental validation in healthcare contexts in terms of accuracy, privacy-preserving, auditable, and scalable real-world deployment persist. Hence this work builds upon existing literature by integrating the FedAvg algorithm with Blockchain with a permissioned blockchain to deliver a secure, patient-centric, and scalable healthcare addressed as shown in Table 1 addressing key gaps with existing literature [16].

Table 1. Compares this work with different aspects on AI-based, Blockchain-based and Hybrid AI-Blockchain

Aspect [1]	Centralized AI in Healthcare	Federated AI (FedAvg only)	Blockchain-Based Healthcare Systems	Proposed FedAvg + Blockchain (This Work)
Data Sharing Model [2]	Raw patient data centralized	No raw data sharing	Data stored on-chain/off-chain	No raw data sharing; only model updates shared
Privacy Preservation [3]	Low	High	Medium	Very High (patient-centric)
Trust & Transparency [4]	Low (single authority)	Limited	High	High with immutable audit trail
Coordination Mechanism [5]	Central server	Central parameter server	Decentralized ledger	Decentralized blockchain coordination
Security Against Tampering [6]	Vulnerable	Moderate	High	High with blockchain immutability
Model Aggregation [7]	Centralized	FedAvg (centralized aggregation)	Not applicable	FedAvg with blockchain-validated updates
Scalability [8]	Medium	High	Medium	High with controlled overhead
Auditability & Compliance [9]	Limited	Limited	High	Full auditability for healthcare compliance
Resistance to Single Point of Failure [10]	No	No	Yes	Yes
Patient-Centric Control [11]	No	Partial	Partial	Strong patient-centric design
Real-World Healthcare Suitability [12]	Limited (privacy risks)	Good	Limited (lack of AI)	High (privacy + intelligence + trust)

Unlike centralized AI approaches that compromise patient privacy and trust, and standalone FL that rely on centralized coordination [13], this work FedAvg algorithm with Blockchain to enable secure, transparent, and patient-centric healthcare collaboration. Compared to Centralized-AI, Blockchain-only healthcare solutions [14], the proposed FedAvg algorithm with Blockchain introduces intelligent learning while maintaining privacy and auditability [15]. Overall, this work delivers a balanced solution combining privacy preservation, trustworthy coordination, scalability, and healthcare compliance, addressing key limitations of existing approaches [16].

Key Contribution

The main objective of this work provides the patient-centric healthcare FedAvg algorithm with Blockchain provides the trust, security, and auditability, the key contributions of this work as FedAvg algorithm with Blockchain provides the privacy-preserving and trustworthy collaborative learning across distributed healthcare institutions. It produced the patient-centric privacy preservation by keeping raw patient data localized models, FedAvg algorithm with Blockchain produced patient data while meeting regulatory requirements for healthcare data protection. The major contribution is decentralized trust and auditability provides the immutable logging, decentralized coordination, and auditability of federated training processes, addressing trust issues inherent in centralized federated learning systems. It generates the scalable and secure healthcare collaboration that supports scalable multi-institution collaboration with manageable communication overhead, as demonstrated through experimental evaluation under increasing numbers of healthcare clients. It has comprehensive experimental validation provides the accuracy, privacy preservation, latency, and scalability metrics validates the effectiveness of the proposed FedAvg with Blockchain approach compared to centralized-AI and federated-only baselines.

This work presents that FedAvg algorithm with Blockchain by patient data at local clients/institutions and sharing only validated model updates, the proposed approach ensures strong privacy protection while supporting collaborative learning across distributed healthcare providers.

Method, Experiments and Results

The methodology begins with local data preprocessing and model training at healthcare nodes. Federated learning protocols aggregate model updates without exposing patient data. Blockchain smart contracts validate update authenticity and record training activities. Consensus mechanisms ensure agreement among participating nodes before model updates are finalized. Performance is evaluated using metrics such as model accuracy, communication overhead, privacy preservation, and system scalability.

