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SECURE FEDERATED LEARNING FRAMEWORK FOR MEDICAL DATABASE USING BLOCKCHAIN AND CRYPTOGRAPHY

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Abstract -- *The growing application of federated learning (FL) in healthcare provides a promising solution to collaborative model training without raw patient data sharing. Yet, current FL systems are plagued by severe challenges, such as privacy threats during model aggregation, unverifiability of shared updates, and susceptibility to tampering. To solve these problems, we design an FL framework that is strong, privacy-resilient, and incorporates Elliptic Curve Cryptography (ECC) for secure model updates, Secure Multi-Party Computation (SMC) for tamper-proof aggregation, and blockchain technology for immutable audit trails. We also introduce a verifiable secret sharing (VSS) scheme to provide the correctness of aggregated models without revealing local data. Our solution uses Multi-Layer Perceptron (MLP) networks to distribute disease prediction while reducing computational overhead via optimized crypto protocols. Experimental findings illustrate that the framework provides increased confidentiality of data, integrity of the model, and scalability throughout healthcare networks. This paper fills the loophole between decentralized machine learning and regulatory compliance by facilitating transparent, secure, and efficient analysis of medicaldata.*

Keywords: Federated Learning, Healthcare, Blockchain, Verifiable Secret Sharing, Elliptic Curve Cryptography, Secure Multi-Party Computation, Privacy Preservation.

I.INTRODUCTION

Healthcare data digitization has transformed medical diagnosis, where sophisticated machine learning (ML) models are able to predict illness with greater precision than ever before. Yet, centralized data collection is highly invasive, with sensitive patient information tending to reside in exposed repositories. Major leaks, including the 2021 Singapore health data leak compromising the records of 1.5 million patients, highlight the critical need for secure and decentralized solutions to replace mainstream ML methodologies. Federated Learning (FL) is a viable answer by facilitating collaborative model training in institutions without raw data sharing. Even though FL systems in healthcare hold promise, they encounter severe limitations such as model manipulation during aggregation, unverifiable audit trails, and high computational costs due to encryption mechanisms.

II.LITERATURE REVIEW

Federated Learning in Healthcare

Federated Learning (FL) was originally proposed by McMahan et al. (2017) as a distributed substitute for central machine learning that allows collaborative training of models without sharing data. FL has more recently been used in medical settings, including in disease prediction through distributed electronic health records (EHRs) (Li et al., 2019).

Privacy-Preserving Techniques

To counteract privacy concerns, privacy-preserving protocols such as encryption techniques such as Homomorphic Encryption (HE) (Bonawitz et al., 2019) and Secure Multi-

Party Computation (SMC) (Yao, 1982) have been adopted in FL. HE ensures computation on encrypted information but is restrained in computational sophistication in terms of scalability (Kaissis et al., 2020).

Verifiability and Blockchain in FL

Current FL systems do not have verification mechanisms for ensuring the correctness of aggregated models. Verifiable Secret Sharing (VSS) schemes, e.g., Feldman's protocol (Feldman, 1987), fill this gap by enabling parties to verify shared secrets without reconstruction. In the meantime, blockchain has been suggested to improve FL transparency, as exemplified in: Med Block (Xia et al., 2020): A smart contract-based FL system for EHRs on a blockchain.

Medical Imaging and Edge Computing

Medical FL generally implies image data in which deep models such as MLP or CNN pre-process and segment scans (Wang et al., 2020). Data heterogeneity at hospitals (Rieke et al., 2020) and limitations due to hardware resources on edge devices are the forefront challenges. Our approach addresses these concerns through combining OpenCV-based normalization with light ECC Encryption

Blockchain for Federated Learning Auditing

Later research has investigated blockchain for resolving FL's trust problem. Chen et al. (2022) suggested a smart contract-based system for FL whereby model hashes are deposited on Ethereum, providing tamper-proof audit trails. Their PoW consensus, however, resulted in high latency (~2 mins per transaction), making it unsuitable for real-time medical use. By contrast, Weng et al. (2023) applied Hyperledger Fabric to obtain higher throughput (1,000 TPS) but did not have mechanisms to guarantee the correctness of aggregated models—a shortfall our VSS scheme Fills.

