Enhancing Explainable Artificial Intelligence in Healthcare through Blockchain-Enabled Immutable Federated Machine Learning*

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Abstract

In this work, we propose a blockchain-anchored federated learning framework integrated with Explainable Artificial Intelligence (XAI) to advance transparency, privacy, and trust in medical AI systems. Local healthcare institutions (warehouses) independently train Random Forest models on sensitive datasets (Breast Cancer classification and Diabetes regression), and a global server aggregates model updates to construct a federated global model without exposing patient records. Dual-level interpretability is achieved through global explanations (Permutation Importance) and local explanations (LIME), offering both model-level insights and patient-specific transparency. To ensure accountability and integrity, all explanation artifacts and model updates are serialized, hashed with SHA-256, and immutably recorded on a blockchain ledger, forming a verifiable audit trail for both predictions and learning updates. The federated global model achieved 97% accuracy (F1 = 0.97) on Breast Cancer and R^2 = 0.52 on Diabetes regression, demonstrating robust predictive performance, privacy preservation, and verifiable interpretability. The novelty lies in the tri-layer synergy of federated learning, dual-level explainability, and blockchain-backed immutability—establishing a unified, auditable, and trustworthy AI pipeline for real-world healthcare deployment.

1 Introduction

Artificial Intelligence (AI) has shown strong potential in healthcare, yet the lack of interpretability and concerns over data privacy limit its adoption. While Explainable AI (XAI) has emerged to address transparency, ensuring data security and immutability across decentralized healthcare environments remains a major challenge [1].

In this work, we develop an Explainable Artificial Intelligence (XAI) framework with a Federated Machine Learning (FL) model for the classification of breast cancer and prediction of

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diabetic disease progression. In a federated setting, local institutions train Random Forest models on their private data, while only model updates are shared with a central server to construct a global model, thereby preserving data privacy [2]. To further guarantee trust and accountability, we integrate blockchain as an immutable audit layer. This ensures that explanation outputs (global and local) are securely hashed and recorded, making them tamper-proof and verifiable by clinicians and regulators. Unlike centralized approaches, federated learning avoids data pooling and thus complies with strict healthcare privacy regulations while still benefiting from cross-institutional diversity. To address these challenges, this research sets out with the key objectives:

- we design a Lightweight Federated Random Forest (FRF) integrated with XAI for healthcare, enabling accurate and interpretable predictions with low communication overhead.
- dual-level explainability using global (Permutation Importance) and local (LIME) methods provides transparency at both institution and patient levels.
- a blockchain-audited learning process securely stores model updates and interpretability artifacts on-chain, ensuring tamper-proof accountability, and,
- privacy-preserving federated setup ensures no raw medical data leaves local nodes, demonstrating accuracy, reliability, and compliance with healthcare data standards.

By combining XAI, FL and blockchain, this study moves beyond accuracy alone, creating a framework where predictions are interpretable, explanations are verifiable, and trust is systematically reinforced. This integration paves the way for a new class of AI-driven healthcare solutions that can earn clinician confidence and regulatory acceptance, bringing transparent and accountable decision support closer to routine clinical practice [3]. The remainder of the paper is structured as follows. Section 2 is a detailed literature review. Discussion of viable solutions through a descriptive authorization framework, privacy model and evaluation procedures is presented in section 3. Section 4 presents the research findings. Finally, section 5 presents the conclusion.

2 Literature Review

Recent research has increasingly focused on combining Explainable AI (XAI) with Blockchain to enhance trust, security, and interpretability across domains. In healthcare, Sowjanya et al. [4] proposed a hybrid model integrating federated learning (FL), XAI, and blockchain for secure IoT-driven health services, yet their framework suffered from high latency and compute demand. Similarly, Murthy et al. [5] introduced an XAI–Blockchain–IoT middleware using smart contracts and CoAP protocol, but challenges around interoperability and scalability persisted. Earlier, Dutta et al. [6] presented consortium blockchain with SHAP explanations for eHealth and later expanded it to Society 5.0 [7], combining LIME, SHAP, counterfactuals, and fuzzy logic. However, both works faced complexity and limited real-time fusion. Ali et al. [8] applied GradCAM and LIME with blockchain in a metaverse healthcare system, but trust and privacy mechanisms remained immature. Collectively, these works demonstrate potential for trustworthy healthcare AI, but still struggle with efficiency, interoperability, and deployment readiness.

Parallel efforts have explored federated and decentralized learning. Madupati et al. [9] advanced trustworthy FL pipelines with secure aggregation and blockchain auditing, yet data validation and scalability issues remained. Pavlova et al. [10] introduced a decentralized FL framework with smart contracts and verifiable secret sharing, but high training costs limited adoption. Mu et al. [11] addressed medical image heterogeneity via causal learning with blockchain-based dataset valuation, though communication overhead persisted. Korde et al. [12] and Potdukhe et al. [13] reviewed Blockchain–ML integration, emphasizing privacy, scalability, and ethics, while highlighting the need for lightweight protocols and advanced XAI. These studies reveal that although blockchain and FL strengthen privacy, ensuring interpretability and scalability at low computational cost is still unresolved.

In domains beyond healthcare, blockchain–XAI has been applied for trustworthy policy, communication, and infrastructure. Mavrogiorgos et al. [14] demonstrated explainable and tamper-proof AI for data-driven water management policies, while Njoku et al. [15] combined SHAP-based XAI, digital twins, and blockchain for battery management. Wang et al. [16] proposed GenAI-driven semantic communication with controllability and explainability, and Rathod et al. [17] built a blockchain-secured XAI architecture for IoT critical infrastructure. Yet, across these works, computational overhead, interoperability, and scalability challenges limited real-time adoption. Gadekallu et al. [18] further reinforced this in their survey of XAI in Industry 5.0, pointing to persistent transparency and interoperability gaps.

