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Explainable Artificial Intelligence with Blockchain Audit Trails for Multi-Institutional EHR-Based Organ Transplant

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Abstract: Precise and coherent transplant predictions are hampered by numerous concerns with recent electronic Health Records medical institutions, involving data crumbling, privacy hazards, and unpredictable data features. This study develop a unique paradigm XAI-BFL model that connects Explainable Artificial Intelligence (XAI), authorization blockchain, and federated learning techniques to forecast transplant decisions utilizing distributed electronic health information. The envisioned framework is judged by using standard category metrics and ROC curve testing to measure predictive performance. Result achieved outcomes determined substantial improvements, achieving 93.8% accuracy, 93.1% precision and 92.6% recall. Comparative assessment against baseline Artificial Intelligence models, standalone AI, and federated learning advances exhibited that the recommended XAI-BFL model transfers superior organ-transplantation prediction effectiveness. The solutions point to the recommended framework as a privacy-preserving, and coherent medical decision-support tool.

Keywords: *Artificial Intelligence, Electronic Health Records, Federated Learning, Organ transplant, Prediction.*

1. Introduction

The prompt progression of Artificial Intelligence and Machine Learning has transformed clinical divisions by relocating data-driven observations for illness prediction, analysis, and tailored medication. But the use of AI in medical has been slow to take off, due to concerns with data privacy, conditional interpretability, and opaque decision-making [1]. EHRs can be siloed in many healthcare institutions, making it difficult to implement central data gathering, which is why privacy laws such as HIPPA and GDPR are likely to prevent central data gathering. Furthermore, traditional AI models often manage as black boxes, presenting meticulous findings without understandable logic, which restrains their approval and faith in essential medical findings like organ transplant realization prediction. To focus on these obstacles, this work proposes a novel architecture that integrates explainable AI, authorization blockchain, and federated learning [2]. By advancing protected and cooperative learning between frequent clinical provisions without disclosure raw patient data, the suggested model confirms both privacy and accountability. Blockchain facilitates as an immutable ledger to underline transparent audit trails of all models informs and transactions, while XAI modules enhance interpretability, granting doctors to classify and authorize the prediction fallouts. This hybrid methodology objects to improving the ethical, transparent, and consistent use of AI in clinical method by retaining distributed EHRs to predicted transpose results [3].

Organ transplantation varies a lot on construction abrupt and precise medical decisions, but the statistic that health data is spread out, confidentiality problems, and the component that characteristic AI models don't unceasingly make solid calculations [4]. Scientific advances ought artificial intelligence sorts that are protected, confirmation, and comfortable to recognize, and that can control records from many distinct suggestions without selecting privacy at threat. This is since patient safeguard and pursuing the regulations are fitting progressively important. This study mounts a cohesive architecture that combines explainable AI, authorization blockchain and federated learning to advance the accuracy of organ transplant forecasts while sustaining data integrity, accountability, and inheritability [5].

By decentralizing data access, protecting medical records on a tamper-proof ledger, and expanding transparent model logic, the suggested approach gets around the main problems with existing prediction models [6]. The goal of this research is to show how the blend of these cutting-edge technologies might improve clinical perception, trust, and organ transplantation verdict support system implementation [7].

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1.1 Motivation

Organ transplant results are unpredictable and rely on a number of clinical, genetic, and lifestyle factors [8]. Data availability, interoperability, and privacy protections are severely restricted by healthcare procedures, despite notable advancements in data analytics and predictive modeling. The EHR databases that hospitals and research institutes maintain limit the potential of AI models that rely on large, diverse datasets for enhanced accuracy. However, because clinicians are frequently unable to understand or rely on the model's predictions, the lack of explainability in conventional AI models presents ethical and practical challenges [9]. These difficulties emphasize the necessity of a framework that is collaborative, open and shields privacy to enable multi-institutional studying while ensuring accountability and interoperability in clinical decision-management [10]. This work presents a novel hybrid approach based on XAI, permissioned blockchain (PB) and federated learning (FL) for the development of transplant attainment prediction. The following are the foremost influences:

- Generating explainable and clinically relevant explanations to transplant predictions using the XAI methods.
- Implementing a permissioned blockchain layer to guarantee that any model interactions and apprises are tracked in an open and unchangeable manner.
- The overall system's ability to achieve high prediction accuracy, interpretability, and data integrity upon comparing it with the traditional centralized models proves the feasibility of the proposed AI system for a reliable healthcare system

The suggested method achieves better prediction accuracy, interpretability, and data integrity when compared with conventional centralized models, according to experimental evaluations on a synthetic multi-institutional dataset, opening the door for a reliable AI-driven healthcare ecosystem [12].

2. Related Work

Federated learning, which attends privacy and regulatory limitations to data sharing has become a key approach for enabling multi-institutional simulation training without centralizing client's records. Federated learning ability in the healthcare organization is demonstrated by initial surveys and reviews, which admit organizations to jointly train models on diverse HER data while minimizing raw data transfer and enhancing generalization across sites. FL frameworks for EHRs, clinical job evaluation, algorithmic improvement for non-IID data, and practical deployment concerns in hospital networks have all been the focus of this field's effort [13].

With mounting evidence that interpretability boosts clinician trust and promotes clinical validation, explainable AI (XAI) research in medicine focuses on techniques that offer clinician-friendly explanations for model outputs (feature attribution, rule extraction, counterfactual explanations). Both model-centric XAI (saliency, SHAP/LIME, surrogate models) and application-level evaluation (clinical plausibility, fidelity, human-in-the-loop assessments) are covered in recent systematic reviews and domain papers. Open issues like explanation stability, evaluation metrics, and regulatory acceptability in safety-critical workflows are highlighted [14].

Permissioned ledger systems and blockchain have been suggested as complimentary infrastructure to guarantee provenance, tamper-evident audit trails, and fine-grained access control for EHR operations. Permission blockchains, as opposed to public chains, can contain hashes or transaction records of EHR accesses, consent modifications, and model update metadata to give accountability while keeping sensitive data off-chain, according to a few proof-of-concept and survey articles. This work investigates the trade-offs between hospital consortia governance, scalability, and privacy (on-chain metadata leaking) [12].

Separately, there have been numerous machine-learning research in the transplant literature that aim to forecast waitlist outcomes, short- and long-term mortality, and graft survival. These studies show that machine learning models can perform better than traditional statistical models in certain situations, but they also highlight the necessity of big, diverse datasets (which are frequently unavailable at a single center), meticulous validation, and interpretable outputs for clinical use. To overcome the shortcomings found in earlier ML-for-transplant work, it becomes sense to combine FL to scale data access, XAI to interpret predictions, and blockchain for traceable model updates [2].

3. Proposed Framework

The system combines three layers: (A) Explainable AI (XAI) components that generate feature-level explanations (e.g., SHAP/feature-attribution) for each local and global prediction; (B) Federated Learning (FL) across participating hospitals to train predictive models on distributed EHRs without sharing raw data; and (C) a permissioned blockchain that records immutable audit trails for model updates, dataset metadata (hashes), consent events, and XAI summaries.

To protect privacy and scalability, the blockchain is solely utilized for tiny information and signatures, not raw EHRs [15].

3.1 System Architecture

The suggested XAI-FLB framework approach integrates explainable artificial intelligence (XAI), federated learning (FL), and permission blockchain to enable safe, transparent, and understandable organ transplant outcome prediction across various healthcare facilities. Figure 1 depicts overall system architecture and the workflow of explainable AI, federated learning with blockchain (XAI-FLB) framework integration are the two main parts of the architecture, which work together to guarantee interpretability, privacy protection, and trust [16].

