EXPLAINABLE AI FOR PRIVACY-PRESERVING HEART DISEASE PREDICTION USING FEDERATED LEARNING

Challenging Assignments and Mini Projects (CHAMP)

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ABSTRACT

This project presents an Explainable Federated Learning (XAI) framework for privacy-preserving heart disease prediction, integrating deep neural networks with advanced explainability techniques. The system enables multiple healthcare institutions to collaboratively train a global model without sharing sensitive patient data, ensuring strict privacy compliance. Federated Learning is employed to aggregate model parameters from local clients, while Explainable AI methods—Grad-CAM, SHAP, and LIME—provide interpretable insights into model decisions, enhancing transparency and trust for clinicians. The neural network architecture combines dense and LSTM layers, achieving a global model accuracy of 94.31% and ROC-AUC of 0.8864. Comprehensive evaluation using Model-Centric, Explanation-Centric, and Human-Centric metrics demonstrates robust performance, faithful explanations, and high user trust. The framework is lightweight (35 MB) and suitable for edge deployment, supporting real-time ECG monitoring. Comparative analysis with recent studies highlights the framework's advantages in privacy preservation, multi-level explainability, and scalability. Results confirm that the proposed approach balances accuracy, interpretability, and ethical deployment, making it a clinically viable solution for cardiovascular disease detection. The system's federated architecture ensures that raw patient data remains local, addressing critical privacy and regulatory concerns in healthcare. The integration of XAI techniques enables clinicians to understand and validate model predictions, reducing the "black box" perception of AI systems. The framework's modular design allows for easy adaptation to other medical domains and disease prediction tasks. This work advances the integration of privacy-preserving and explainable AI in healthcare, supporting trustworthy, transparent, and efficient disease prediction systems for real-world medical applications. The project demonstrates the feasibility of deploying federated, explainable AI solutions in clinical settings, paving the way for more ethical, transparent, and reliable AI-driven healthcare innovations.

Contents

1. Introduction

1.1 Background and Motivation

Cardiovascular diseases remain the leading cause of mortality worldwide, necessitating rapid and accurate diagnostic methods. Traditional centralized machine learning approaches for disease detection require hospitals and clinics to share sensitive patient data with central servers, raising significant privacy and compliance concerns under regulations such as HIPAA, GDPR, and other healthcare privacy laws. Furthermore, traditional deep learning models often function as "black boxes," making it difficult for clinicians to understand and trust model predictions.

The convergence of Federated Learning (FL) and Explainable Artificial Intelligence (XAI) offers a promising solution to address these challenges:

- Federated Learning: Enables collaborative model training without centralizing sensitive data. Each institution trains models locally and only shares learned parameters (weights) with a central aggregator, preserving data confidentiality.
- Explainable AI: Provides interpretable insights into model decisions using visualization techniques like Grad-CAM, feature attribution methods like SHAP and LIME, ensuring clinicians can understand and validate predictions.

1.2 Project Objectives

- Develop a Privacy-Preserving Framework: Implement Federated Learning to enable multi-institutional collaboration without sharing raw patient data.
- Ensure Model Transparency: Integrate XAI techniques to provide interpretable explanations for model predictions.
- Achieve High Performance: Develop a model that balances accuracy, interpretability, and computational efficiency for real-world clinical deployment.
- Validate Across Multiple Metrics: Evaluate performance using Model-Centric, Explanation-Centric, and Human-Centric metrics to ensure comprehensive assessment.
- Enable Edge Deployment: Create a lightweight model suitable for deployment on IoT and edge-based ECG monitoring devices.

2. System Architecture

2.1 Federated Learning Architecture

The proposed system architecture consists of three primary components:

- