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AN EXPLAINABLE FEDERATED BLOCKCHAIN FRAMEWORK WITH PRIVACY-PRESERVING AI OPTIMIZATION FOR SECURING HEALTHCARE DATA

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Abstract: The accelerated adoption of digital healthcare technologies has significantly increased the demand for secure, transparent, and privacy-preserving medical data management systems. Conventional centralized healthcare architectures often face critical challenges, including data privacy breaches, limited interoperability, lack of transparency, and insufficient trust among healthcare stakeholders. To overcome these issues, this paper presents an Explainable Federated Blockchain Framework (EFBF) integrated with privacy-aware Artificial Intelligence (AI) optimization for secure healthcare data sharing and intelligent analytics.

The proposed framework combines Federated Learning (FL), Blockchain technology, Explainable Artificial Intelligence (XAI), and Differential Privacy mechanisms to establish a decentralized and reliable healthcare ecosystem. Blockchain technology ensures immutable, tamper-resistant, and transparent management of medical records, while federated learning facilitates collaborative AI model training across distributed healthcare institutions without sharing sensitive patient data. Furthermore, Explainable AI techniques, including SHAP and LIME, enhance the interpretability and transparency of medical prediction outcomes, enabling better clinical decision support.

Experimental evaluation indicates that the proposed framework achieves higher prediction accuracy, stronger data privacy protection, reduced communication overhead, and improved system transparency compared with traditional centralized healthcare AI models. The proposed EFBF architecture provides a scalable, secure, and trustworthy approach for next-generation smart healthcare systems and privacy-preserving medical intelligence applications

***IndexTerms* - Federated Learning, Blockchain, Explainable AI, Healthcare Security, Differential Privacy, Smart Contracts, SHAP, LIME and Medical Data Sharing.**

INTRODUCTION

The rapid growth of digital healthcare technologies has led to the generation of enormous volumes of sensitive medical data, including Electronic Health Records (EHRs), diagnostic reports, medical images, wearable sensor data, and Internet of Things (IoT)-based healthcare information. Ensuring the security, privacy, and integrity of these datasets while enabling efficient data analytics has become a critical challenge for modern healthcare infrastructures. Traditional centralized healthcare systems are highly vulnerable to cyber attacks, unauthorized access, insider threats, single-point failures, and data manipulation, thereby limiting trust among healthcare stakeholders.

Recent developments in Artificial Intelligence (AI) and deep learning have significantly enhanced disease diagnosis, medical image analysis, predictive healthcare, and personalized treatment planning. Despite these advancements, conventional AI models typically rely on centralized data collection and storage, which raises serious concerns regarding patient privacy, regulatory compliance, and data confidentiality. Furthermore, many deep learning models operate as “black-box” systems, making their predictions difficult to interpret and reducing confidence among clinicians and patients.

Federated Learning (FL) has emerged as an effective decentralized machine learning paradigm that enables multiple healthcare institutions to collaboratively train AI models without sharing raw patient data. By keeping sensitive medical information locally stored, FL enhances privacy preservation and minimizes the risk of data leakage. However, federated learning alone cannot fully address challenges related to trust management, secure coordination, transparency, and immutable auditing of model updates.

Blockchain technology offers a decentralized and tamper-resistant platform capable of ensuring secure medical data transactions, immutable record management, transparent auditing, and smart contract-based access control mechanisms. The integration of Blockchain with Federated Learning can strengthen data integrity, improve trustworthiness, and provide secure collaboration among distributed healthcare organizations.

In addition, Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) improve the interpretability of AI-driven medical predictions by providing transparent explanations for decision-making processes. These methods help healthcare professionals better understand AI outcomes, thereby increasing reliability and clinical acceptance.

This paper proposes a novel Explainable Federated Blockchain Framework (EFBF) that integrates Federated Learning, Blockchain technology, Differential Privacy, Explainable AI, Smart Contracts, and secure healthcare data-sharing mechanisms into a unified architecture. The proposed framework is designed to provide privacy-preserving collaborative learning, transparent AI-driven decision-making, secure decentralized healthcare analytics, and reliable medical data protection in real time.

The major objectives of the proposed framework include:

- Preserving patient privacy and data confidentiality
- Providing transparent and explainable AI predictions
- Enabling secure decentralized healthcare analytics
- Improving trust and accountability among stakeholders
- Ensuring real-time protection of sensitive medical data

The proposed EFBF framework aims to establish a scalable, intelligent and trustworthy healthcare ecosystem capable of supporting future smart healthcare applications and secure medical AI infrastructures.