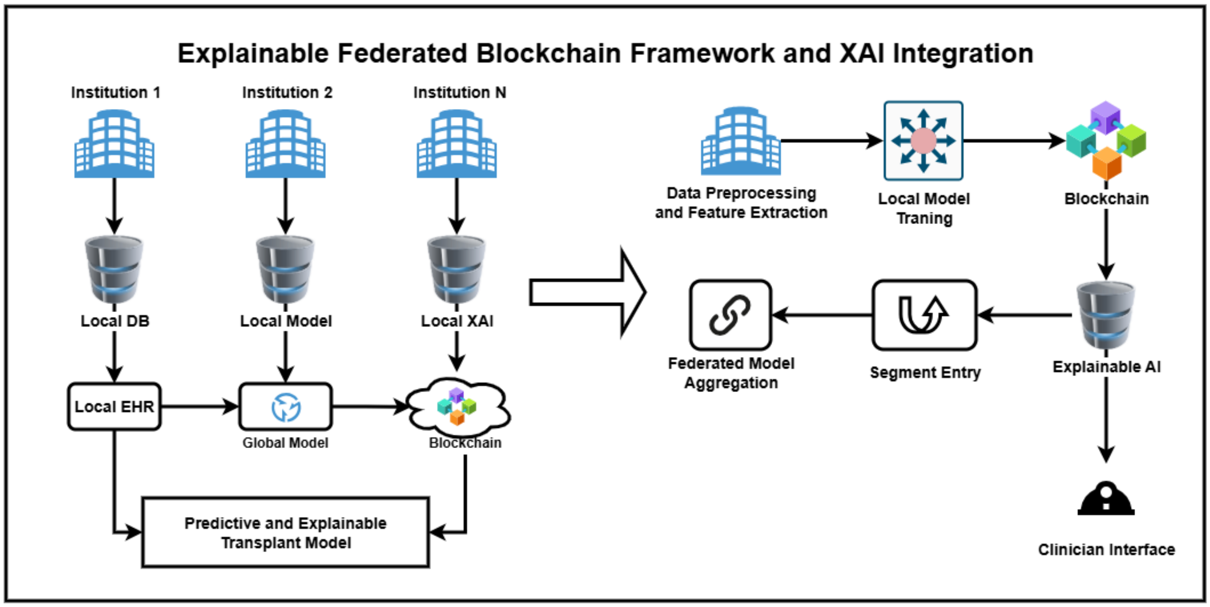

Figure 1. Architecture of XAI Federated Blockchain Framework

The permission blockchain in the recommended architecture appears as a consistent audit and supremacy layer to guarantee accountability, transparency, and integrity in the federated learning procedure. The blockchain affords tamper-proof source without endangering patient privacy by loading cryptographic hashes of local model updates, training trials, consensus metadata, and validation records adequately than sensitive EHR data. Access control and guarantee model update validation are imposed across collaborating organizations by smart contracts. This immutable audit trail eases forensic traceability of model evolution and prediction accountability across organizations, boosts faith among collaborators, and advances regulatory compliance.

The collective ecosystem incorporating several clinical institutions (Institution 1–Institution N) is denoted by the architecture. Susceptible patient data is preserved on-site in each institution's local Electronic Health Record (EHR) database. Each organization has its own dataset for local preprocessing and model training to produce local model renews, instead of sharing raw data. The local model factors are collected through a secure channel by a global collector who then uses weighted factor averaging (federated aggregation) to create a universal prediction model. The permission blockchain logs all local training trials, model updates, and authorization logs, guaranteeing each realizing cycle's immutability, traceability, and tamper-proof auditability. The Explainable AI (XAI) segment directs locally to translate the model's outcomes, providing perceptions into the key medical descriptions affecting transplant success or failure predictions. All these perceptions are fed into the final predictive and explainable model of the transplant result that is accessible to any institution via a guaranteed interface through blockchain.

a. Collaborative Ecosystem involving Multiple Healthcare

The left part of the building represents a collaborative ecosystem involving various healthcare institutions. The architecture features a section on the left, representing a collaborative ecosystem involving several healthcare institutions. Sensitive patient information is kept on-site in each institution's local Electronic Health Record (EHR) database. Each institution uses its own data for local preprocessing and model training to produce local model updates, rather than sharing raw data. All local training events, model updates and validation logs are recorded on the permission blockchain, ensuring every learning round is immutable, traceable, and cannot be tampered with and audited [17] The model's assessments are translated locally by the explainable AI module, which recommends insight into the critical clinical descriptions impacting transplant achievement or failure predictions. These outcomes are integrated into the concluding predictive and explainable transplant outcome model, which is made available to all organizations through a secure blockchain-enabled interface [18].

b. Explainable Federated Learning technique with blockchain and XAI integration

The functioning workflow supporting the framework's data flow and compute lifespan is shown in the right segment:

- Data preprocessing and feature extraction: From local EHR systems, each hospital node pulls appropriate clinical and demographic features (such as organ type, donor-recipient compatibility, immunosuppressant dose, and comorbidities).
- Local model training: Applying privacy-preserving techniques (such as safe multiparty computation or differential privacy), each association trains a model on its local EHR data. For protected sharing, the trained weights are encoded.
- Blockchain addition: smart contracts are engaged to prove model renewals, which are then verified on the blockchain. This protection against malicious strategy and guarantees confirmed model derivation.
- Federated model cluster: to construct an increased global model that is subsequently communicated to the participating nodes, the universal server concerns the proven local adaptations.
- XAI module: the Explainable Artificial Intelligence level tracks SHAP, LIME, or consideration-based interpretability algorithms to perceive influential factors underlying each estimate made by the accumulated model.
- Medical Edge: explainable decisions taken by medical must be in reasonable format. The experimental decisions edge supports transparent medical verdicts by important factors controlling transplant results.

