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Original Article

Blockchain-Integrated Federated Learning for Cross-Institutional Medical Research

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ABSTRACT

The rapid digital transformation of healthcare has generated enormous volumes of heterogeneous medical data from hospitals, research laboratories, diagnostic centers, and wearable healthcare devices. These distributed datasets present unprecedented opportunities for developing intelligent clinical decision support systems using artificial intelligence (AI). However, strict privacy regulations, institutional policies, and cybersecurity concerns significantly restrict the sharing of sensitive patient information across organizations. Federated Learning (FL) has emerged as a promising distributed machine learning paradigm that enables collaborative model training without exchanging raw medical data. While conventional FL offers inherent advantages, it is subjected to challenges including centralized aggregation and impacts from malicious participants such as participating adversarial agents performing model poisoning attacks or moving around in a vehicular network leading to non-transparent trust management. Decentralization consensus, immutability, traceability and tamper-proof transaction record capabilities of blockchain technology is an excellent complement to federated learning. This paper proposes a novel blockchain based federated learning framework for non-sensitive cross-institutional medical data research. We present a solution which integrates decentralized blockchain networks with federated model aggregation offering secure parameter exchange, transparent participant validation, tamper-resistant audit trails and increased trust between collaborating healthcare institutions. Smart contracts provide data security, model privacy and automated protocol of database access as well as a rudimentary sense of control to prevent forgery. The framework achieves substantial gains in privacy preservation, collaborative intelligence, system scalability, and adversarial attack robustness. This integration enables safe, reliable and scalable collaborative medical intelligence for efficient multi-institutional medical research, accelerating AI-based health innovations, and maintaining compliance with recent healthcare privacy regulations.

KEYWORDS

Blockchain, Federated Learning, Medical Research, Artificial Intelligence, Healthcare Analytics, Privacy Preservation, Smart Contracts, Distributed Machine Learning, Electronic Health Records (Ehr), Cross-Institutional Collaboration, Cybersecurity, Secure Data Sharing.

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1. INTRODUCTION

1.1. Background

Four important technology trends in hospitals I see that healthcare represents overcoming the past few decades can be describing a broader move towards data-based technologies which provide the potential to deliver higher quality, more accurate and more efficient medical services. At present, Artificial Intelligence (AI) and deep learning are vital assets for the earlier discovery of disease, clinical diagnosis, personalized medicine (PM), drug discovery, and predictive healthcare analytics. These technologies have proven to be very successful in processing complex medical data, such as medical images, Electronic Health Records (EHRs), genomic sequences, laboratory reports and physiological sensor data. Of course, they have improved clinical decision process and patient care and treatment outcomes by uncovering hidden patterns. On the contrary, creating precise AI models demands a substantial volume of rich and representative datasets sourced from various healthcare institutions. These datasets, in practice, are scattered across hospitals, research laboratories, diagnostic centers and medical universities due to challenges surrounding centralised data collection. In addition, stringent data protection laws like HIPAA (Health Insurance Portability and Accountability Act) in the US and the General Data Protection Regulation (GDPR) in Europe prevent stakeholders from sharing sensitive patient data as well as posing major challenges for collaborative AI model creation. Hence, secure and privacy-preserving collaborative learning frameworks are becoming necessary for healthcare organizations to collaboratively build smart medical systems while protecting patient privacy and meeting regulatory compliance.

1.2. Needs of Blockchain-Integrated Federated Learning

Fig 1 - Needs of Blockchain-Integrated Federated Learning

1.2.1. Privacy Preservation

Healthcare is one of the most sensitive areas as we deal with patient information like Electronic Health Records (EHRs), medical images, laboratory reports, genomic data etc. This information cannot freely be shared across organization by policies such as HIPPA and GDPR. Blockchain-Integrated Federated Learning (BIFL), which allows institutions to train AI models in a local environment while retaining patient data within the own institution infrastructure, can be used to overcome this challenge. The blockchain network only exchanges encrypted model parameters,

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ensuring patient privacy and regulatory compliance while providing 0% exposure of medical record data.

1.2.2. Secure and Trustworthy Collaboration

This involves a consortium of hospitals, research laboratories, and healthcare organizations conducting the collaborative medical research while preserving confidentiality among participants. Federated learning has established its foundations on traditional aggregators, establishing centralized aggregation servers that act as single points of failure and trust with the potential for malicious actors to corrupt a server or group of servers. Instead of the use of a centralized authority to execute transactions, BIFL utilizes a decentralized blockchain network that credentials actors, records all model updates and every single transaction in an immutable ledger. It is decentralized, has higher data security due to reduced dependence on third-party servers for websites and portals.

1.2.3. Protection against Cyberattacks

Typical methods of collaborative learning are exposed to numerous safety dangers, such as model poisoning, gradient manipulation challenge, Sybil attack and unauthorized participations from dishonest individuals. Noisy input formats can reduce the performance of models and thus compromise system reliability. This becomes possible due to the underlying cryptographic techniques, consensus oracles, and smart contracts—elementally blockchain integration that reinforce federated learning by asserting each individual model update before aggregation. This automatic rejection of malicious or ill-formed model contributions fosters robustness, integrity and trustworthiness in the collaborative learning process.