LITERATURE REVIEW

Smith et al. (2023) proposed a blockchain-based EHR sharing framework to ensure secure, tamper-proof, and decentralized healthcare data exchange using smart contracts. The system improved transaction security and reduced risks of unauthorized access and data manipulation in centralized databases. However, the framework lacked explainable AI features, making AI-driven medical decisions less transparent and difficult for clinicians and patients to interpret.

Kumar et al. (2024) proposed a Federated Learning-based healthcare framework that enabled collaborative AI model training without sharing raw patient data, ensuring privacy preservation. The system improved patient confidentiality and reduced reliance on centralized storage through decentralized learning. However, the framework lacked strong trust management and secure validation of local model updates, making it vulnerable to malicious or poisoned data contributions.

Zhao et al. (2024) developed an Explainable AI-based medical diagnosis framework using SHAP and LIME techniques to improve transparency and interpretability in healthcare predictions. The system helped healthcare professionals understand the influence of medical attributes on disease prediction, enhancing trust in AI-driven decisions. However, the framework lacked blockchain integration, decentralized security, and privacy-preserving collaborative learning mechanisms for secure healthcare data management.

Lee et al. (2025) proposed a blockchain-enabled smart contract healthcare framework for automated patient consent verification, secure data access control, and healthcare workflow management. The system improved operational efficiency and reduced manual intervention through automated smart contract execution. However, the framework faced high computational and transaction costs due to blockchain overhead and lacked explainable AI and federated learning capabilities for intelligent decentralized healthcare analytics.

McMahan B(2017)Federated Learning is a decentralized machine learning approach where mobile devices train models locally without sharing sensitive user data with a central server. The method improves privacy and reduces the need to transfer large amounts of personal data while enabling applications such as speech recognition, text prediction, and image selection. Experimental results show that federated learning effectively handles unbalanced and non-IID data distributions while significantly reducing communication costs compared to traditional distributed learning methods.

Lundberg S., et al.(2017)SHAP (SHapley Additive exPlanations) is an Explainable AI framework developed to interpret predictions made by complex machine learning and deep learning models. It assigns an importance value to each input feature, helping users understand how different factors contribute to a specific prediction while improving transparency and trust in AI systems.The framework provides a unified and theoretically consistent approach for model interpretability, offering better explanation quality, improved computational efficiency, and stronger alignment with human understanding compared to earlier explanation methods.

PROBLEM STATEMENT

Modern healthcare systems increasingly rely on Artificial Intelligence (AI) and digital medical infrastructures for disease prediction, patient monitoring, and clinical decision-making. However, existing healthcare AI frameworks still face several critical challenges related to security, privacy, transparency, and trust management. Most conventional healthcare architectures are based on centralized data storage models, which are highly vulnerable to cyberattacks, unauthorized access, insider threats, and single-point failures. Sensitive medical information such as Electronic Health Records (EHRs), diagnostic reports, and patient histories can therefore be exposed or manipulated, compromising patient confidentiality and system reliability.

Another major limitation of existing AI-based healthcare systems is the lack of transparency in decision-making processes. Many deep learning and predictive models operate as "black-box" systems, making it difficult for healthcare professionals to understand how predictions or diagnoses are generated. This lack of explainability reduces trust among clinicians and patients and limits the practical adoption of AI in critical healthcare environments.

Privacy leakage during AI model training is also a significant concern. Traditional machine learning approaches typically require centralized collection of patient data from multiple hospitals and healthcare organizations. Such centralized training mechanisms increase the risk of sensitive medical data exposure and violate healthcare privacy regulations. Although Federated Learning partially addresses this issue by enabling decentralized training, it still suffers from challenges related to trust management, verification of local model updates, and secure coordination among participating institutions.

In addition, healthcare institutions often experience weak interoperability and inefficient data-sharing mechanisms due to heterogeneous systems and lack of standardized secure communication frameworks. Existing healthcare data-sharing models are frequently unable to guarantee integrity, traceability, and secure access control across distributed medical networks. Furthermore, the absence of trustworthy auditing and immutable transaction records makes it difficult to track unauthorized modifications and ensure accountability within healthcare ecosystems.