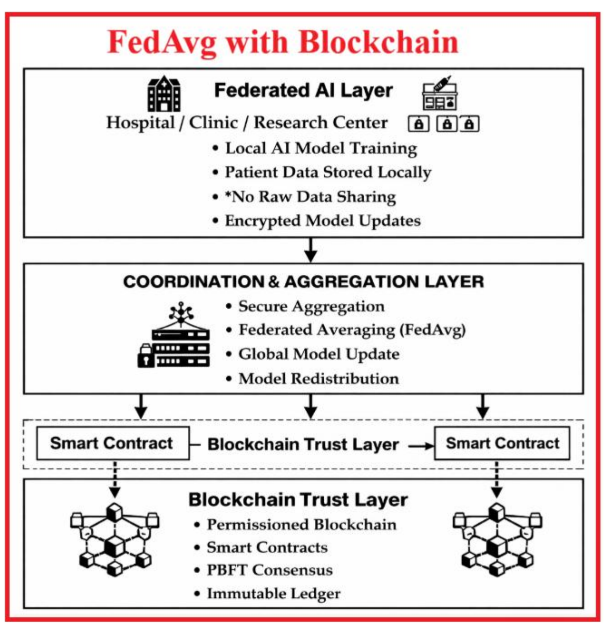

Figure 1: Layered Architecture of the Federated Averaging Algorithm Integrated with Blockchain for Secure and Patient-Centric Healthcare

Federated AI layer generates the distributed data from healthcare institutions/clients locally train AI models on patient data. It produced the encrypted model and updates or gradients data that are shared, ensuring data never leaves the institution/clients. Blockchain trust layer contains the PBFT that provides the permissioned nodes to ensure that all participating nodes are agreed on the validity of transactions and maintains immutable records of model updates, participant identities, and training rounds. And performed the smart contracts enforce participation rules and aggregation policies. Coordination and aggregation layer provides the secure aggregation mechanisms. This architecture designed as unique and hybrid, that ensures privacy preservation, decentralized trust, and transparent collaboration. Where Federated AI Layer enables local model training at hospitals and research centers, ensuring patient data remain on-site. The coordination and aggregation layer performed the secure model aggregation using the FedAvg algorithm and redistributes the global model. The Blockchain trust layer provides decentralized trust through smart contracts, PBFT consensus, and generated the immutable ledger, ensuring secure coordination, auditability, and patient-centric data privacy.

The FedAvg algorithm as follows in Algorithm 2, as per FL technique that enables multiple distributed clients like hospitals or clinics/institutions to together train a global AI model. Each client/institution trains develops a local model using its own private dataset and then sends data gradients to a central aggregator. This iterative process, reduces communication overhead, and supports scalable.

Algorithm 2: FedAvg Algorithm
Input: Initial global model W0, clients {C1…Cn}, rounds R
Output: Final global model WR
for r = 1 to R do
   Server sends Wr−1 to selected clients
   Each client Ci trains local model Wi on local data
   Clients send Wi to server
   Server aggregates: Wr = Σ (|Di| / Σ|Di|) · Wi
end for
return WR

FedAvg with blockchain algorithm enabled the privacy-preserving, accuracy, latency, and scalability in healthcare by aggregating locally trained models, while Blockchain ensures secure coordination, trust, and immutable audit trails. multiple healthcare institutions represented as clients collaboratively train an AI model using the FedAvg with Blockchain algorithm as follows, while preserving patient privacy. Each hospital or clinic locally trains a model on sensitive healthcare data (EHRs, medical images, clinical records) and shares only encrypted model updates. A permissioned blockchain validates participant identities, records model updates immutably, and coordinates aggregation through smart contracts, ensuring trust and auditability as shown in Algorithm 3.