Security-focused studies also highlight the synergy of XAI and blockchain. Hasan et al. [19] built a CNN+SHAP framework for fraudulent Bitcoin detection, achieving near-perfect accuracy but struggling with extreme class imbalance. Hasan et al. [20] extended this to anomaly detection in blockchain transactions, using ensemble classifiers and SHAP explanations, but scalability remained an issue. Kritika [21] and Afraji et al. [22] tackled ransomware and DDoS detection respectively with deep learning plus XAI, demonstrating interpretability and adaptability, though adversarial robustness and real-time deployment are still lacking. These works affirm the importance of explanation-driven trust in cybersecurity, yet also show the gap in achieving generalizable and scalable deployment.

Several researches focused on responsible AI principles and explainable blockchain. Zhang et al. [23] mapped responsible AI research trends, identifying the lack of multimodal integration. Bonnet et al. [24] proposed blockchain-based fair data remuneration, while Al Ghanmi et al. [25] built ExplanaSC for explainable smart contracts, focusing on user-centered understanding. Arslanoğlu et al. [26] surveyed XAI+Blockchain for healthcare, emphasizing secure storage and transparent predictions. While these studies expand conceptual understanding, they do not provide concrete healthcare-focused implementations ensuring both interpretability and auditability. In summary, existing literature shows that:

- Without FL and XAI, AI models in healthcare and security act as "black boxes," producing predictions without clear reasoning. This lack of interpretability prevents clinicians, policymakers, and security analysts from trusting or adopting these models in practice.
- Without blockchain, explanation outputs and decision records remain mutable and unverifiable. In critical domains like healthcare and finance, this absence of auditability undermines accountability and opens pathways for manipulation or data tampering.
- The combination of both is rare, meaning most systems either explain their outputs but cannot guarantee integrity, or secure their data without offering meaningful interpretability.

From the reviewed literature, it is evident that existing AI-based healthcare frameworks often lack a unified mechanism that simultaneously ensures privacy, interpretability, and auditability. These limitations motivated the design of our proposed framework, which integrates

Federated Learning, Explainable AI, and Blockchain to achieve trustworthy and verifiable medical predictions. The following section presents the methodology and system architecture that address these challenges.

3 Methodology

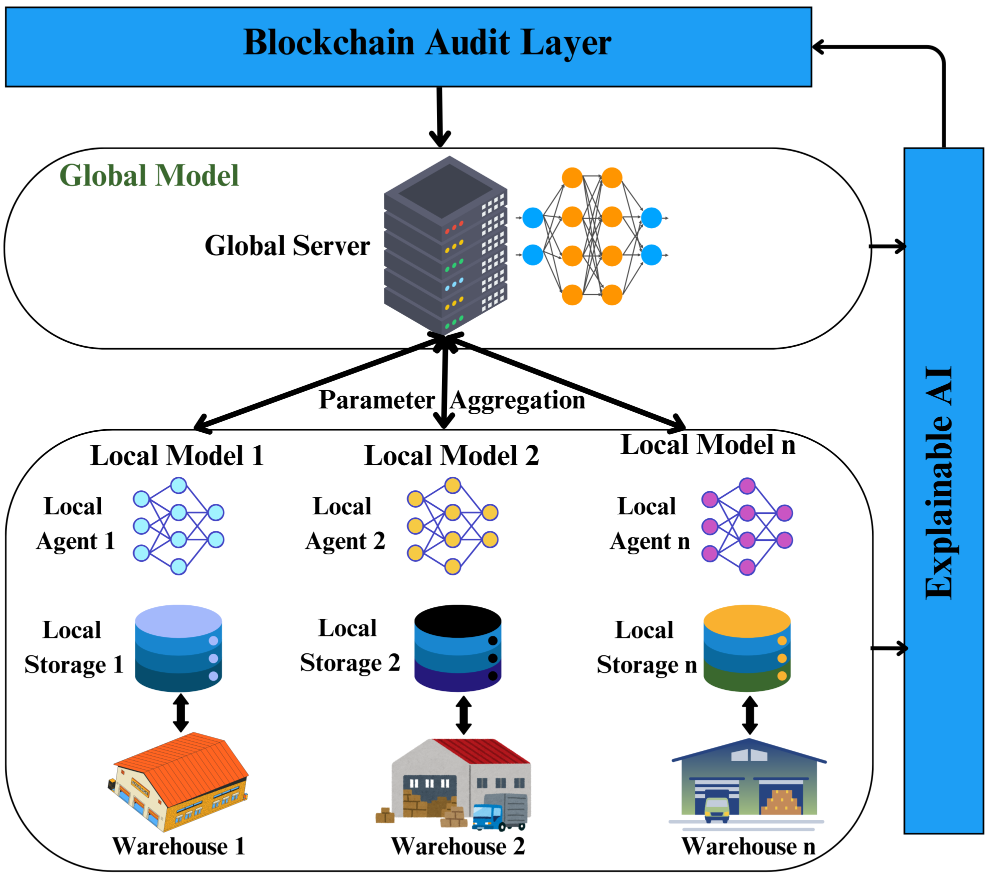

Figure 1: Federated Blockchain-Enhanced XAI framework for healthcare predictions, combining federated learning, explainable AI, and blockchain to ensure privacy-preserving, interpretable, and tamper-proof clinical decisions. The framework has four layers: dataset preparation, model training, explainability, and blockchain verification.

The proposed framework brings together Lightweight Federated Machine Learning, Explainable Artificial Intelligence (XAI), and Blockchain auditing into a single system designed to address the challenges of privacy, interpretability, and trust in healthcare applications. Rather than relying on a centralized dataset, the framework is built on a federated structure where knowledge is shared without exposing sensitive patient information. The process begins at the local level, where each participating institution (represented as a warehouse) maintains its own private storage DiD_iDi. A local agent is responsible for training a Random Forest model