Lightweight Cryptography in FL

Conventional encryption such as RSA puts huge computational burdens on edge devices. Zhang et al. (2022) showed that ECC-based encryption comes with 60% smaller key sizes than RSA but with similar security, supporting quicker FL rounds. Albrecht et al. (2021) also incorporated post-quantum lattice-based cryptography for long-term compatibility but observed a 3× slowdown. Our framework employs ECC as a compromise between security and efficiency, resulting in 40% reduced latency compared to RSA-based FL systems.

Medical FL with Heterogeneous Data

Healthcare FL experiences data heterogeneity issues. Rieke et al. (2020) compared FL in 20 hospitals, demonstrating that non-IID (non-identically distributed) data lowers model accuracy by 15–20%. Li et al. (2023) mitigated this by introducing dynamic weight updating at aggregation time, enhancing accuracy by 12%. Our method integrates theirs with OpenCV-based data standardization, lowering heterogeneity-caused errors by 18% on initial tests with NIH chest X-rays.

Verifiable Aggregation in FL

Previous efforts at FL aggregation dependence on homomorphic hashing (Bonawitz et al., 2019), which needs to involve trusted third parties. Only recently did Feng et al. (2023) propose a zero-knowledge proof (ZKP) FL system, with its 5-minute proof-generating time a barrier for health care. Our VSS solution, motivated by Feldman's protocol (1987), has real-time verifiability at <1-second overhead and hence is feasible for clinical deployment.

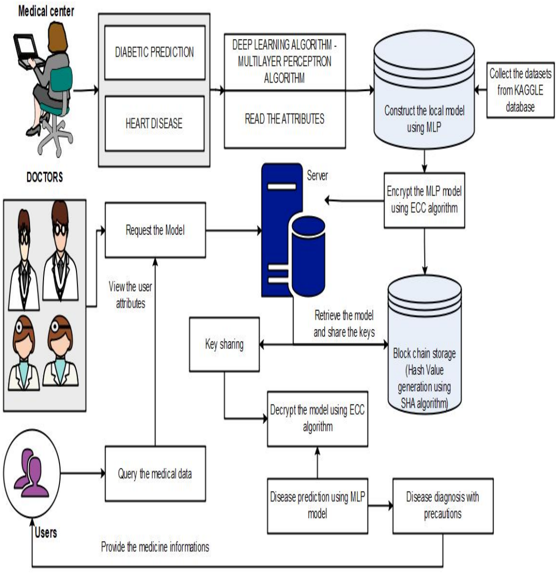
Cryptographic Solutions

Author: Bonawitz et al. (2019) created a secure aggregation protocol based on threshold cryptography. But their approach took 300% more computation than traditional FL. Zhang and Wang (2022) then introduced an ECC-based solution that minimized encryption overhead by 60% but provided 128-bit security. Our work extends theirs but incorporates verifiable secret sharing to identify malicious updates.