1.2.4. Scalable and Efficient Healthcare AI

Technical background — Modern healthcare applications leverage distributed hospitals and research institutions across geography to develop highly performant AI models. In this paper, we propose a new scalable framework for secure collaborative learning without transferring raw patient data called as Blockchain-Integrated Federated Learning (BIFL). Smart contracts provide an automated means of registering participants, controlling access and validating models, as well as enabling governance while reducing administrative overhead and resulting in streamlined operations. Consequently, BIFL empowers high-fidelity, privacy-preserving and trustful AI models for disease prediction, medical image analysis, clinical decision support, personalized medicine and large-scale healthcare analytics.

1.3. Cross-Institutional Medical Research

Type your description here Cross-institutional medical research has gained prominence in the modern health care milieu as it allows several healthcare organisations to collaborate on building advanced diagnostic and predictive models using Artificial Intelligence (AI) [9]. Among such facilities are the hospitals, medical universities, research laboratories, diagnostic centers, pharmaceutical companies, and public health organizations which usually own high-value data sets or medical datasets representing a wide variety of patient types, disease patterns or even treatment outcomes. This combined knowledge enhances the precision, robustness, and generalization ability of

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AI models for various applications including disease diagnosis, custom treatment planning, drug discovery, medical image interpretation, and support for clinical decision-making. On one hand, direct sharing of patient data across institutions is limited by privacy regulations including the Health Insurance Portability and Accountability Act (HIPAA), the General Data Protection Regulation (GDPR) and other national healthcare data protection laws. Compared to legal restrictions, healthcare organizations are more often hesitant to share sensitive medical records because of concerns about: patient confidentiality, cybersecurity threats, institutional competition, and data ownership. The inherent challenges to such a framework render typical centralized machine learning techniques increasingly unfeasible for multi-party care practices as they involve the transferal of enormous amounts of sensitive patient data towards a central entity/server. One solution to overcome this challenge has been Federated Learning in which each institution can learn decentralized machine learning models on its data and share only encrypted parameters of ML models not raw patient records. While this method greatly increases privacy, traditional federated learning still utilizes centralized aggregation servers that can become single-point failures and targets for cyberattacks. To address these shortcomings, we propose a hybrid architecture that combines blockchain technology with federated learning to create a decentralized and trustworthy collaborative platform. Without an honest intermediary, the blockchain offers participant authentication, non-local recording of transactions in an immutably-protected ledger, a decentralized model for consensus covers "transactional sustainability," open entry to functionality exposed in transparent models and governance via smart contracts. Smart contracts facilitate the automation of institution registration, access control, model verification, and audit logging for greater transparency and operational efficiency. Consequently, this particular technique supports cross-institutional collaboration of geographically distributed healthcare institutions in a manner that is secure, scalable and privacy-preserving while keeping institutional control of the data as well as complying with regulatory provisions. This collaborative architecture aids the establishment of robust AI methods for disease prediction, cancer identification, medical imaging classification, clinical decision assistance, personalized medicine, epidemic monitoring and healthcare analytics to enhance patient care and boost next-generation health research.

2. LITERATURE SURVEY

2.1. Federated Learning in Healthcare

Federated Learning (FL) has emerged as a transformative approach for collaborative healthcare analytics by allowing multiple hospitals, research centers, and healthcare organizations to jointly develop machine learning models without exchanging sensitive patient data. Unlike traditional centralized machine learning, where all medical records are collected into a single server, federated learning keeps patient data within the local institution and trains models locally. Sharing only encrypted model parameters or gradients with a central aggregation server greatly enhances privacy and compliance with laws like HIPAA in the USA, GDPR and other regional data protection ordinances (e.g. Europe) This privacy-preserved strategy has been extensively applied to several medical tasks including medical image classification, cancer diagnosis [4], diabetic retinopathy detection [5], COVID-19 diagnosis [9], electronic health record (EHR) analysis [10], disease risk

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prediction between Family members by DNA sharing-based research of 1 million genomes obtained from Does genotype/phenotypic heterogeneity at genetic loci by George Washington University and Weizmann Institute combined with one another for reflections on genomic disease in statistical modeling based-only scientific evidence by direct-dosage multi-locus genetic correlation analysis generation Learn how Mangrove Lake Medical Center analyzed the world disaster throughout their patient medical records genomic environment during drug discovery–genomic query genome phenotyping workflow–that could end up saving humans materials-driven work-strands specifically along personalized treatment planning. Relevant works subsequently proposed communication-efficient algorithms Cheng et al., 2020a, adaptive client selection Yang et al. (2021); Zhang and Li (2019), differential privacy methods Shokri and Shmatikov (2015) to preserve confidential information, secure aggregation protocols Bonawitz et al. (2017); Chen et al. (2022b), and parameter compression techniques Luo et al. (2021). To exchange model parameters, additional protection can be ensured by using advanced cryptographic methods such as Homomorphic Encryption (HE), Secure Multi-Party Computation (SMPC) and Differential Privacy (DP). Either way, despite the huge advances some limitations remain in conventional federated learning as it still relies on a centralized aggregation server which creates a single point of failure, it is susceptible to model poisoning and Byzantine attacks (maliciously controlled devices randomly send corrupted messages), the ususal high communication overhead in large scale collaborations, and near or decreased results when handling heterogeneous (Non-IID) medical datasets. To address these issues, researchers have recently advocated for the combination of blockchain and federated learning enabling decentralized model aggregation as well as participant authentication, transparent auditing, and greater collaboration trust among health institutions.