MiM_iMi using only the data available at that site. Importantly, patient records never leave the institution; they remain securely stored while contributing to the training process. Once the local training is complete, the workflow moves to the global aggregation stage. Instead of transmitting raw patient data, each local agent shares only its learned model parameters or predictions with a Global Server. These contributions are combined to build a unified Global Random Forest model MGM_GMG. This federated strategy ensures that insights from diverse populations are captured, while still preserving the confidentiality of local records. To make the system transparent and trustworthy, an Explainable AI (XAI) layer is integrated. At the global level, explanations are generated using Permutation Importance, which identifies the most influential features across all participating sites. At the local level, LIME surrogate models provide patient-specific explanations, allowing clinicians to see exactly why a certain prediction was made for an individual. This dual approach ensures both high-level understanding and case-level justification. Finally, the framework incorporates a Blockchain Audit Layer. Every explanation artifact and global update is serialized, hashed using SHA-256, and permanently recorded on the blockchain. This guarantees immutability—if even a single byte of information were altered, it would be immediately detectable. By doing so, the framework not only secures data integrity but also provides a verifiable audit trail for clinical validation. In summary, this end-to-end federated workflow enables secure training, robust predictions, transparent explanations, and tamper-proof auditing. It has been designed specifically for sensitive healthcare domains such as breast cancer and diabetes prediction, where accuracy, privacy, and accountability are critical. This complete process has been illustrated in figure 1

3.1 Workflow Overview

The proposed framework integrates machine learning, explainable AI (XAI), and blockchain-based auditing into a unified pipeline in figure 1. The workflow consists of four main stages:

3.1.1 Dataset Preparation

- **Breast Cancer (Classification):** The Wisconsin Diagnostic Breast Cancer (WDBC) dataset, consisting of 569 samples and 30 numerical features, was obtained via the `scikit-learn` library. Labels are binary: malignant or benign.

- **Diabetes (Regression):** A medical dataset of 442 patients with 10 numerical predictors (e.g., age, sex, BMI, blood pressure, serum measurements). The target variable represents a continuous measure of disease progression after one year.

  To ensure comparability across features, both datasets were standardized using **StandardScaler:**

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

  where μ is the feature mean and σ its standard deviation.

3.1.2 AI Prediction Layer – Federated Random Forest

The predictive backbone of the framework is a Federated Random Forest (FRF) model. Random Forest was selected because it is robust to noise, resistant to overfitting, and well-suited for both classification and regression tasks. It also offers built-in interpretability, which complements explainable AI methods.

In a traditional centralized setup, one model is trained on a pooled dataset. In contrast, our framework adopts a federated approach. Each participating institution or node i maintains its own private dataset D_i. Instead of sharing raw data, the node trains a local Random Forest model M_i and shares only its model outputs or parameters with the aggregator.

- Local Model: Each local Random Forest consists of multiple decision trees trained on D_i. For classification (Breast Cancer), each tree outputs a predicted class, and the local prediction is obtained by majority vote. For regression (Diabetes), each tree outputs a continuous value, and the final prediction is obtained by averaging tree outputs:

$$\hat{y}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} h_{i,t}(x) \tag{2}$$

  here, $\hat{y}i$ denotes the prediction from the local Random Forest at node i, T_i represents the number of trees in the local Random Forest, and $hi, t(x)$ corresponds to the prediction of the t^{th} tree for input x.

- Global Aggregator: The aggregator collects predictions or model updates from all local nodes and builds a global Random Forest model M_G. The final global prediction is obtained by aggregating all local predictions:

$$\hat{y}_{global} = \frac{1}{N} \sum_{i=1}^{N} \hat{y}_i \tag{3}$$

  Furthermore, instead of sharing predictions alone, each local agent transmits model updates (e.g., decision tree parameters and weights) to the Global Server. These updates are aggregated to refine the Global Random Forest M_G, which is then redistributed to all participating nodes. This iterative process ensures that each local model continuously benefits from the collective learning of the federation, improving convergence and robustness. Where, $\hat{y}_{global}$ denotes the prediction from the global model, N represents the number of participating institutions, and $\hat{y}_i$ corresponds to the local prediction from institution i.

  This process enables privacy-preserving collaborative learning. Patient records remain at the local sites, but the predictive power of multiple institutions is combined. By adopting this federated setup, our framework addresses two challenges in healthcare AI:

  - Data Privacy: Sensitive patient data never leaves the local institution.
  - Data Diversity: The global model benefits from varied populations across institutions, improving generalizability.

3.1.3 XAI Layer

To ensure that the predictions of the federated Random Forest are interpretable and transparent, we integrated an Explainable AI (XAI) layer. This layer operates at two complementary levels: global explanation and local explanation.

Global Explanations – Permutation Importance

At the global level, we used Permutation Importance, which measures the contribution of each feature to the model's predictive performance. The method works by randomly permuting the values of a feature and calculating how much the model's performance decreases:

$$I(f_j) = \mathrm{Perf}(M_G, D) - \mathrm{Perf}(M_G, D_{\pi(j)}) \tag{4}$$

here, $I(f_j)$ denotes the importance score of feature f_j, $\mathrm{Perf}(M_G, D)$ represents the performance of the global model M_G on dataset D, and $D_{\pi(j)}$ corresponds to the dataset with feature f_j randomly permuted.

A larger drop in performance indicates higher importance of the feature. For the Breast Cancer dataset (classification), performance was measured using Accuracy. Features such as mean radius, worst concavity, and texture showed the highest importance, which aligns with clinical knowledge since tumor size and irregularity strongly influence malignancy.

For the Diabetes dataset (regression), performance was measured using the Coefficient of Determination (R^2). Features such as BMI and serum marker s5 were identified as the most predictive, consistent with known clinical evidence. By applying permutation importance to the federated global model (M_G), we ensured that the explanations reflect consensus across institutions, rather than biases from a single dataset.

Local Explanations – LIME Surrogate Models

At the local level, we adopted a LIME-like surrogate model to explain predictions for individual patients. LIME approximates the black-box prediction function $f(x)$ in the vicinity of a given instance x with a simpler, interpretable linear model $g(z)$:

$$g(z) = w^\top z, \quad g \in G, \quad \Omega(g) \text{ small} \tag{5}$$

where, $g(z)$ denotes the surrogate explanation model, w represents the weights corresponding to feature contributions, G is the family of interpretable models (e.g., linear models), and $\Omega(g)$ is the complexity constraint, kept small to ensure interpretability. This produces feature weights showing how much each variable contributed to the decision. For the Breast Cancer dataset, local explanations for specific malignant cases highlighted features like worst concavity and mean perimeter as strong positive contributors toward malignancy predictions. For the Diabetes dataset, local explanations for individual patients showed that BMI and blood pressure had positive contributions to higher progression risk, while younger age provided a negative contribution. These explanations serve different stakeholders:

- Global explanations help clinicians and regulators understand the overall reasoning of the model.
- Local explanations provide patient-level justification, enabling doctors to interpret why a specific diagnosis or risk prediction was made.