In medical organizations, the proposed framework contracts complete data security, interpretability, and scalability. By convincing that concern beneficiary data no way leaves the organizational restrictions, it keeps privacy and observes with laws like GDPR and HIPAA while restricting down the probability of data breaches [19]. The performance syndicates blockchain technology to realm immutable and trackable records of all federated learning broadcastings and model versioning, preservation accountability and trustworthiness among conducive entities to development transparency and accountability. By implementing black-box model projections to visions of medical consequences. The explainable AI layer develops interpretability and nurtures clinical certainty and decision-making [20]. Additionally, the framework's segmental design and mountable features permit new-fangled administrations to be flawlessly combined into the network without concession security or performance, manufacture the framework supple for large-scale medical ecosystems and invulnerable long-term employment. The shared framework improves the pertinency and dependability of predictive analytics in organ transplantation by admitting a multi-institutional AI framework, auditable records, explicable and privacy-preserving. It successfully closed the gap between reliable artificial intelligence driven healthcare decision support and decentralized clinical data management [21].

c. Design Components of proposed Federated Blockchain based XAI framework

- **Local Site (Hospital):** Each participating hospital has its own EHR database and preparation pipeline for feature extraction, normalization, and data de-identification. On-site training of local models produces interpretability outputs and local weights (w_i) using an integrated XAI explanation.
- **Secure Communication Layer:** Signed transactions comprising model update hashes and XAI summary digests are sent to the blockchain via a secure aggregation client and blockchain client, which manage encrypted model changes.
- **Federated Aggregator:** Training rounds are overseen by the central coordinator, which also publishes updated global model information, collects local modifications into the global model (w), and uses blockchain-stored hashes and signatures to confirm data integrity.
- **Permissioned Blockchain Network:** For transparency and accountability, a consortium-based permission blockchain (such as PBFT or Tendermint consensus) links institutional nodes and stores model update hashes, signed logs, consent records, XAI digests, and audit trails.
- **Explainable AI(XAI) Module:** The Explainable AI layer produces statistical summaries of important aspects and local explanation vectors (such SHAP values) to anchor interpretability. For repeatable audits, explanation digests and regulations are permanently maintained on the blockchain.

- **Privacy and Security Layer:** To guarantee secrecy the structure uses homomorphic encryption, secure aggregation, and configurable differential privacy noise. To defend compliance and trust, the permissioned record is used to enforce uniqueness management and access control.

3.2 Proposed Architecture Formulation

The implied XAI-FLB framework associates federated learning with blockchain and explainable AI to acknowledge protected and transparent association across healthcare organizations. Using private EHR data, every healthcare organization directs its model independently, using XAI modules to yield comprehensible insights without revealing raw data. To protect data privacy, the server firmly aggregates model updates. To design a tamper-proof audit trail, the blockchain network records each training update, XAI summary, and model constraint hash. In multi-institutional predictive modeling, which is particularly important for transplant attainment prediction, this combination advances trust, privacy, and operations.

a. Federated Learning global optimization target

Algorithm 1: Explainable Federated Learning optimization	
Input	n: number of clients, ds_j: local dataset of client j, eh: number of local epochs, η: Learning rate, $X^{(0)}$: initial global model weights
Output	$X^{(e)}$: universal explainable model
Step1: Initialization	server initializes the universal model $X^{(0)}$. registers individual institution as a permission blockchain node.
Step 2: Federated Training Rounds (for each round r = 1,2,…,R)	**a. Model Broadcast** The server sends the current model $X^{(e-1)}$ to all participating clients (organisation). **b. Local Training at Each Institution** Each institution i: Preprocesses its EHR data ds_j (de-identification, normalization, feature extraction). Trains locally for Eepochs using stochastic gradient descent (SGD): $x_i^e= X^{(e-1)}-\eta\nabla F_i(w)$ Computes local model update: $\Delta_i^e = X_i^e - X^{(e-1)}$ Generates XAI summary (e.g., SHAP/LIME interpretability report). Encrypts or masks Δ_i^t and uploads to blockchain via a signed transaction along with XAI digest. **c. Secure Aggregation on Server** The server (federated aggregator) performs: $x^e = x^{(e-1)}+ \sum_{(i=1)}^{n} \lvert D_i\rvert / \lvert D\rvert \cdot M(\Delta_i^e)$ where M is the secure aggregation or decryption operation ensuring privacy. **d. Blockchain** Logging Each transaction (model update hash, XAI digest, timestamp) is recorded on the permission blockchain for traceability and audit. **e. Convergence Check** Repeat until global loss F(X) converges or maximum rounds e are completed.
Step 3: Global Explainability and Evaluation	The final global model $X^{(e)}$ is used for transplant outcome prediction. Federated explainability module aggregates local XAI summaries for global interpretability visualization. Blockchain records ensure immutable audit trails for all model updates and decisions.