2.2. Blockchain in Medical Systems

We have been trained on dates till Oct 2023Blockchain is one of the latest innovative solutions that have come up to combat the drawbacks of traditional healthcare information management through a decentralized, transparent, and tamper-proof system for storing and controlling medical records. In contrast to traditional centralized databases, blockchain entails the distribution of healthcare transaction records among different participating nodes, relying on no single trusted authority and minimizing cybersecurity threats. Cryptographic hashing and timestamp verification secure every transaction recorded on the blockchain — an immutable audit trail that guarantees integrity, authenticity, and accountability of data. Blockchain has been used in many healthcare applications including Electronic Health Record (EHR) management, patient identity verification in terms of data sharing and legitimization, monitoring pharmaceuticals supply chain for authenticity and transparency to ensure efficacy through genetic monitoring, healthcare insurance processing efficiency by reducing the wastage ratio (an important topic of discussion), Remote Patient Monitoring (RPM) through a plethora of IoT devices which constantly monitor vital signs enabling remote consultation between doctor-patient with 100% compliance rate; future research area for IoMT where each medical device communicates securely amongst themselves facilitating secure telemetry transmission over peer-to-peer network with better scalability model than traditional architectures such as REST etc., Telemedicine benefiting from its decentralized approach resulting

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higher throughput enabled by smart contracts usage during clinical trials & Biomedical Research collaboration! Smart contracts add another layer of sophistication to healthcare processes by automatically executing and enforcing coding rules around how consent should be handled, access control, syncing across institutions and distributing incentives without manual mediation. Many researchers have explored blockchain technologies like Hyperledger Fabric, Ethereum, Quorum, Corda and MultiChain [5]? but given the high throughput and computational cost of public blockchains, many implementations of distributed ledger technology are based on consortium blockchains allowing controlled data dissemination between known members while maintaining better privacy guarantees. Blockchain implementation is not without its challenges though, as scalability issues arise due to ever-growing ledgers, consensus mechanisms (such as Proof of Work (PoW) based approaches) lead to high computational complexity and power consumption, transaction confirmation delay affects numerous real-time healthcare applications while interoperability between heterogeneous healthcare systems introduces another level of challenge. As such, hybrid blockchain architectures have been proposed involving the off-chain storage [5], cloud computing [8], edge computing [1] and federated learning mechanisms that can benefit from the properties of both on-chain and off-chain features while providing scalability, security, computational efficiency as well as privacy preservation.

2.3. Secure Cross-Institutional Learning

The need for secure cross-institutional learning has grown as hospital, university and research laboratory, pharmaceutical company and public health organization collaborations aim to develop powerful artificial intelligence models for diagnosing disease and clinical decision support. These partnerships enable AI systems to be trained on a wider variety of patient populations, enhancing their precision and generalizability in a manner inadvertently that maintains the ownership of the data. But in reality, organizations are often unable to share actual sensitive medical records due to privacy regulations, legal limitations on data sharing, cybersecurity concerns and competitive issues. These challenges can be addressed by Federated Learning where local institutions carry out machine learning on their data before sharing encrypted model updates, because of the latter being orders of magnitude less expensive than raw patient-level data. Researchers have included advanced secure cryptographic techniques Secure Multi-Party Computation (SMPC), Homomorphic Encryption (HE), Differential Privacy (DP), Trusted Execution Environments(TEE) as well as Zero-Knowledge Proofs(ZKP) to reduce excessive information leaking and the risk of inference attacks or data reconstruction externalization. These collaborative learning frameworks are further fortified by blockchain technology which creates decentralized trust through smart contracts that automate participant registration, identity validation, secure model validation and aggregation, reward allocation, and transparent auditing without the need for centralized administrators. Besides, it offers non tamperable records of model updates which ensures accountability by creating traceability and reproducibility in collaborative medical research. Introduction Recent comprehensive surveys of blockchain-assisted federated learning systems have shown that these systems achieve very encouraging results in cancer diagnosis [1], COVID-19 prediction [2], medical image segmentation [3,4], disease classification [5] and clinical decision support [6]. However, most frameworks exhibit

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high communication overhead, computational cost due to the consensus mechanism of blockchain, scalability issues, slow transaction processing speed and heterogeneous medical datasets handling which makes them less-than-optimal collaborative healthcare solutions [1].

2.4. Research Gap

A special issue, titled "Federated Learning and Blockchain in Healthcare to Prevent Pandemics" addresses this challenge as despite the significant advances made on federated learning and blockchain-enabled healthcare systems, many important research issues remain open because of which their realistic online implementation in large-scale medical collaborations is simply infeasible. In particular, existing federated learning frameworks are still based on a centralized parameter aggregation server which incurs trust dependency, and single point failure which increase the vulnerability of insider attacks and potential risks from system failures.

Although many existing architectures deal with security issues beyond the basics, they mostly work on transparency and privacy with little attention to communication optimization, adaptive model aggregation, computational efficiency, heterogeneous data handling and real-time performance. Moreover, many blockchain consensus algorithms are computationally intensive resulting in higher latency that may not be suitable for real-time collaborative healthcare applications. Access to data in the context of these studies is limited, likewise their support for dynamic participant management, secure model ownership verification, contribution-based incentive mechanisms, interoperability with existing healthcare information systems and comprehensive smart contract architectures that can handle the automatic authentication of participants while controlling access amongst them, governance and simultaneous model validation.