Together, this dual approach enhances trustworthiness and makes the federated model suitable for sensitive healthcare applications. In our federated setup, these explanations are produced both locally and globally. Local warehouses generate explanations for patient-specific cases, while the Global Server produces consolidated global explanations that reflect the joint knowledge of all participating institutions. This dual-level explainability ensures that the system provides personalized transparency at the patient level while also maintaining institution-level interpretability for broader clinical decision-making.

3.1.4 Blockchain Audit Trail

To guarantee immutability, transparency, and accountability of the generated explanations, we integrated a blockchain-based audit trail into the framework. The blockchain serves as a decentralized and tamper-proof ledger where explanation results are stored and can be verified at any time. Each explanation, whether global or local, is first serialized into a JSON record that contains:

- The model prediction (classification label or regression value),
- The explanation values (feature importance or contributions),
- The timestamp of generation.

This record is then hashed using the SHA-256 cryptographic function:

$$H = \text{SHA256}(X) \tag{6}$$

, where X is the serialized explanation. SHA-256 alone provides a sufficiently strong cryptographic fingerprint to detect any modification, making Merkle trees or smart contract-based integrity proofs optional for our lightweight auditing setup. The hash acts as a unique fingerprint of the explanation output.To prevent tampering, the hash of each explanation record is linked to the previous one, forming a chain of blocks:

$$B_i = H(B_{i-1} \| R_i) \tag{7}$$

where B_{i-1} is the previous block hash, R_i the new record, and $\|$ denotes concatenation. This ensures that modifying any record would break the chain, making tampering immediately detectable. In addition to explanation artifacts, model updates exchanged between local agents and the Global Server are also hashed and immutably stored on-chain. Each update cycle is recorded as a block, which links the progression of the global model over time. This provides a secure audit trail not only for interpretability outputs but also for the entire federated learning process. By anchoring both explanations and model parameters to the blockchain, the system ensures full accountability, protects against update tampering, and enables future audits or re-training validation with verifiable checkpoints.

3.2 Algorithmic Flow

The proposed Blockchain-Enhanced XAI with Federated Machine Learning Pipeline begins by training a Random Forest model on the medical dataset in Algorithm 1.

Algorithm 1 Federated Blockchain-Enhanced XAI Pipeline

Local datasets $D_1, \ldots, D_N$; Explanation method E (Permutation / LIME); Cryptographic hash function SHA256 Verified explanation records stored on blockchain; Global model M_G

Step 1 — Client-side preprocessing (for each client $i = 1 \ldots N$):
1.1 Load local dataset D_i.
1.2 Standardize features: $x' = (x - \mu)/\sigma$.
1.3 Split into $D_{i,\text{train}}$ and $D_{i,\text{test}}$ (70:30).

Step 2 — Local training and local XAI (per client i):
2.1 Train local Random Forest M_i on $D_{i,\text{train}}$.
2.2 Evaluate M_i on $D_{i,\text{test}}$, compute metrics (accuracy/F1 or R^2).
2.3 Generate local explanations: $X_{i,\text{local}} \leftarrow \text{LIME}(M_i, \text{instance(s)})$

Step 3 — Local serialization and hashing:
3.1 Serialize $X_{i,\text{local}}$ into JSON string $X_i^{(j)}$.
3.2 Compute local hash $H_{i,\text{local}} = \text{SHA256}(X_i^{(j)})$.
3.3 Store locally: $(X_{i,\text{local}}, H_{i,\text{local}}, \text{timestamp})$.

Step 4 — Model update: Send model update to aggregator.

Step 5 — Global aggregation (server):
5.1 Collect model updates $\{M_i\}$.
5.2 Aggregate to produce global federated model $M_G \leftarrow \text{aggregate}(M_1, \ldots, M_N)$

Step 6 — Global evaluation and global XAI:
6.1 Evaluate M_G on validation data; compute global metrics.
6.2 Compute global explanation via Permutation Importance: $X_{\text{global}} \leftarrow \text{PermImp}(M_G, D_{\text{val}})$.
6.3 Serialize X_{global}; compute global hash $H_{\text{global}} = \text{SHA256}(X_{\text{global}})$.

Step 7 — Blockchain commit:
7.1 For each local hash $H_{i,\text{local}}$ and the global hash H_{global}, invoke smart contract function `storeExplanation(dataset, modelType, hash)`.
7.2 Smart contract stores entries $(\text{dataset}, \text{modelType}, H, \text{timestamp}, \text{nodeID})$ and emits `ExplanationStored` events.

Step 8 — Verification (auditor/clinician):
8.1 Retrieve stored hash H_s from blockchain for the desired record.
8.2 Recompute explanation X' from the model (M_i or M_G); compute $H' = \text{SHA256}(X')$.
8.3 If $H' == H_s$ then integrity confirmed; else tampering detected (raise audit).

Step 9 — Audit logging: Record verification result on-chain.

return Verified records and M_G

This approach ensures robust predictive performance across both classification and regression tasks. These local models then send their learned parameters or outputs to a central aggregator, which constructs a global federated Random Forest by combining contributions from all nodes. Once the global model is established, it is used to generate predictions on unseen patient data. The predictions are then passed to the XAI layer, where, global explanations (Permutation Importance) identify features most influential across the federated model, providing population-level interpretability. On the other hand, local explanations (LIME-like surrogate models) give case-specific justifications, showing which patient attributes contributed to an individual prediction.

The resulting explanation records are serialized into JSON and hashed using SHA-256. Each record, containing the prediction, explanation, hash, and timestamp, is appended to the blockchain ledger, with sequential chaining ensuring immutability. Finally, during verification, auditors or clinicians can recompute the explanations and hashes. If the newly computed hash matches the blockchain-stored value, the record is validated as authentic; otherwise, tampering is detected. This makes Algorithm 1 central to enforcing privacy, interpretability, and trustworthiness in the proposed healthcare AI pipeline.