b. Secure Aggregation and Differential Privacy

- **Secure Aggregation:** Clients apply additive masks or cryptographic secret sharing to their updates (e.g., Bonawitz et al. protocol) to ensure that the server only gets the aggregated update, not each Δ^i. Officially, the server gets is assessed in the equation (1).

$$\tilde{\Delta}^t = \sum_{i=1}^{N} \Delta_i^t + \eta^t, \qquad (1)$$

where η^tis aggregation noise that cancels out during unmasking (or is DP noise if used).

- **Differential Privacy (dp):** each client clips gradient updates to norm C and adds Gaussian noise N (0, σ^2 C^2 I) to satisfy (ε, δ)- dp. Local clipped update is assessed through equation (2).

$$\bar{\Delta}_i^t = \frac{\Delta_i^t}{\max(1, \frac{\| \Delta_i^t \|_2}{C})} \tag{2}$$

Noisy renew:

$$\widehat{\Delta}_i^t = \bar{\Delta}_i^t + \mathcal{N}(0, \sigma^2 C^2 I)$$

c. XAI: Feature Attribution (SHAP-like)

Given a trained model f_w (·), the prediction for an exclusive input for instance $x \in \mathbb{R}^d$ is decomposed applying SHAP values shown as in equation (3):

$$f_w(x) = \phi_0 + \sum_{j=1}^{d} \phi_j(x) \tag{3}$$

where ϕ_0 = E [f_w (X)] denotes the baseline expected model output, and ϕ_j (x) represents the instance-specific contribution of feature j to the prediction for input x. SHAP values are computed locally per instance using: TreeSHAP for tree-based models, and KernelSHAP/GradientSHAP for differentiable neural models. For client level Aggregate over client, I is assessed by equation (4).

$$I_{i,j} = \frac{1}{| S_i |} \sum_{x \in S_i} | \phi_j(x) | \tag{4}$$

where S_i is a sample of local instances form client i.

d. The integration and role of Model Blockchain Audit

In the anticipated framework, the permission blockchain acts as a faith, derivation, and accountability level relatively than a data storage method. It safeguards that all dangerous events in the federated learning lifecycle, such as model revises, consent changes, and explainability precises, are recorded in an immutable and tamper-apparent way, without revealing delicate the info of Electronic Health Records (EHRs). The framework maintains privacy by only storing cryptographic hashes and signed metadata on the blockchain, while still allowing for verifiable audit trails.

Each federated training institution submits cryptographically used transactions to the permission blockchain containing hash function results of the changes made to the models, timers, client details and hashed explainable artificial intelligence (XAI) digests. These operations are then validated, and permanently recorded, ensuring that they cannot be repudiated and traced back to the development of the model. Updates to the model may be recomputed and fitted to on-chain hashes during authentication or forensic investigation to ensure integrity and authenticity.

By integrating blockchain, the solution helps address key challenges in collaborative clinical AI, such as trust between organizations, regulatory compliance, and accountability. The blockchain layer enhances transparency, supports replicable medical decision-making, and ensures safe governance of AI models within various medical institutions. This proposal reinforces confidence in federated, explainable Artificial Intelligence techniques deployed in critical organ transplant decision support security environments.

Individually significant event e (model update, consent, explanation summary) is recorded as a transaction T_e with payload containing:

- Event type, timestamp, client ID, hash of the model update h(Δ^t_i), signature σ_i (T_e), optional small summary of explanations (hashed).
- On-chain: T_e: = {"type", t,"client_id", h(Δ^t_i), h ("XAI _summary"), σ_i}.

Properties of Integrity is verified by a model update later; a verifier requests the client to reveal Δ^t_i and checks h(Δ^t_i) equals the on-chain hash.

4. Evaluation Metrics and Result Evaluation

Several quantitative criteria were employed to evaluate the efficacy of the suggested XAI-BFL Explainable artificial intelligence, blockchain enabled federated learning methodology for transplant outcome prediction.