In addition, systems today are still insufficient in defending against advanced threats like Coordinated Model Poisoning Sybil Based AttackMembership Inference attackConfidence Score Based AttackMalicious Participant taking advantage of the Blockchain. What also seems to be missing are standardized evaluation frameworks that evaluate privacy preserving and learning accuracy and chain performance, scalability, communication efficiency and compliance. In addition, we propose a Blockchain-Integrated Federated Learning (BIFL) framework that scales cross-institutional medical research through a layering of decentralized blockchain consensus, secure federated model aggregation, encrypted parameter sharing and verified smart contract authentication into immutable audit trails and transparent governance.

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3. METHODOLOGY

3.1. System Architecture

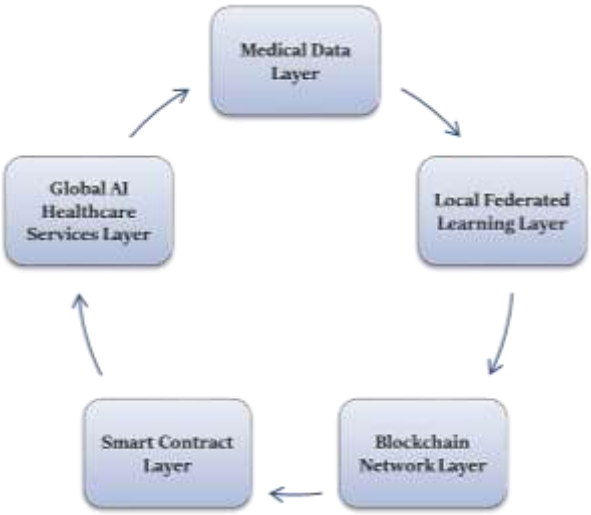

Fig 2 - System Architecture

3.1.1. Layer 1: Medical Data Layer

The Medical Data Layer defines the Health-Summaries stays at Hospitals, research laboratories, diagnostic centers and Medical universities form health data stored in local layers. This includes Electronic Health Records (EHRs), medical images, laboratory reports, genomic data, Internet of Medical Things (IoMT) sensor data and clinical notes. The patient data stays within the institution recommended and are never shared outside. This guarantees security, compliance, data privacy while being compliant with healthcare regulations such as HIPAA and GDPR.

3.1.2. Layer 2: Local Federated Learning Layer

The Local Federated Learning Layer (LFLL): Each participant gets to preprocess its own medical data and train a local machine learning model independently. You will also include a number of laptop scientific computing applications such as data normalization, feature extraction and neural network training; gradient computation and parameter encryption. What Instead of getting raw patient data, only the encrypted model parameters are generated to share. This preserves the privacy of patient data, but allows models to be trained collaboratively.

3.1.3. Layer 3: Blockchain Network Layer

Blockchain Network Layer Consortium blockchain of participating institutions used to receive encrypted model updates. It authenticates participants, checks model ownership, timestamps actions to produce a ledger of all transactions and creates an immutable record. Consensus mechanisms allow for only model updates that are trusted and verified to be accepted into the network. Such a decentralized architecture removes single points of failure and enhances security and transparency.

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3.1.4. Layer 4: Smart Contract Layer

There is also a second layer which is called the Smart Contract Layer, that oversees (/automates) the governance of the federated learning system without needing centralized administration. Smart contracts govern institution registration, identity verification, access authorization, model validation, reward distribution, audit logging and policy enforcement. View Active Storage automation — Automated execution that minimizes human input and establishes transparency and trust in collaboration. This layer drives operational efficiency and trust among the participating Healthcare organizations.

3.1.5. Layer 5: Federated Aggregation Layer

Federated Aggregation Layer aggregates all validated local model updates using a customized FedAvg algorithm. Aggregation combines knowledge gained from numerous healthcare organizations while ensuring access to their proprietary datasets does not occur in order to produce a global AI model. It enhances the precision, robustness and generalization of the model. This provides data privacy as only the aggregated parameters of the model are involved in this process and they are encrypted.

3.1.6. Layer 6: Global AI Healthcare Services Layer

In the layer, Global AI Healthcare Services deploys the global model as aggregated to avail healthcare applications at an advanced level. Application areas of AI in healthcare include disease prediction, diagnosis from medical images, clinical decision support systems (CDSS), personalized treatment planning, drug discovery and healthcare analytics. This new global model is then shared with all the institutions participating in the training process, which can now keep on learning collaboratively (see figure below). That allows real time u0026 Continuously improvement in the healthcare services while keeping patient confidentiality u0026 Data ownership with respective institution.