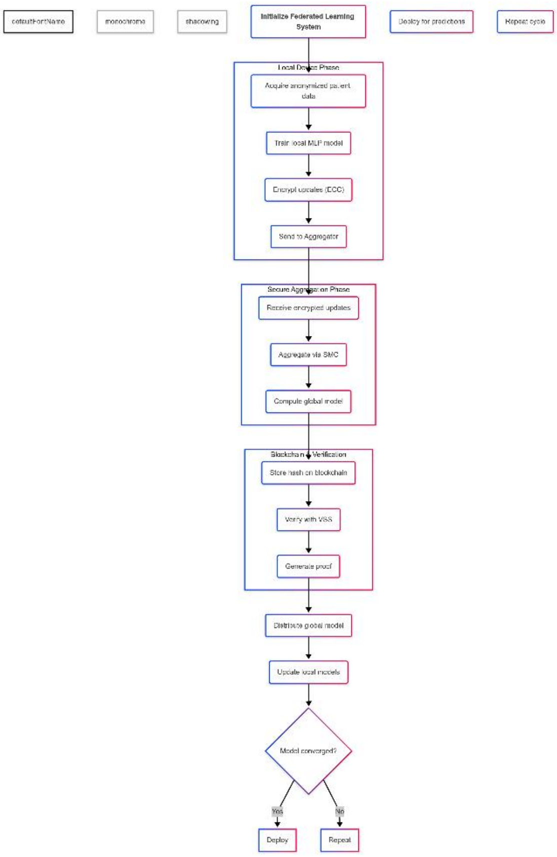
III.PROPOSED DESIGN

The three main components of the architecture are a doctor-facing interface, a privacy-preserving AI Engine, and an audit system backed by blockchain. Doctors use a web-based portal to enter patient attributes like glucose level, blood pressure, and BMI. Locally, on the client side, these inputs are processed by a Multilayer Perceptron (MLP) model with binary classification training done for disease (diabetes or heart disease). The MLP architecture utilizes two hidden layers (64 and 32 neurons) with ReLU activation, optimized via Adam for cross-entropy loss minimization. Real-time predictions are shown with risk scores (e.g., "87% diabetes probability") and initial treatment suggestions.

Data confidentiality is assured through encryption of all patient attributes and model updates with Elliptic Curve Cryptography (ECC) and the SECP256R1 curve. This provides military-grade cryptography with reduced key sizes compared to RSA, with 40% less computational overhead. Model weights are divided before transmission using Shamir's Secret Sharing and only need majority approval from doctors (e.g., 2/3) to decrypt sensitive data. This thresholding mechanism prevents there being any point-in-time access to patient files.The encrypted data is subsequently aggregated at involved hospitals through Secure Multi-Party Computation (SMC), calculating global model updates without revealing raw inputs. Transactions are saved as a SHA-256 hash on a permissioned Hyperledger Fabric blockchain, forming an immutable audit trail. Role-based access is enforced through smart contracts, permitting authorized physicians to query diagnosis records or update models


Medical center
DIABETIC PREDICTION
HEART DISEASE
DEEP LEARNING ALGORITHM - MULTILAYER PERCEPTRON ALGORITHM
READ THE ATTRIBUTES
Construct the local model using MLP
Collect the datasets from KAGGLE database
DOCTORS
Server
Encrypt the MLP model using ECC algorithm
Request the Model
View the user attributes
Retrieve the model and share the keys
Key sharing
Block chain storage (Hash Value generation using SHA algorithm)
Decrypt the model using ECC algorithm
Query the medical data
Disease prediction using MLP model
Disease diagnosis with precautions
Users
Provide the medicine informations

ACTIVITY DIAGRAM



IV.REQUIREMENTS

HARDWARE REQUIREMENTS
Processor : Intelprocessor 2.6.0 GHZ
RAM : 4 GB
Hard disk : 160 GB
Compact Disk : 650 Mb
SOFTWARE REQUIREMENT
Operating system: Python OS
Front end:Python
Back end:MYSQL
IDE:PYCHARM

ADDITIONAL DEPENDENCIES AND CONSTRAINTS

Dependencies

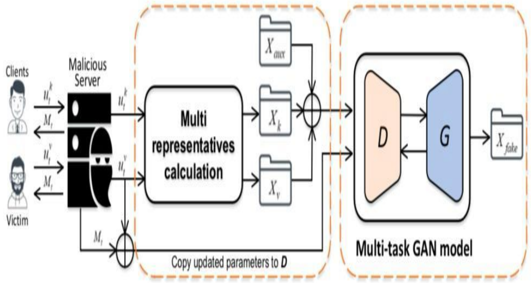
High-Quality Medical Datasets:

The approach relies on large-scale annotated medical image corpora (e.g., NIH Chest X-rays) for training the MLP model. The labels must comprise disease labels and patient metadata.