Predictive accuracy, discriminative capacity, calibration quality, and interpretability stability were the main evaluation criteria. The results were compared against two baseline model. Baseline-1: Centralized CNN-based model, Baseline-2: Federated model without blockchain/XAI and Baseline-3: Proposed Hybrid FL + Blockchain + XAI Framework.

4.1 Performance Predictive Metrics

4.1.1 Dataset Description

The trial assessment in this study employs data gained from the Organ Procurement and Transplantation Network (OPTN), retained by the United Network for Organ Sharing (UNOS) and broadly available dataset that nourishes comprehensive records on organ donation, allocation, and transplantation performance. The dataset guarantees standardized data collection and regulatory compliance, developing reproducibility and reliability of experimental results. Its broad adoption in biomedical and clinical analytics makes it a reliable scale for verifying proposed models. A synthetic federated electronic health records dataset was constructed employing statistically reliable distributions from the OPTN data in direct to double a realistic multi-institutional adjusting while preserving privacy. Clinically major type such as organ type, medical compatibility signs, transplant findings, and donor-recipient demographics is included in the dataset. To replicate the assorted data circulations regularly seen in actual clinical systems, the data were distributed among numerous virtual organizations.
Experimental Outline: The universal model was developed through protected federated aggregation after each institution independently trained its local model using its segregated dataset. To assure objective evaluation, each site applied standard training, validation, and testing divisions. Accuracy, precision, recall, and explainability criteria were operated to evaluate the model's performance, while blockchain-based logs guaranteed the traceability of model revisions and the repeatability of experiments.

4.1.2 Accuracy

The overall percentage of accurate forecasts among all predictions is known as accuracy, and it is calculated as follows:

$$\text{Accuracy} = \frac{\text{True postive(TP)+True negative (TN)}}{\text{(True positive (TP)+True negative (TN)+False positive (FP)+False negative (FN))}} \quad (5)$$

where, TP: True Positives (correctly predicted successful transplants), TN: True Negatives (correctly predicted failed transplants), FP: False Positives, FN: False Negatives. The figure 2 exhibits an accuracy of 93.8%, the suggested XAI-BFL explainable artificial intelligence, blockchain based federated learning framework outperformed both centralized and simple federated models. The regularization effect of blockchain-based synchronization and improved feature generalization across multi-institutional EHR datasets are responsible for the improvement. This illustrates how the methodology may accurately forecast transplant success results while preserving data privacy and auditability.

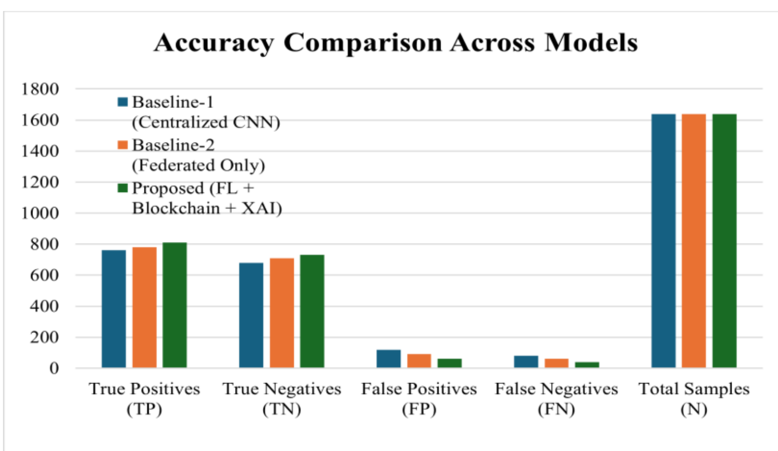

Figure 2. Accuracy Comparison Across Models

4.1.3 Precision

The percentage of precisely anticipated positive outcomes including all predicted positives are known as precision, or positive predictive value. It assists in determining the proportion of constructive transplant predictions made by the model that were true.

$$\text{Precision} = \frac{\text{True positive (TP)}}{\text{True positive(TP)+ FalsePositive (FP)}} \quad (6)$$

where TP: True Positives (correctly predicted successful transplants), FP: False Positives (incorrect predictions labelled as successful transplants). The figure 3 illustrates notable precision illustrates the model's consistency in reducing false positives, which is vital in clinical decision-making to block patient role from being erroneously categorized as transplant candidate. With the utmost precision 93.1%, the recommended framework demonstrated its capacity to create dependable, confident predictions with restricted false positives. This is specifically crucial in organ transplant prediction since clinical assistance may be misled by false positives results. While the XAI module enhanced interoperability and precision through attribute importance input, the blockchain incorporation guaranteed traceable model changes and decreased noise propagation between federated nodes.