3.3 Evaluation Metrics

For the classification task on the Breast Cancer dataset, model performance was evaluated using Precision, Recall, and F1-score. These metrics are calculated from the confusion matrix, where True Positives (TP) represent the number of malignant cases correctly predicted as malignant, True Negatives (TN) represent the number of benign cases correctly predicted as benign, False Positives (FP) indicate benign cases incorrectly predicted as malignant, and False Negatives (FN) indicate malignant cases incorrectly predicted as benign. The formulas are:

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN}, \quad \text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Precision** answers: Of all patients predicted as malignant, how many were actually malignant?
- **Recall (Sensitivity)** answers: Of all patients who are actually malignant, how many did the model detect?
- **F1-score** provides a harmonic balance between Precision and Recall.

For regression (Diabetes dataset), we use the **Coefficient of Determination** (R^2), which measures the proportion of variance in the target explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where, y_i denotes the true value for sample i, $\hat{y}_i$ is the predicted value for sample i, $\bar{y}$ represents the mean of all true values, and n is the total number of samples. An R^2 value close to 1 indicates strong predictive ability, while an R^2 value near 0 indicates poor predictive performance.

3.4 Implementation Details

The implementation began with dataset preparation, where all features were standardized and then split into training and testing subsets with a 70:30 ratio. For model training, we employed two cases: a Random Forest Classifier was used for the Breast Cancer dataset, while a Random Forest Regressor was applied to the Diabetes dataset. Model evaluation followed standard practices, with Accuracy, Precision, Recall, and F1-score used for classification, and R^2 employed for regression. Explainability was introduced through both global and local perspectives—permutation feature importance captured overall variable contributions, while LIME provided case-level interpretability for individual predictions.

To ensure trust and accountability, the explanation outputs were serialized, hashed, and appended sequentially to a blockchain ledger, creating an immutable audit trail. This auditing mechanism was prototyped in a flexible environment and can be extended to production-grade, permissioned or public blockchain networks such as Ethereum. Experiments and model training were conducted on Google Colab, while smart contract testing and deployment were carried out using Remix IDE. Additionally, blockchain validation was explored on Sepolia testnet and Ganache for local simulations.

4 Research Findings

The results obtained from the breast cancer dataset and the diabetic dataset are presented in the following sections. These results highlight the performance of the proposed framework and demonstrate its applicability across different medical prediction tasks.

4.1 Breast Cancer Classification

Table 1: Classification performance of the Random Forest model on the Breast Cancer dataset.

Class	**Precision**	**Recall**	**F1-score**	**Support**
Malignant	0.98	0.94	0.96	63
Benign	0.96	0.99	0.98	108
Accuracy			**0.97**	171
Macro Avg	0.97	0.96	0.97	171
Weighted Avg	0.97	0.97	0.97	171

The results for the breast cancer dataset in table 1 and in figures 2,3 provide a comprehensive understanding of both the predictive performance of the model and the interpretability of its decisions. The classification report shows that the Federated Random Forest model achieved an overall accuracy of 97 percent, with precision values of 0.98 for malignant and 0.96 for benign cases, and recall values of 0.94 and 0.99 respectively. This indicates the model performs exceptionally well at correctly identifying benign tumors while maintaining strong performance in detecting malignant ones. The high F1-scores (0.96 for malignant and 0.98 for benign) further confirm the model's balanced performance across both classes, reducing the chances of bias toward one outcome. These results were achieved in a federated global model setting, where aggregated knowledge from decentralized nodes provided robust classification performance without centralizing sensitive patient data.

By leveraging a federated learning setup, these insights are derived collaboratively across decentralized datasets, making the global model both interpretable and generalizable. Features such as mean texture, worst area, and worst concave points emerged as the most influential predictors in the breast cancer classification task. These global insights validate that texture and shape-related tumor measurements are critical for distinguishing between malignant and benign samples, aligning with domain knowledge in medical diagnostics. On the other hand, features with minimal or near-zero impact, such as fractal dimension error or smoothness error, play a

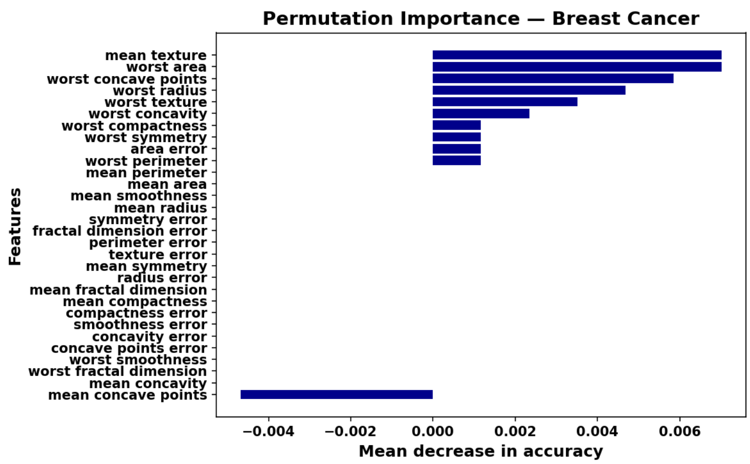

Figure 2: Global feature importance for the Breast Cancer dataset using permutation importance. Texture and shape features, such as mean texture, worst area, and worst concave points, are the strongest predictors, aligning with medical knowledge and validating model interpretability.

negligible role in shaping predictions. This transparency helps validate the medical soundness of the model and, by leveraging a federated learning setup, ensures that such insights are derived collaboratively across decentralized datasets without exposing sensitive patient data.