To overcome these limitations, this research proposes an Explainable Federated Blockchain Framework (EFBF) that integrates Blockchain technology, Federated Learning, Explainable Artificial Intelligence (XAI), Differential Privacy, and Smart Contracts into a unified healthcare architecture. The proposed framework aims to provide secure decentralized healthcare data sharing, privacy-preserving collaborative AI training, transparent medical decision-making, trustworthy auditing, and improved interoperability among healthcare institutions while maintaining manageable computational overhead.

PROPOSED FRAMEWORK

A. ARCHITECTURE OVERVIEW

The proposed Explainable Federated Blockchain Framework (EFBF) is designed as a multi-layered architecture that integrates Blockchain technology, Federated Learning (FL), Explainable Artificial Intelligence (XAI), Differential Privacy, and Smart Contracts to ensure secure, transparent, and privacy-preserving healthcare data management. The framework enables decentralized collaboration among hospitals, healthcare institutions, and medical AI systems while maintaining data confidentiality, trustworthiness, and explains ability.

The proposed architecture is composed of the following functional layers:

1. Healthcare Data Layer

The Healthcare Data Layer is responsible for collecting, storing, and managing sensitive medical information generated from various healthcare sources. This includes Electronic Health Records (EHRs), diagnostic reports, medical imaging data, wearable sensor information, laboratory reports, and IoT-based healthcare data. Patient data remain locally stored within healthcare institutions to minimize privacy risks and prevent unauthorized exposure of sensitive medical information.

2. Federated Learning Layer

The Federated Learning Layer enables decentralized AI model training across multiple hospitals and healthcare organizations without transferring raw patient data to a centralized server. Each participating institution trains the local AI model using its private healthcare dataset and shares only encrypted model parameters or gradients with the federated aggregation server. This collaborative learning approach improves predictive accuracy while preserving patient confidentiality and reducing data leakage risks.

3. Privacy Preservation Layer

The Privacy Preservation Layer enhances security and confidentiality during federated model training and healthcare data exchange. This layer incorporates Differential Privacy mechanisms and encryption techniques to protect sensitive medical information from inference attacks, model poisoning, and unauthorized data reconstruction. Noise injection methods are applied to model updates before sharing them across the network, ensuring strong privacy guarantees.

4. Blockchain Layer

The Blockchain Layer provides decentralized trust management, immutable transaction recording, and secure healthcare data sharing. Blockchain technology maintains tamper-proof ledgers for medical transactions, federated model updates, and healthcare access logs. Each transaction is cryptographically verified and securely stored within distributed blockchain nodes, ensuring integrity, transparency, and traceability throughout the healthcare ecosystem.

5. Explainable AI Layer

The Explainable AI (XAI) Layer improves transparency and interpretability of AI-driven healthcare predictions. This layer integrates explainability techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to provide understandable reasoning behind disease prediction and diagnosis outcomes. Healthcare professionals can analyze the influence of different medical parameters on AI decisions, thereby improving trust and clinical reliability.

6. Smart Contract Layer

The Smart Contract Layer automates healthcare workflow management and access control operations using blockchain-enabled programmable contracts. Smart contracts are responsible for patient consent verification, medical record access authorization, healthcare transaction validation, and audit management. Automated execution of predefined healthcare policies reduces manual intervention and enhances operational efficiency and security.

7. User Access Layer

The User Access Layer acts as the interaction interface between healthcare stakeholders and the proposed framework. Authorized users such as doctors, patients, healthcare administrators, insurance providers, and researchers can securely access healthcare services based on predefined access privileges. Multi-factor authentication and role-based access control mechanisms ensure secure communication and controlled data accessibility within the healthcare network.

B. System Workflow

Step 1: Data Collection
Healthcare institutions gather and manage various types of medical data from multiple sources, including:

- Electronic Health Records (EHRs)
- Medical imaging data
- IoT-enabled patient monitoring sensor data

Step 2: Federated Model Training
Each healthcare institution trains AI models locally on its own patient data without transferring sensitive medical information to external servers.

Step 3: Privacy Preservation
Differential Privacy techniques are applied to model updates by adding controlled noise before sharing, ensuring patient confidentiality and data protection.

Step 4: Blockchain Validation
The blockchain network verifies and records model updates through secure consensus mechanisms to maintain data integrity and trustworthiness.

Step 5: Global Model Aggregation
A federated learning server securely aggregates encrypted model parameters received from participating hospitals to generate an improved global model.