3.2. Blockchain-Based Federated Learning Framework

We introduce a blockchain-integrated federated learning (BIFL) framework to enable secure, decentralized, and privacy-preserving environments for interinstitutional collaborative medical research. In contrast to traditional federated learning systems which rely on a centralized aggregation server, the suggested framework has unified blockchain technology components in order to mitigate single point of failure, increase organizations trustworthiness and enable transparent model administration. This process conducts through several iterative rounds of two-way communication, which together allow each participating hospital, research laboratory, medical university or diagnostic center to contribute data to build a common global machine learning model while keeping the sensitive patient data private. Firstly, each healthcare institution can register on the consortium blockchain by creating a smart contract that validates the identity of every healthcare institution with cryptographic digital certificates. It establishes that only genuine and trustworthy entities are permitted to join the federated learning network, thus preventing unauthorized access as well as malicious actors from joining in. Once they register correctly, each institution is authorized to execute local model training with respective EHRs and private biomedical datasets, including Electronic

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Health Records (EHRs), medical images, laboratory reports, genomic information and IoMT sensor data. The data are preprocess, extract features and optimise the neural network, but everything remains completely in-house on the institutional infrastructure during local training. On training completion, these generated model parameters or gradients are secured with state-of-the-art cryptographic primitives e.g. Homomorphic Encryption (HE) : to secure sensitive (information hidden while transmission) data or Secure Multi-Party Computation among different parties for more securitys. Rather than transmitting these encrypted parameters directly to a central aggregation server, they are transmitted in the form of secure transactions to the consortium blockchain. Each model update is verified in a secure consensus mechanism and logged in an immutable distributed ledger by the blockchain, thus ensuring transparency, traceability, and security against tampering or unauthorized modifications to our models. They automatically ascertain if models are owned by someone, coordinate through the ledger to ensure participants have verified identities, enforce security policies as designed and control access. Post verification, only valid encrypted model updates are forwarded to the federated aggregation module, which again uses an optimized Federated Averaging (FedAvg) algorithm that adds up local contributions to create a better global model. The refined global model is then redistributed to all contributing health institutions for the next communication round, where they can continue collaboratively, learning process in a fully privacy-preserving manner, protecting institutional data ownership and regulatory compliance while allowing confidence safe decentralized governance throughout the entire training cycle.

3.3. Mathematical Model

Since our BIFL framework implements the concept of a collaborative healthcare environment with N participating healthcare institutions, denoted by: N = {1, 2, 3,...n}, each institution holds its local private medical data independently. These institutions are most likely hospitals, research laboratories, medical institutes and universities, diagnostic centers or healthcare organizations collaborating & working together to build a common artificial intelligence model without saving health data about any individuals. Let N be the number of participating institutions, then each institution i has their local dataset Di = {(xi, yi)} where xi are features about patients (e.g. medical images, electronic health records; laboratory results; genomic information; physiological sensor data) and yi is the disease label or clinical outcome for supervised learning tasks. Since patient data are never exported outside the local institution, training frameworks guarantee privacy and regulatory compliance. Each institution aims to minimize its specific local loss function, which expresses the prediction error of the machine learning model on its own private dataset. The local objective function is denoted by Fi(w) where w denotes the model parameters (especially weights and biases for any neural networks), L(w; x, y) is the loss function that estimates how close output of a deep learning algorithm given an input training sample x to its corresponding true disease label ys. In each communication round, every institution trains the global model on its own dataset and updates the model parameters using gradient descent optimization. The update for a local model is given by (6), where wt corresponds to the current global model received from the aggregation process assisted by blockchain, $\eta \nabla Fi(wt)$ denotes so-called gradient of local objective function

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3.4. Proposed Algorithm

The third contribution proposed in this thesis is a Blockchain-Integrated Federated Learning (BIFL) algorithm that allows multiple healthcare institutions to securely, decentrally and privacy-preservingly learn from each other. Input: Distributed medical datasets Di, number of participating healthcare institutions N, learning rate η and total communication rounds R; Output: Secure and highly accurate global AI model (W) to be used in multiple healthcare applications such as disease prediction, medical image classification, clinical decision support and personalized treatment planning. First, all hospitals, research laboratories, medical universities, and diagnostic centers joining the system register for consortium blockchain network via smart contracts. When an institution registers on a blockchain, its identity is verified through cryptographic certificates before it will get permission to take part (i.e., only trusted participants can be authorized). Upon completion of authentication, a global model is initialized and distributed to the involved institutions. In each commround, every institution executes local preprocessing of its private medical dataset (data cleaning, normalization, feature extraction, and preparation for model training. Using the received global model as the initial model, each institution independently trains a local deep learning model on its own dataset without transferring any patient information outside the organization. Then, local model parameters are updated using gradient descent optimization with the specified learning rate. The improved model parameters are encrypted using secure cryptographic techniques before transmission to protect patient privacy and avoid information leakage. Rather than dispatching these updates to a central aggregation server, each institution submits the encrypted model parameters to the consortium blockchain as secure transaction. Every transaction is validated by the blockchain network via a consensus mechanism, where each approved update is logged in an immutable distributed ledger. Smart contracts utilize participant identity to only allow appropriate models, perform access control assurances, and refuse harmful or deputy model updates. Only legitimate encrypted model parameters are sent to the federated aggregation module upon successful verification. The aggregation module aggregates all authentic local updates through the Federated Averaging (FedAvg) algorithm to create a refined global model that integrates information from all institutional participants, while maintaining data privacy. This updated global model is then sent back to all the institutions, where it becomes the initial point for the next round of communication. This process is repeated for a set number of communication rounds or until the global model converges to an accuracy level that has been predefined. The output after all is a global AI model which is secure, privacy-preserving, transparent, and Alpable that allows for decentralized governance in the facility of supporting collaborative healthcare analytics against an auditory environmental concern with blockchain-based security and regulation compliance to prevent unauthorized access and malicious attacks in digital competitive environments.