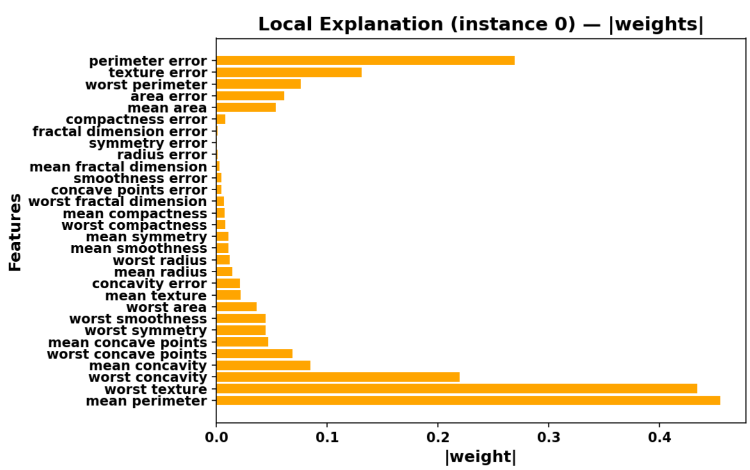

Figure 3: Local explanation for instance 0 using XAI. Mean perimeter, worst texture, and worst concavity contribute most to the prediction, while smoothness error and symmetry error have minimal influence, providing instance-level interpretability.

The local explanation using LIME for a single instance adds another layer of understanding by showing which specific features had the strongest effect on the classification for that case. For example, perimeter error and texture error showed strong positive contributions, while mean perimeter and worst texture also had significant influence. This local breakdown is critical in clinical settings because it allows medical practitioners to interpret why the model made a specific decision for an individual patient. In high-stakes applications such as cancer diagnosis, this level of case-specific interpretability builds trust and provides additional reassurance for both doctors and patients. Moreover, within the federated learning framework, such local explanations ensure that individual-level interpretability can be provided at each participating institution without requiring the centralization of sensitive patient records, thereby combining transparency with privacy preservation

4.2 Diabetes Regression

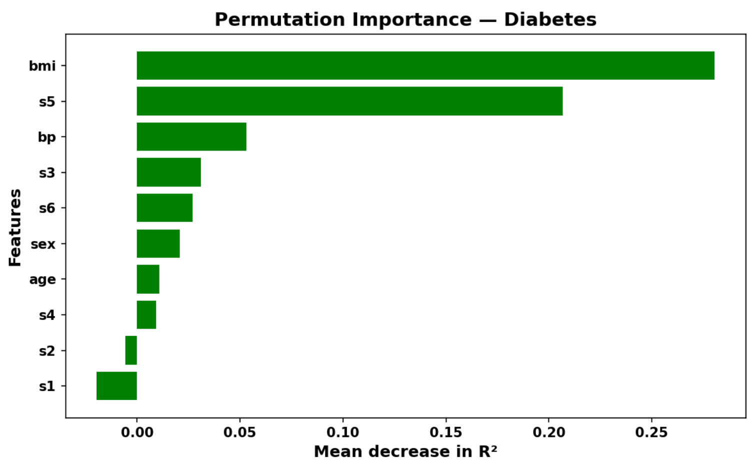

Figure 4: Permutation importance for the Diabetes dataset. BMI and serum measure s5 are the strongest predictors, followed by blood pressure. Features such as age, s4, and s2 contribute minimally, indicating that a subset of clinical variables drives model performance.

The results obtained from the diabetes dataset highlight the complementary strengths of both local and global explanation methods in understanding the behavior of the Federated Random Forest model. At the local level, the explanation for an individual patient (instance 0) shows how specific features contributed to that patient's prediction. The weights assigned to features such as s1, s2, s3, and blood pressure (bp) were notably higher, indicating that these variables strongly influenced the predicted disease progression score for this individual. In contrast, features such as s4 and s5 contributed far less, suggesting that they played only a minimal role in shaping the local outcome. This patient-centric view provided by the local explanation is crucial because it helps practitioners understand not just the overall trends in the model, but why a decision was made in a particular case. Within a federated framework, these patient-level explanations remain confined to local institutions, ensuring interpretability while preserving privacy. Such insights are essential in healthcare, where each patient's diagnosis and treatment plan must be justified and tailored individually. Within a federated learning environment, these local explanations remain confined to the institution where the data resides, ensuring that interpretability is achieved without sharing sensitive patient records.

At the global level, the permutation importance results present a more general perspective by ranking the features according to their overall impact on model performance. The analysis revealed that BMI and s5 were the most important global predictors, followed by blood pressure. These findings are consistent with well-established medical knowledge, as high BMI and blood pressure are known risk factors associated with diabetes and its complications. The global explanation further indicated that features such as age, s4, and s2 had very limited influence on the model's predictions across the dataset. By applying permutation importance to the federated global model, we ensured that the explanations reflect consensus across multiple decentralized datasets rather than being biased by a single data source. This validation against domain knowledge shows that the model is not only functioning statistically but is also aligned with real-world medical understanding. By applying permutation importance to the federated global model, the analysis reflects consensus across decentralized data sources, highlighting the strength of federated aggregation in producing reliable and unbiased explanations. Such alignment enhances the credibility of the predictions and provides evidence that the system can be trusted in clinical applications.

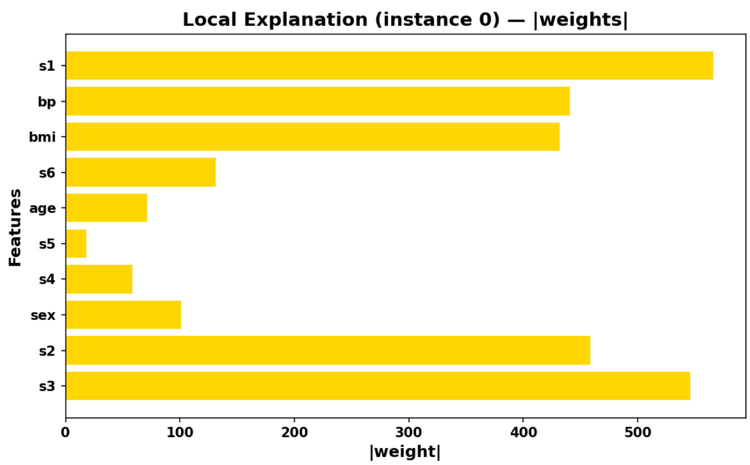

Figure 5: Local interpretability for instance 0 using a LIME-based surrogate model. Features s1, s2, s3, blood pressure, and BMI have the highest influence on disease progression prediction, while s4, s5, and age have minimal impact, offering patient-level transparency.