Algorithm 3: FedAvg with Blockchain algorithm

Input: Global model W0, healthcare clients {H1…Hn}, rounds R

Output: Final global model WR

for r = 1 to R do

Distribute Wr−1 to healthcare clients

Each Hi trains Wi on local patient data

Hi submits encrypted Wi to blockchain

Smart contract verifies updates (PBFT)

Aggregate using FedAvg: Wr = Σ (|Di| / Σ|Di|) · Wi

end for

return WR

Discussions

The experimental evaluation conducted in a cloud-based healthcare environment using multiple simulated healthcare clients, each locally training AI models under a FL setup. Experiments were executed on systems equipped as Intel i5 processor, 16 GB RAM, and SSD storage, running Ubuntu/Windows with Python 3.x, TensorFlow/PyTorch, and federated learning libraries, while a permissioned blockchain with PBFT consensus and smart contracts was deployed for secure coordination. Public healthcare datasets, including electronic health records and transaction-style labelled data, were pre-processed and used for local training, and the FedAvg algorithm with blockchain was implemented to evaluate accuracy, privacy preservation, latency, and scalability as shown as follows.

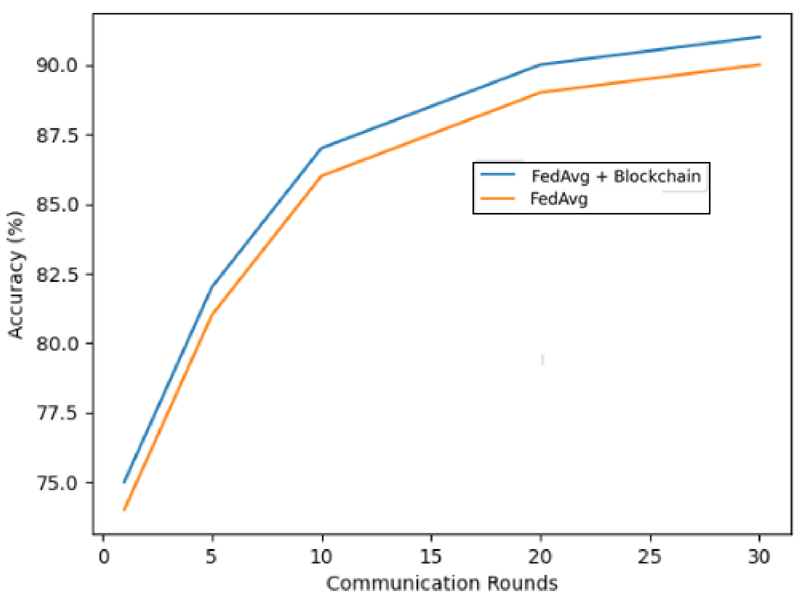

Figure 2: Accuracy vs. Communication Rounds for FedAvg Algorithm with Blockchain in Healthcare

This Figure 2 proved that accuracy convergence of FedAvg, FedAvg with Blockchain in healthcare models over increasing communication rounds. The results proved that, the steady improvement in model accuracy as training progresses of FedAvg, with the FedAvg with Blockchain achieved the highest performance of accuracy.