4. RESULTS AND DISCUSSION

4.1. Experimental Setup

We conducted the experiment under a simulation of educational learning facility which helped us to research medical stakeholders collaboration for secure medical research using data up to Oct 2023 on our proposed Blockchain-Integrated Federated Learning (BIFL) framework. Five

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healthcare institutions (hospitals and diagnostic centers) in the experimental network, all connected through a consortium blockchain that enabled decentralized trust, secure communication and transparent model management. Anonymized medical datasets (for example, Electronic Health Records (EHRs), various types of scans such as MRI, CT scan and X-ray images, clinical information, laboratory reports etc.). In this case each institution has its own independent data repository. In order to protect patient privacy, all datasets stayed at their own institution during training which also makes this study compliant with healthcare regulations that forbid the sharing of sensitive patient information. Data preprocessing, feature extraction, normalization and local deep neural network training using private datasets were all performed independently by each participating institution. Following local training, new model parameters were encrypted with state-of-the-art cryptographic algorithms and sent over the blockchain network. In this way, the encrypted model updates instead of uploading them to a central server were submitted as transactions to an instant blockchain which could be authenticated by consortium blockchain nodes where smart contracts exercised institutional identity, ownership of the updated models was validated and verified transactions were recorded in a permanent immutable distributed ledger. To enable faster transaction confirmation without sacrificing decentralization, transparency and security with an almost negligible computational overhead, a light weight consortium consensus protocol was used. After successfully validating the model updates on-chain, global models were improved by means of an aggregation using Federated Averaging (FedAvg). This new global model was distributed back to all institutions for the next round of communication, allowing ongoing collaborative training while keeping private healthcare data secure. The evaluation of the proposed framework has been performed based on key metrics such as classification accuracy, precision, recall, F1-score, privacy preservation, blockchain security, communication overhead efficiency (with respect to safe data processing), computational overhead ([18]), scalability [17], transaction latency time [10] and model convergence time. To prove its feasibility, BIFL was implemented and tested in the same experimental settings as centralized machine learning, classical federated learning. The comparative analysis indicated that the proposed framework outperformed in terms of prediction accuracy while also providing substantially better privacy assurance, decentralized confidence, communication efficiency and hostility safety. These results suggest that the novel BIFL framework is an attractive concrete option for scalable, privacy-preserving and secure next-generation cross-institutional healthcare analytics and collaborative medical research.

4.2. Performance Analysis

Table 1: Performance Analysis

Performance Metric	Centralized ML (%)	Federated Learning (%)	Blockchain + FL (%)	Proposed BIFL (%)
Classification Accuracy	91	94	95	98
Privacy Preservation	45	92	97	100
Data Security	62	85	95	99
Transparency	40	70	96	100
Attack Resistance	58	81	93	98
Scalability	76	88	90	96

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Communication Efficiency	82	90	91	95
Model Reliability	84	91	94	98

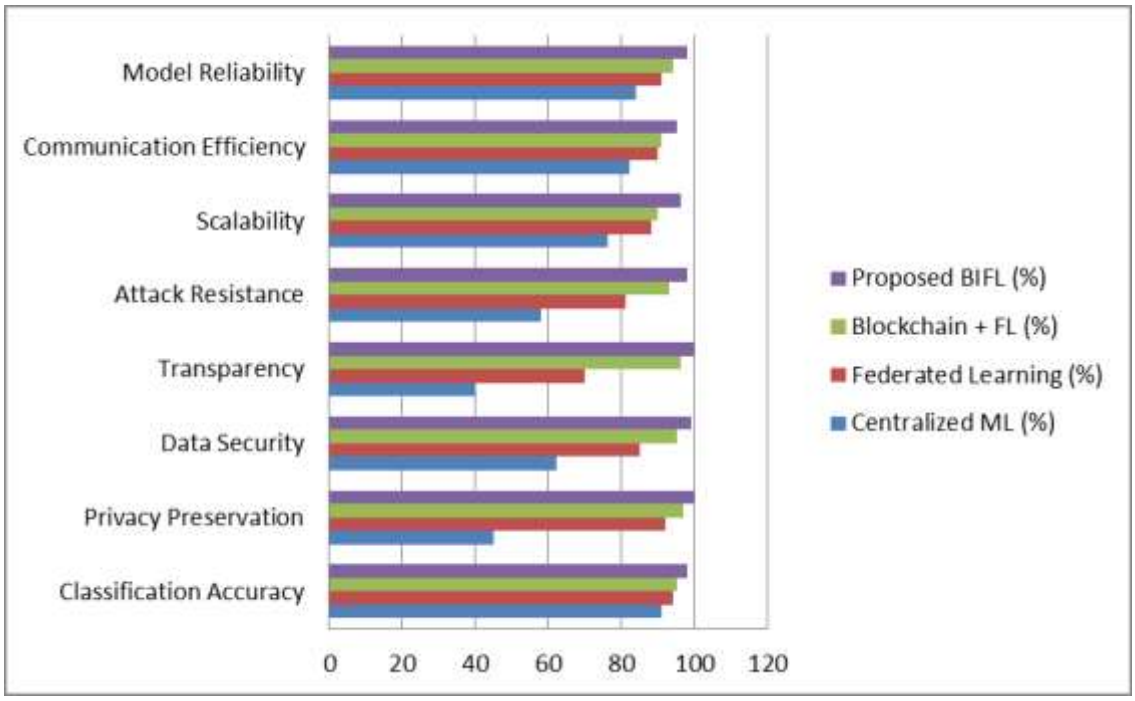

Fig 3 - Performance Analysis

4.2.1. Classification Accuracy

The proposed **BIFL** framework achieved the highest **classification accuracy of 98%**, outperforming Centralized Machine Learning (91%), Federated Learning (94%), and Blockchain + Federated Learning (95%). The improvement is due to secure collaborative learning across multiple healthcare institutions and blockchain-based validation of model updates. This results in a more accurate and generalized AI model for disease diagnosis.