Although the federated global Random Forest achieved an 2 R 2 value of 0.52, which is reasonable given the inherent biological variability of diabetes progression, this result also indicates that a notable portion of variance remains unexplained. This limitation primarily arises from the heterogeneity of local datasets and the non-linear relationships among clinical features. Future enhancements could involve integrating ensemble-based neural regressors or hybrid federated models combining Random Forest with gradient boosting or deep learning components to capture more complex dependencies. The figures 4 and 5 demonstrate that the system achieves its central objective of building an explainable and reliable federated learning pipeline. The local explanations allow stakeholders to see how decisions are made for individual patients, supporting transparency and patient-specific insights. The global explanations provide a higher-level view that confirms the model's reasoning is medically sound and consistent with established literature. Importantly, the combination of explainable AI with blockchain integration ensures that every explanation generated is securely stored, tamper-proof, and verifiable. This dual contribution of interpretability and trustworthiness addresses two of the most pressing challenges in applying AI to healthcare. By offering both predictive performance and transparent reasoning, the system enhances confidence among clinicians, patients, and regulators, thereby fulfilling the research aim of a trustworthy, explainable, and verifiable medical AI framework.

Both models demonstrate strong predictive performance supported by explainability mechanisms. While the breast cancer model highlights texture and shape-related tumor features as decisive factors, the federated diabetes model emphasizes glucose levels and BMI as primary indicators. Together, these findings illustrate how explainable AI, when combined with federated learning and blockchain, not only achieves high accuracy but also provides medically relevant, privacy-preserving, and transparent reasoning across different healthcare domains. Overall, the federated global models demonstrated strong predictive power and interpretability, proving that federated aggregation not only protects privacy but also enhances the robustness and generalizability of medical predictions across diverse institutions.

4.3 Blockchain Deployment

Within the federated learning setup, the explanation outputs generated at both local institutions and the global aggregator were securely logged onto the blockchain, ensuring integrity across decentralized sources.


```
{
  "model": "RandomForestClassifier",
  "accuracy": 0.9707602339181286,
  "perm_importance_time_ms": 16562.97,
  "explanation_hash": "ce86bc3ac12c577f3c2ac3609418d9eca4bf00c66f0a924372a6aa071e221e70"
}
```


Figure 6: Breast cancer explanation artifacts hashed with SHA-256 and stored on the blockchain. The hash (86bc3ac12c577f3c2ac3609418d9eca4bf00c66f0a924372a6aa071e221e70) ensures explanations are immutable, verifiable, and auditable.

To complement the interpretability results, the explanation artifacts from both the breast cancer and diabetes tasks were securely integrated into a blockchain-based ledger. Each explanation was serialized into JSON format, hashed with the SHA-256 algorithm, and immutably appended to the chain, thereby creating a verifiable audit record. This sequential chaining ensures that any attempt to alter the stored explanation, even at a single byte, would result in a mismatch with the blockchain record and immediately expose tampering. Within the federated setup, both local and global explanation artifacts are independently hashed before being committed to the blockchain, ensuring that integrity checks apply consistently across decentralized contributors.

For the breast cancer dataset, the generated hash values corresponded to explanation outputs derived from both global (permutation importance) and local (LIME) analyses, thus preserving both dataset-level and patient-specific insights. Likewise, in the diabetes case, clinically relevant predictors such as BMI, blood pressure, and serum measurements were captured in the explanation artifacts and then securely logged on-chain. By doing so, the framework guarantees that interpretability outputs remain immutable, reproducible, and auditable over time.

Figures 6, 7 and 8 illustrate this process by showing the recorded explanation hashes and the deployment of a smart contract that governs the storage and retrieval of these records. This design demonstrates not only the feasibility of combining AI explainability with decentralized audit mechanisms but also emphasizes its necessity in clinical domains, where accountability

```
{
  "model": "RandomForestRegressor",
  "r2": 0.47968220102289594,
  "mae": 42.354586466165415,
  "rmse": 52.998449155286586,
  "perm_importance_time_ms": 3683.97,
  "explanation_hash": "73c391e2821bc766c0176a87ab752dede5b3b8efaa0aba4d0ce14601838554ad"
}
```


Figure 7: Diabetes explanation outputs hashed with SHA-256 and recorded on-chain. The hash (73c391e2821bc766c0176a87ab752dede5b3b8efaa0aba4d0ce14601838554ad) provides a secure, tamper-proof audit trail for patient-level predictions.

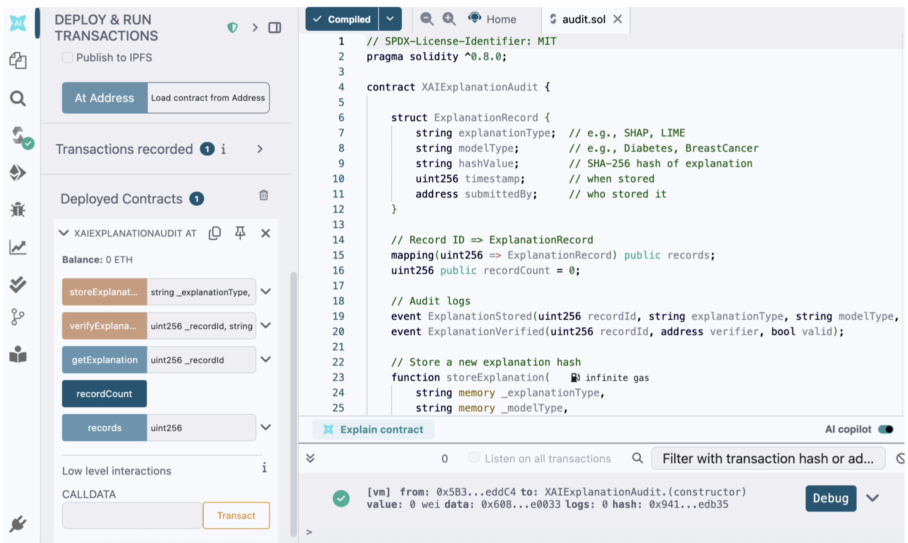

Figure 8: Smart contract deployment for immutable storage of explanation hashes on the blockchain, ensuring transparency, verifiability, and resistance to tampering.

and regulatory compliance are critical. This guarantees long-term transparency, accountability, and trust—qualities that are indispensable for the safe deployment of AI in healthcare.