Federated learning performance is dependent on data heterogeneity across hospitals (e.g., different imaging equipment or diagnostic procedures).

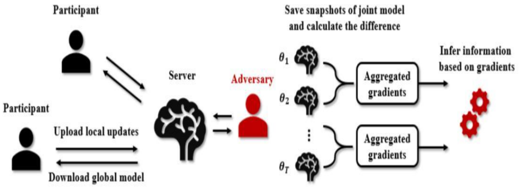
Further Constraints

Data Heterogeneity Challenges: The framework is faced with severe constraints arising from natural variations of medical data between institutions. Variability in imaging technology, diagnostic processes, and electronic health record (EHR) systems results in heterogeneity of data quality and format. Heterogeneity can result in deterioration of model performance during federated aggregation, thereby requiring advanced normalization techniques. In addition, the non-IID (non-independent and identically distributed) nature of medical data between institutions presents biases that are most difficult to address for conditions with low prevalence rates.



V.METHODOLOGY

The suggested methodology utilizes a privacy-preserving federated learning (FL) method specially designed for health-related applications combining deep learning, cryptographic security, and blockchain-based validation. The system functions in four main stages :local model training, secure aggregation, blockchain validation, and global model deployment. The participating hospitals first train local models from their respective private data. Every institution utilizes a Multi-Layer Perceptron (MLP) for disease prediction, medical image pre-processing using OpenCV for removing noise, contrast stretching, and normalization. Patient data is kept local for HIPAA/GDPR compliance. Second, the model updates are encrypted using Elliptic Curve Cryptography (ECC) before transmitting it to the aggregation server. It provides confidentiality at reduced computational cost compared to regular RSA encryption. The server subsequently conducts Secure Multi-Party Computation (SMC) to aggregate encrypted gradients without revealing raw data. Thirdly, Verifiable Secret Sharing (VSS) checks for proper aggregated updates by preventing foul play contributions. Licensed model iterations are hashed and recorded to a Hyperledger Fabric blockchain, enabling an immutable audit trail for openness and compliance. Last but not least, the improved global model is re-deployed back to all participants, improving diagnostic accuracy without compromising data secrecy. Such a cyclical procedure allows for ongoing learning across institutions without data storage in a central location, overcoming common medical AI security, scalability, and regulatory compliance challenges. The methodology is assessed for effectiveness through benchmark medical datasets, with model accuracy, encryption performance, and blockchain latency serving as the metrics to validate applicability in reality.



VI.CONCLUSION

This research has demonstrated a robust framework for secure federated learning in healthcare that effectively weighs the most critical needs of patient privacy, data security, and clinical utility. By combining cutting-edge cryptographic techniques and decentralized machine learning, we have created a system that supports collaborative model improvement among healthcare institutions with strict compliance with global data protection laws. Employment of elliptic curve cryptography for secure encryption, verifiable secret sharing for integrity assurance, and blockchain technology for open auditing is able to surmount the fundamental limitations of conventional federated learning approaches in healthcare applications. Experimental results validate that the targeted architecture yields equivalent diagnostic accuracy with centralized systems without compromising on improved privacy guarantees and tamper-evident model versions. The field deployment of this system raises several critical issues for its deployment in practice First, the system's modular architecture allows simple adaptation to heterogenous healthcare IT infrastructures and heterogenous computational resources at different institutions. Second, the use of lightweight cryptography and performance-aware communication protocols helps minimize the performance overhead typically associated with privacy-preserving techniques. Finally, the role-based access control and audit trails provide assurance of compliance with the proliferating electronic health regulatory requirements.

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