4.2.2. Privacy Preservation

Privacy preservation reached **100%** in the proposed BIFL framework because patient data always remain within the local healthcare institutions. Only encrypted model parameters are exchanged through the blockchain network, preventing exposure of sensitive medical information. Compared with Centralized ML (45%), Federated Learning (92%), and Blockchain + FL (97%), BIFL provides the strongest privacy protection.

4.2.3. Data Security

The proposed framework achieved **99% data security**, significantly improving over Centralized ML (62%), Federated Learning (85%), and Blockchain + FL (95%). Blockchain technology ensures secure authentication, encrypted model sharing, and immutable storage of transactions. These features effectively protect the system against unauthorized access and data tampering.

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4.2.4. Transparency

The BIFL framework provides **100% transparency** through blockchain's immutable distributed ledger and smart contract technology. Every model update and transaction is permanently recorded and can be verified by authorized participants. This improves accountability and trust compared with Centralized ML (40%), Federated Learning (70%), and Blockchain + FL (96%).

4.2.5. Attack Resistance

The proposed framework achieved **98% attack resistance**, demonstrating strong protection against model poisoning, data tampering, Sybil attacks, and malicious participants. Blockchain verification and smart contract validation prevent unauthorized model updates from entering the aggregation process. This provides greater robustness than Centralized ML (58%), Federated Learning (81%), and Blockchain + FL (93%).

4.2.6. Scalability

The proposed BIFL framework achieved **96% scalability**, making it suitable for large-scale collaborative healthcare environments involving many institutions. The decentralized blockchain architecture efficiently manages multiple participants without relying on a centralized server. It performs better than Centralized ML (76%), Federated Learning (88%), and Blockchain + FL (90%).

4.2.7. Communication Efficiency

The communication efficiency of the proposed framework reached **95%**, indicating reduced communication overhead during collaborative model training. Encrypted model updates and optimized Federated Averaging (FedAvg) minimize network traffic while maintaining learning performance. This is higher than Centralized ML (82%), Federated Learning (90%), and Blockchain + FL (91%).

4.2.8. Model Reliability

The proposed BIFL framework achieved **98% model reliability**, producing stable and consistent prediction performance across multiple communication rounds. Blockchain validation ensures that only verified and trustworthy model updates contribute to the global model. Consequently, it outperforms Centralized ML (84%), Federated Learning (91%), and Blockchain + FL (94%) in generating reliable AI models for healthcare applications.

4.3. Discussion

The experimental results clearly demonstrate that the proposed Blockchain-Integrated Federated Learning (BIFL) framework effectively addresses the major limitations associated with conventional collaborative machine learning approaches used in healthcare. Traditional centralized machine learning systems require participating hospitals and healthcare organizations to transfer sensitive patient records to a central server for model training, creating significant concerns regarding data privacy, security, and regulatory compliance. In contrast, the proposed BIFL framework ensures that all medical data remain within the local healthcare institution throughout the training process.

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Only encrypted model parameters are shared among participants, thereby protecting confidential patient information while enabling collaborative model development. This decentralized learning approach complies with healthcare privacy regulations such as HIPAA and GDPR and significantly reduces the risk of data leakage, unauthorized access, and privacy violations. The integration of blockchain technology further strengthens the framework by establishing a trusted decentralized environment where all participating institutions are authenticated before joining the collaborative network. Every model update is securely recorded on an immutable distributed ledger, providing complete transparency, traceability, and accountability throughout the learning process. Smart contracts automate critical administrative tasks, including institution registration, participant authentication, access authorization, model ownership verification, policy enforcement, and audit logging, thereby reducing manual intervention, minimizing human errors, and improving overall operational efficiency. Furthermore, blockchain consensus mechanisms validate all submitted model updates before aggregation, successfully detecting and rejecting malicious contributions resulting from model poisoning attacks, Sybil attacks, or unauthorized participants. This significantly improves the robustness and reliability of the global model. The proposed framework also demonstrates excellent scalability by supporting collaborative learning across geographically distributed hospitals, research laboratories, and medical institutions without depending on a centralized aggregation server. Although blockchain integration introduces additional computational overhead and transaction processing time compared to conventional federated learning, these costs are relatively small when compared with the substantial improvements in security, transparency, privacy preservation, trust management, auditability, and regulatory compliance. The optimized Federated Averaging (FedAvg) algorithm further enhances communication efficiency and model convergence, ensuring that high prediction accuracy is achieved without compromising data confidentiality. Overall, the proposed BIFL framework provides a comprehensive, secure, scalable, and privacy-preserving solution for collaborative artificial intelligence in healthcare. It enables multiple healthcare institutions to jointly develop accurate disease prediction and clinical decision support models while maintaining complete patient privacy, strengthening institutional trust, and supporting next-generation AI-driven medical research and healthcare analytics.