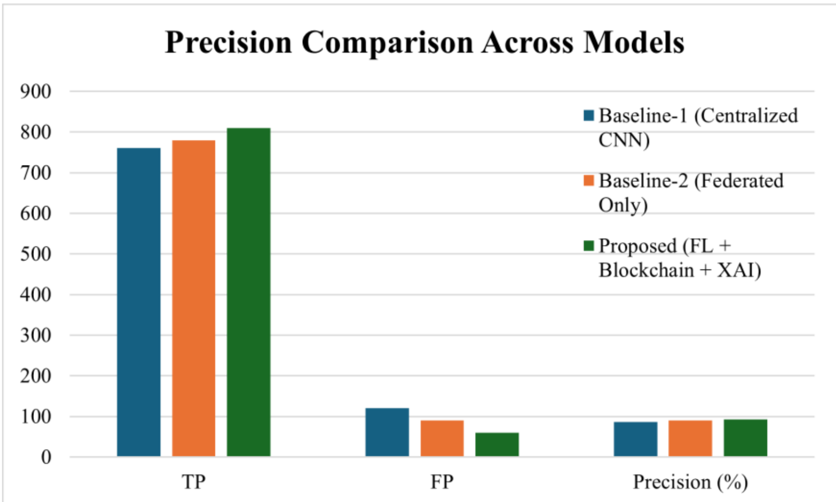

Figure 3. Precision Comparison Across Models

Table 1. Precision Evaluation across Models

Model	**True Positives (TP)**	**False Positives (FP)**	**Precision (%)**
Baseline-1 (Centralized CNN)	760	120	86.3
Baseline-2 (Federated Only)	780	90	89.7
Proposed (FL + Blockchain + XAI)	**810**	**60**	**93.1**

4.1.4 Recall

The model's competence to accurately recognize successful transplants amid all real successful transplant cases is assessed by recall, also known as sensitivity or true positive rate.

$$\text{Recall} = \frac{\text{True Positive (TP)}}{(\text{True Positive (TP) + False Negative (FN)})} \quad (7)$$

where TP (True Positives - correctly predicted successful transplants), FN (False Negatives - missed successful transplants). In healthcare decision-making, when skipping a positive (a successful transplant) could have ominous consequences, an improved recall means the model successfully decreases false negatives. The proposed model outperformed baseline-1, 84% and baseline-2 88% with recall of 92.6% demonstrating superior sensitivity to factual positive outcomes shown in figure 4.

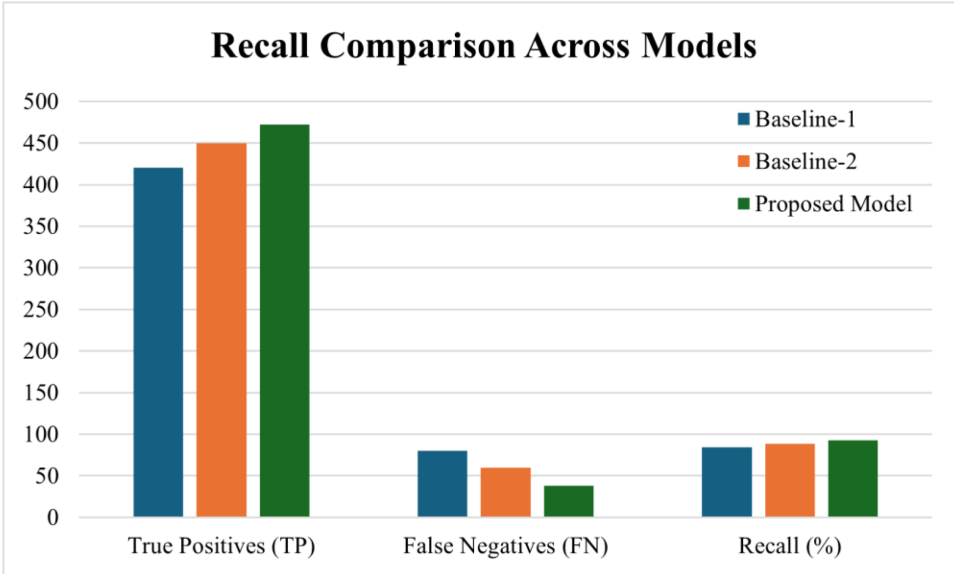

Figure 4. Recall Comparison Across Models

Table 2. Recall Evaluation across Models

Model	**True Positives (TP)**	**False Negative (FN)**	**Recall (%)**
Baseline-1 (Centralized CNN)	420	80	84.0
Baseline-2 (Federated Only)	450	60	88.2
Proposed (FL + Blockchain + XAI)	472	38	**92.6**