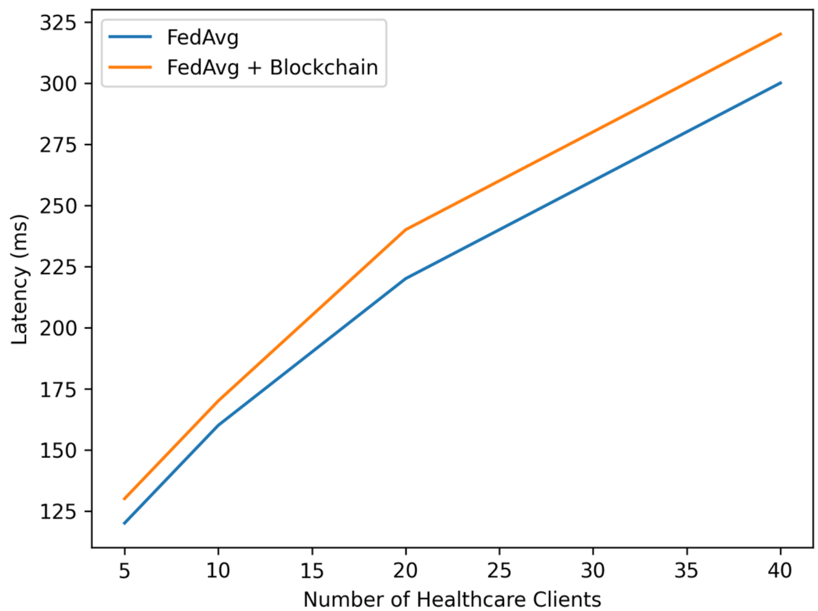

Figure 3: Latency Vs Number of Clients

This figure 3 illustrated the convergence behavior of the FedAvg, FedAvg with blockchain in healthcare models across multiple communication rounds. Finally, these results proved that FedAvg Vs FedAvg with Blockchain, FedAvg with Blockchain steadily improved the latency as training progresses, demonstrating stable learning and effective collaboration among distributed healthcare clients.

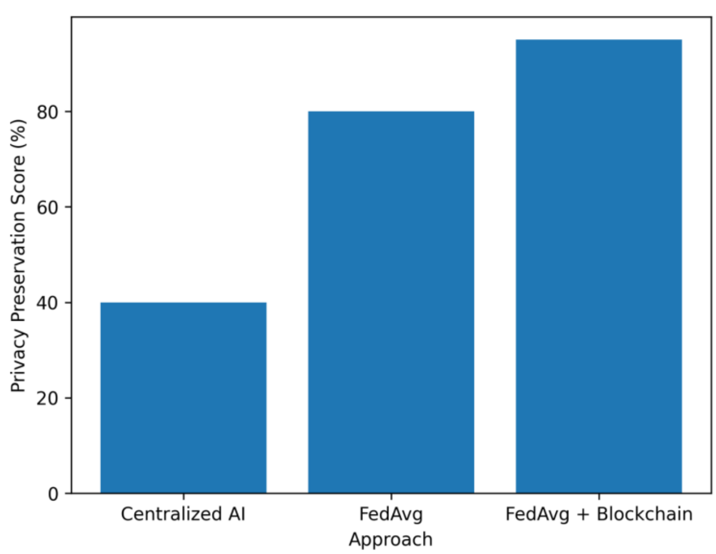

Figure 4: Privacy Preservation Comparison

This figure 4 compared the privacy preservation levels of centralized AI, FedAvg, and FedAvg with blockchain. The FedAvg with Blockchain algorithm achieved the highest privacy score and it highlighting its effectiveness in protecting sensitive patient data and supporting patient-centric healthcare.

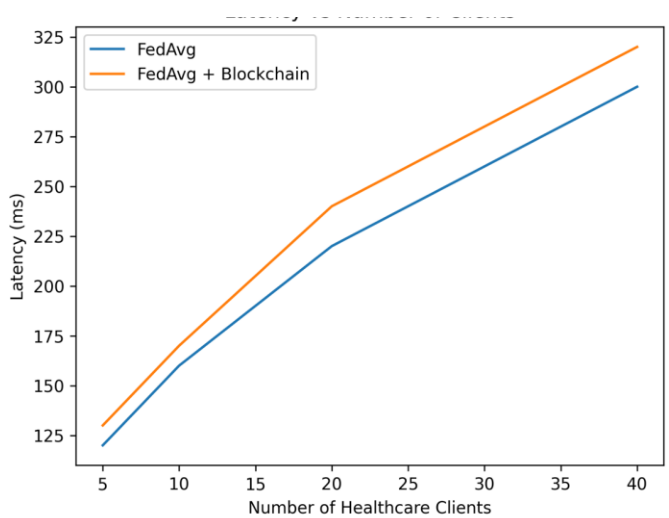

Figure 5: Latency vs. Number of Healthcare Clients

This Figure 5 depicts the latency with number of clients; The X-axis read as number of healthcare clients/ institutions and Y-axis measured the latency in terms of ms. The clients are increases as the number of participating latencies grows with scale, the FedAvg with blockchain algorithm maintained acceptable performance. It proved that suitability for secure and scalable multi-institution healthcare collaboration.