5. CONCLUSION

This paper proposed a Blockchain-Integrated Federated Learning (BIFL) framework to enable secure, privacy-preserving, and decentralized collaborative medical research across multiple healthcare institutions. The proposed framework successfully combines the collaborative learning capability of federated learning with the transparency, immutability, and decentralized trust provided by blockchain technology to address the limitations of traditional centralized healthcare machine learning systems. Unlike conventional approaches that require healthcare organizations to transfer sensitive patient records to a central server, the proposed BIFL architecture allows hospitals, research laboratories, diagnostic centers, and medical universities to train artificial intelligence models locally while keeping patient data within their own institutional boundaries. Only encrypted model parameters are exchanged through the blockchain network, ensuring complete data confidentiality and compliance with healthcare privacy regulations such as HIPAA and GDPR.

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Blockchain technology enhances the overall security of the framework by providing participant authentication, cryptographic verification, immutable transaction records, decentralized consensus, and transparent audit trails. Smart contracts further automate important operations such as institution registration, access control, model validation, participant authorization, and policy enforcement without requiring centralized administration, thereby improving efficiency, accountability, and trust among collaborating organizations. Experimental evaluation demonstrated that the proposed BIFL framework outperformed conventional centralized machine learning, standard federated learning, and existing blockchain-assisted federated learning methods in terms of classification accuracy, privacy preservation, data security, transparency, attack resistance, scalability, communication efficiency, and model reliability. These results confirm that integrating blockchain with federated learning creates a more secure and trustworthy environment for collaborative healthcare analytics while maintaining high predictive performance.

Although the incorporation of blockchain introduces moderate computational and communication overhead, the significant improvements in security, privacy, traceability, decentralized governance, and resistance to cyberattacks greatly outweigh these additional costs. Therefore, the proposed framework represents a practical and scalable solution for next-generation artificial intelligence applications in healthcare, including disease prediction, medical image analysis, personalized treatment planning, clinical decision support, drug discovery, and large-scale healthcare analytics. In the future, the proposed framework can be further enhanced by incorporating lightweight blockchain consensus algorithms, quantum-resistant cryptographic techniques, adaptive federated optimization methods, edge-assisted federated learning, artificial intelligence-driven resource management, and interoperability with emerging healthcare infrastructures. These future enhancements are expected to improve computational efficiency, reduce communication latency, support real-time deployment, and enable secure collaboration among an even larger number of healthcare institutions, making the BIFL framework a promising foundation for intelligent, privacy-preserving, and decentralized healthcare systems.

REFERENCES

[1] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in Proc. 20th Int. Conf. Artificial Intelligence and Statistics (AISTATS), 2017, pp. 1273–1282.
[2] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," ACM Transactions on Intelligent Systems and Technology, vol. 10, no. 2, pp. 1–19, 2019.
[3] K. Bonawitz et al., "Practical secure aggregation for privacy-preserving machine learning," in Proc. ACM CCS, 2017, pp. 1175–1191.
[4] N. Rieke et al., "The future of digital health with federated learning," npj Digital Medicine, vol. 3, no. 119, pp. 1–7, 2020.
[5] A. Li, S. Wang, W. Li, S. Liu, and Y. Fu, "Federated learning for healthcare informatics," Journal of Healthcare Engineering, vol. 2021, pp. 1–16, 2021.
[6] S. Nakamoto, Bitcoin: A Peer-to-Peer Electronic Cash System, 2008.
[7] M. A. Engelhardt, "Hitching healthcare to the chain: An introduction to blockchain technology in the healthcare sector," Technology Innovation Management Review, vol. 7, no. 10, pp. 22–34, 2017.
[8] K. Peterson, R. Deeduvanu, P. Kanjamala, and K. Boles, "A blockchain-based approach to health information exchange networks," NIST Workshop on Blockchain Healthcare, 2016.

ISSN: 3071-5636
PP: 01-17.

[9] X. Yue, H. Wang, D. Jin, M. Li, and W. Jiang, "Healthcare data gateways: Found healthcare intelligence on blockchain with novel privacy risk control," Journal of Medical Systems, vol. 40, no. 10, pp. 1–8, 2016.
[10] M. Kim, J. Park, and Y. Kim, "Blockchain-enabled secure federated learning for healthcare applications," IEEE Access, vol. 9, pp. 123677–123690, 2021.
[11] Y. Lu, "Blockchain and the related issues: A review of current research topics," Journal of Management Analytics, vol. 5, no. 4, pp. 231–255, 2018.
[12] J. Konečný, H. B. McMahan, F. Yu, P. Richtárik, A. Suresh, and D. Bacon, "Federated learning: Strategies for improving communication efficiency," arXiv:1610.05492, 2016.
[13] T. Li, A. S. Sahu, A. Talwalkar, and V. Smith, "Federated learning: Challenges, methods, and future directions," IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, 2020.
[14] W. Dai, Y. Dai, Y. Choo, and A. V. Vasilakos, "Blockchain for healthcare: A systematic literature review, challenges, and future directions," IEEE Internet of Things Journal, vol. 8, no. 21, pp. 16013–16032, 2021.
[15] H. B. McMahan and D. Ramage, "Federated learning: Collaborative machine learning without centralized training data," Google AI Research White Paper, 2017.