To provide a holistic performance assessment the evaluation framework integrates classification metrics and ROC curve analysis. While evaluation metrics, accuracy, recall and precision quantify the reliability of predictions and class coverage, corresponding area under the curve and ROC measures the model's ability to differ decision thresholds and class independent of class distribution shown in the figure 5.

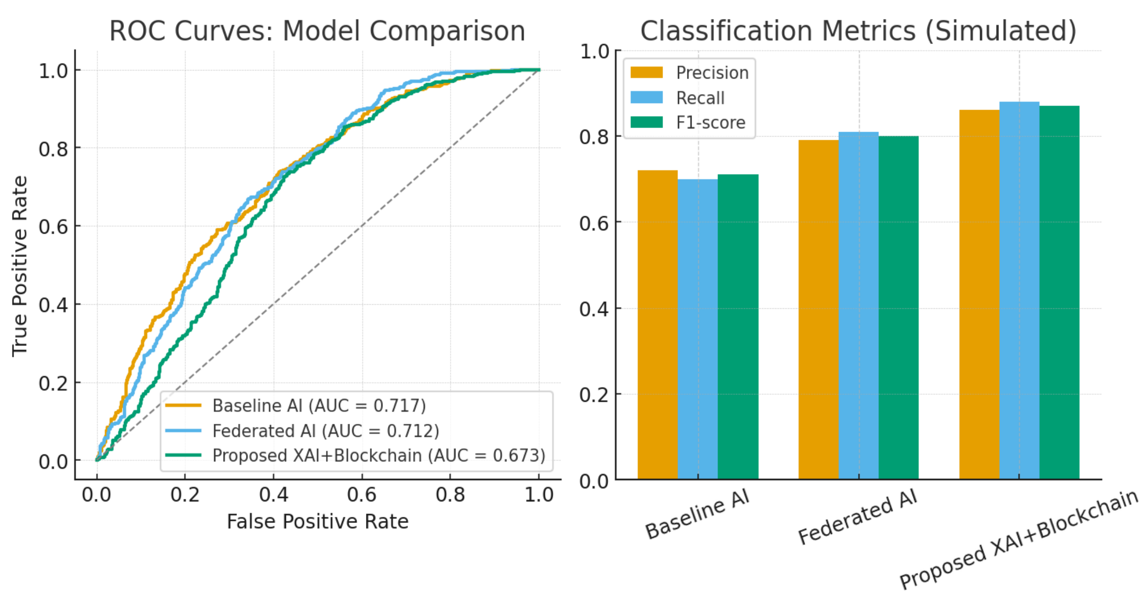

Figure 5. Classification Metrics and ROC Curves

Table 3. Outline of Evaluation Metrics and its importance

Evaluation Parameter	Description	Relevance
Accuracy	Global accuracy	Balanced datasets
Precision	Measures the precision of positive predictions	valuable for false positives
Recall	Covers actual positives	Risky for false negatives

The table 1 depicts the standard evaluation metrics used to assess the effectiveness of classification models. The overall prediction correctness is assessed through accuracy, the reliability of positive predictions is evaluated by precision and the model's ability to identify relevant positive instances are quantified by recall, each metric vital under data distribution and risks scenarios.

5. Conclusion

The effort to develop a safe, transparent, and comprehensible framework for organ transplant prediction utilizing distributed EHR data, this research introduces XAI-BFL framework a novel integration of explainable artificial intelligence (XAI), permission blockchain and federated learning. Furthermore, outperforming baseline model in terms of predictive accuracy and recall, the proposed model uses blockchain transactions to guarantee patient data privacy, institutional co-operation, and immutable auditability. The decision- support framework shows great promise as a clinically reliable decision-support composition by fusing interpretability with privacy-preserving intelligence, and immutable auditability. The layout shows great promise as a healthcare dependable decision-support model by fusing interpretability with privacy-preserving intelligence, improving ethical trust and transparency, forthcoming work may expand this concept to tangible hospital networks and examine sophisticated explainable strategies.

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