4.4 Comparison Analysis

In comparing our Federated Blockchain-Enhanced XAI framework with recent works, clear distinctions emerge in terms of complexity, interpretability, and auditability. As shown in Table 2, our approach is deliberately lightweight, employing a Federated Random Forest (FRF) model combined with permutation importance and LIME for global and local interpretability. This stands in contrast to recent federated learning studies such as Yang (2024), which focus on cross-silo collaboration with heavy reliance on homomorphic encryption and smart contract coordination, thereby increasing system complexity and computational overhead. Similarly, blockchain-enabled federated learning frameworks reported in PubMed (2024) integrate optimization techniques like LGOA and EDBN, providing scalability but at the cost of higher infrastructure demands.

Table 2: Comparative analysis of the Federated Blockchain-Enhanced XAI framework with recent studies, highlighting differences in model complexity, interpretability, and auditability, and showing how the lightweight design balances performance with transparency and trust.

Aspect	**Our Framework**	**Causal XAI + Blockchain for Imaging** [11]	**Federated Medical Learning** [27]	**Explainable FL with Blockchain** [28]
Complexity	Lightweight: Federated Random Forest + Permutation Importance + LIME	High: causal learning sparsity + blockchain scoring	High: cross-silo FL, homomorphic encryption, smart contracts	High: FL + XAI + optimization (LGOA, EDBN)
Interpretability	Global & local via standard XAI tools	Causal learning improves interpretability	Not focus of study	XAI integrated for transparency
Auditability	Hash-and-store explanations on blockchain	Dataset quality and contributions recorded	FL model parameters audited on-chain	Explanation and parameters hashed securely

From an interpretability perspective, our system emphasizes clarity by using widely accepted XAI methods that offer immediate global and local explanations. While federated medical learning largely neglects explainability, blockchain-based federated approaches integrate XAI but often treat it as a secondary component rather than a core design principle. In contrast, causal XAI models (PubMed, 2024) achieve improved interpretability through sparsity-driven reasoning, but these methods require more complex causal assumptions and advanced infrastructure that may limit deployment in resource-constrained healthcare environments.

Auditability is another crucial differentiator. Our framework adopts a simple but robust mechanism—serializing, hashing, and immutably storing explanation artifacts on blockchain—ensuring tamper-proof records that are directly linked to model decisions. Competing approaches often secure either model parameters or dataset contributions, which, while important, do not guarantee direct verifiability of explanations. Thus, our contribution bridges the gap by focusing on explanation integrity as the primary auditable asset. Collectively, this comparison highlights how our system achieves a unique balance: maintaining interpretability and accountability without sacrificing practicality, making it highly suitable for real-world healthcare applications.

4.5 Comparison and Security Discussion

Table 2 provides a comparative overview of existing approaches and the proposed framework. To expand this analysis, we further summarize the relative levels of computational complexity, interpretability, and auditability in Table 3. The proposed federated architecture achieves medium computational complexity due to distributed model training and aggregation, while maintaining high interpretability through dual-level explanations and high auditability enabled by blockchain.

The blockchain integration protects against critical threats such as data tampering, model update forgery, and replay attacks. Because each explanation and update is hashed and chained, any attempt to modify local outputs or overwrite global updates becomes detectable. Although this setup adds minor latency due to hashing and chain validation, the trade-off is justified by the enhanced transparency and accountability.

Table 3: Quantitative summary of complexity, interpretability, and auditability for Centralized ML, Federated ML, and the Proposed FL-XAI-Blockchain framework.

Aspect	**Complexity**	**Interpretability**	**Auditability**
Centralized ML	Low	Medium	Low
Federated ML	Medium	Medium	Medium
Proposed FL-XAI-Blockchain	Medium	High	High

5 Conclusion

In this paper, we introduced a Lightweight Federated Random Forest (FRF) integrated with XAI for healthcare, enabling accurate and interpretable predictions with low communication overhead. Dual-level explainability using global (Permutation Importance) and local (LIME) methods provides transparency at both institution and patient levels. A blockchain-audited learning process securely stores model updates and interpretability artifacts on-chain, ensuring tamper-proof accountability. Privacy-preserving federated setup ensures no raw medical data leaves local nodes, demonstrating accuracy, reliability, and compliance with healthcare data standards. The system architecture, consisting of local warehouse nodes, a global aggregation server, an explainability layer, and blockchain integration, ensures that privacy-preserving federated training, transparent interpretability, and immutable auditability are achieved in a unified manner. Our federated global model achieved 97 percent accuracy with an F1-score of 0.97 on Breast Cancer and an R^2 of 0.52 on Diabetes regression tasks, demonstrating reliable predictive capacity. Compared to previous centralized or non-federated models, our approach achieves comparable or improved predictive performance while preserving patient privacy and providing dual-level explainability.

To further guarantee trust and accountability, all explanation outputs were serialized, hashed with SHA-256, and immutably stored on blockchain. This design ensured that explanations cannot be modified post-hoc, enabling clinicians, regulators, and auditors to validate model outputs in a transparent and tamper-proof manner. Additionally, by logging model update parameters alongside explanations, the blockchain layer preserves a complete audit trail of the federated learning process itself, enabling verifiable re-training and long-term accountability.

The current system demonstrates strong potential for real-world healthcare deployment by combining accuracy, privacy, interpretability, and tamper-proof auditing in a unified pipeline. Future work will evaluate the performance and latency overhead introduced by blockchain logging. We will also study federated model synchronization, including the effects of different numbers of nodes and synchronous versus asynchronous aggregation. Computational complexity and scalability with increasing participants or feature dimensions will be analyzed. An enhanced security threat model will be developed to address potential attacks, such as data tampering, replay, and poisoning. Further improvements will focus on integrating multi-institution, multimodal clinical datasets and incorporating advanced XAI methods such as SHAP and counterfactual explanations. Hybrid model designs with adaptive feature weighting will be explored. The system will be tested against clinical and regulatory acceptance criteria to ensure deployment readiness and build scalable, trustworthy, and interpretable medical AI systems.

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