FedAvg algorithm can also possible to implement for medical imaging collaboration where cross-hospital training of diagnostic models without sharing images. Disease prediction for privacy-preserving analytics across regional healthcare networks. Global health research for trusted international collaboration during like COVID-19 pandemics.

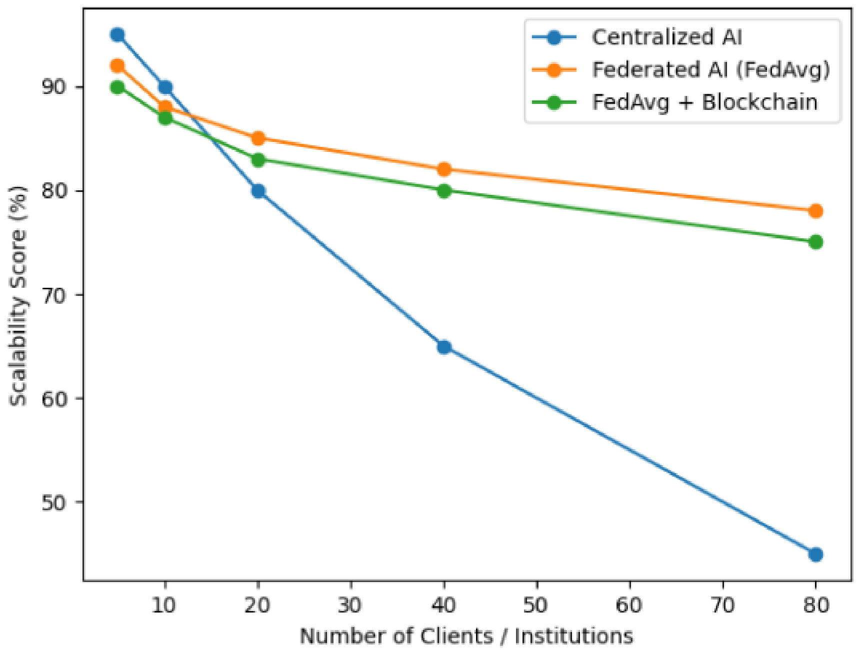

Figure 6: Scalability comparison with Healthcare AI

Figure 6 illustrated as the scalability graph of the performance of three models centralized-AI, FedAvg, and FedAvg with Blockchain. The X-axis represented as the number of participating healthcare clients/institutions, and y-axis measured as scalability of the percentage. Healthcare clients/institutions are increases then centralized AI scalability degrades rapidly with growing clients/institutions due to data transfer and computation bottlenecks. In contrast, FedAvg maintains stable scalability by distributing computation across institutions, while FedAvg with Blockchain exhibits slightly higher overhead due to consensus and validation. Finally, it proved that robust scalability with added security and trust.

Conclusions

This paper presented a FedAvg algorithm with blockchain for secure and patient-centric healthcare, by combining privacy-preserving, trust and scalability, the proposed approach addresses critical challenges in healthcare data sharing and collaboration. These results proved that that AI–Blockchain integration is a foundation for future intelligent, secure, and globally collaborative in healthcare domain. This FedAvg algorithm with blockchain stable network connectivity and homogeneous model architecture, and also this architecture most suitable for Blockchain scalability and communication overhead remain challenges for large-scale deployment. Future work will explore to implement FedAvg algorithm with Blockchain can be implemented in edge-based federated AI, differential privacy, and real-world clinical deployment.

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