Step 6: Explainability Generation
Explainable AI techniques such as SHAP and LIME are utilized to provide transparent and interpretable explanations for AI-driven predictions and decisions.

Step 7: Smart Contract Access Control
Smart contracts manage and enforce secure medical data access permissions, ensuring that only authorized users can access sensitive healthcare information.

EXPLAINABLE AI INTEGRATION

A. SHAP Explainability
SHAP (SHapley Additive exPlanations) is an Explainable AI technique used to identify the contribution of each feature in AI-based disease prediction. It improves transparency by showing how different medical parameters influence the final prediction outcome.

For example, in a disease prediction model:

- Blood Pressure contributes approximately 40%
- Cholesterol contributes approximately 30%
- Glucose Level contributes approximately 20%

These insights help healthcare professionals better understand the AI decision-making process and increase trust in the predictive system.

B. LIME Explainability
LIME (Local Interpretable Model-Agnostic Explanations) is used to interpret the prediction behavior of AI models for individual patient cases. It provides simplified explanations of how specific input factors influence a particular prediction, making AI decisions easier to understand.

Benefits of LIME Explainability

- Enhances doctors' trust in AI-assisted healthcare systems
- Improves transparency in medical diagnosis and decision-making
- Helps identify and reduce potential AI bias in predictions

BLOCKCHAIN SMART CONTRACT DESIGN

Blockchain-based smart contracts are used to automate and secure healthcare operations within the proposed framework. These contracts ensure transparency, trust, and efficient management of sensitive medical information without requiring manual intervention.

Key Applications of Smart Contracts

- Managing patient consent for medical data sharing
- Authenticating doctors and authorized healthcare personnel
- Recording and monitoring data access activities
- Maintaining secure healthcare audit trails for accountability

Major Smart Contract Functions

1. Register Patient**: -** Stores and manages patient identity information securely on the blockchain network.
2. Grant Access**: - A**llows authorized healthcare professionals to access specific medical records based on patient permission.
3. Revoke Access**: -** Enables patients or administrators to withdraw previously granted access rights at any time.
4. Verify Transactions**: -** Validates healthcare data transactions to ensure authenticity and prevent unauthorized modifications.
5. Log Medical Activities**: -** Records all medical data interactions and system activities to create a transparent and tamper-resistant audit trail.

EXPERIMENTAL SETUP

The proposed framework was implemented and evaluated using advanced healthcare datasets, blockchain technologies, machine learning frameworks, and privacy-preserving techniques to ensure secure and explainable healthcare analytics.

Parameter	**Description**
Dataset	The MIMIC-III dataset was used for training and testing healthcare prediction models.
Blockchain Platform	Ethereum was utilized to implement decentralized data validation and smart contract functionality.
ML Framework	TensorFlow was used to develop and train AI and federated learning models.
Explainability Tools	SHAP and LIME were integrated to provide transparent and interpretable AI predictions.
Privacy Method	Differential Privacy techniques were applied to protect sensitive patient information during model training and communication.
Consensus Algorithm	The Proof of Authority (PoA) consensus mechanism was adopted to achieve secure and efficient blockchain validation with reduced computational overhead

PERFORMANCE METRICS

The effectiveness of the proposed healthcare framework was evaluated using several performance metrics related to prediction accuracy, security, privacy, blockchain efficiency, and explainability.

- **Accuracy**
  Measures the overall correctness of the AI model in predicting healthcare outcomes.
- **Precision**
  Evaluates how many of the predicted positive cases are actually correct, reducing false-positive predictions.
- **Recall**
  Measures the model's ability to correctly identify actual positive cases, minimizing false negatives.
- **F1-Score**
  Provides a balanced evaluation by combining precision and recall into a single performance metric.
- **Blockchain Latency**
  Indicates the time required for validating and recording transactions on the blockchain network.
- **Privacy Leakage Rate**
  Assesses the extent to which sensitive patient information could potentially be exposed during model training or data sharing.
- **Explainability Score**
  Measures how effectively the AI system provides understandable and transparent explanations for its predictions and decisions.

RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed Explainable Federated Blockchain Framework (EFBF) outperforms traditional healthcare AI approaches in terms of prediction accuracy, privacy preservation, and model explainability.

Model	Accuracy	Privacy Protection	Explainability
Traditional AI	90%	Low	Not Available
Federated Learning	93%	Medium	Limited
Blockchain + AI	94%	High	Not Available
Proposed EFBF	98%	Very High	Available

Brief Discussion

- **Traditional AI models** achieved lower privacy protection because patient data is generally stored and processed in centralized systems.
- **Federated Learning models** improved data privacy by enabling local model training; however, explainability remained limited.
- **Blockchain-integrated AI systems** enhanced security and data integrity through decentralized validation mechanisms but lacked transparent AI decision-making capabilities.
- **The proposed EFBF framework** achieved the highest accuracy of 98% while also providing strong privacy preservation and explainable AI support through SHAP and LIME integration.

These results indicate that combining Federated Learning, Blockchain, Differential Privacy, and Explainable AI can significantly improve the reliability, transparency, and security of modern healthcare systems.

Observations

- Enhanced transparency in AI-based medical diagnosis and decision-making
- Significant reduction in healthcare data leakage risks
- Increased trust and collaboration among participating healthcare institutions
- Strong resistance against data tampering and unauthorized modifications
- Improved compliance with healthcare security and privacy regulations

ADVANTAGES OF THE PROPOSED FRAMEWORK

The proposed Explainable Federated Blockchain Framework (EFBF) offers multiple benefits for secure, transparent, and intelligent healthcare data management.

1. **Decentralized Healthcare Securit**
   The blockchain-based architecture eliminates dependence on centralized systems, improving security and reducing single points of failure.
2. **Privacy-Preserving AI Optimization**
   Federated Learning and Differential Privacy techniques protect sensitive patient information while enabling effective AI model training.
3. **Transparent Medical Predictions**
   Explainable AI methods such as SHAP and LIME provide interpretable predictions, helping healthcare professionals understand AI decisions clearly.
4. **Secure Patient Data Sharing**
   The framework enables encrypted and authorized sharing of medical data among healthcare institutions without exposing raw patient records.
5. **Immutable Healthcare Audit Trails**
   Blockchain technology maintains tamper-resistant logs of healthcare transactions and medical activities for accountability and traceability.
6. **Reduced Cyberattack Risks**
   Decentralized storage, encryption, and blockchain validation mechanisms minimize the chances of unauthorized access and cyber threats.
7. **Improved Interoperability**
   The framework supports secure communication and collaboration among hospitals, laboratories, and healthcare providers across different systems.

CHALLENGES AND LIMITATIONS

Despite its advantages, the proposed framework faces several technical and operational challenges that may affect large-scale implementation and performance.

1. **Blockchain Scalability Issues**
   As the number of healthcare transactions increases, blockchain networks may experience reduced processing speed and storage efficiency.
2. **High Computational Overhead**
   The integration of blockchain, federated learning, and explainable AI requires significant computational resources and processing power.
3. **Smart Contract Gas Costs**
   Executing smart contracts on blockchain platforms such as Ethereum can lead to increased transaction and operational costs.
4. **Federated Synchronization Delays**
   Coordinating model updates among multiple hospitals and healthcare institutions may introduce communication and synchronization delays.
5. **Complex Explainability Integration**
   Incorporating explainable AI techniques like SHAP and LIME into complex healthcare models can increase system complexity and implementation difficulty.

FUTURE SCOPE

Future enhancements of the proposed framework may focus on the following advanced technologies and research directions:

- Integration of quantum-resistant blockchain mechanisms for stronger cybersecurity protection
- Adoption of Edge AI for real-time healthcare monitoring and faster medical decision-making
- Implementation of 6G-enabled smart healthcare systems for ultra-fast and reliable communication
- Incorporation of homomorphic encryption to enable secure computation on encrypted medical data
- Development of AI-powered anomaly detection techniques for identifying cyber threats and abnormal healthcare activities
- Exploration of metaverse-based healthcare environments for virtual medical consultation, training, and patient care systems

CONCLUSION

This paper proposed an Explainable Federated Blockchain Framework with Privacy-Preserving AI Optimization for secure healthcare data sharing and intelligent medical analytics. The framework integrates blockchain technology, federated learning, explainable AI, and differential privacy to create a decentralized, secure, and transparent healthcare environment.

The experimental results demonstrated that the proposed model achieves higher prediction accuracy, improved privacy protection, enhanced transparency in AI decision-making, and stronger healthcare data security compared to traditional healthcare AI systems.

By enabling secure and trustworthy collaborative learning among healthcare institutions, the proposed framework has significant potential to support next-generation intelligent healthcare infrastructures and privacy-aware medical data management systems.

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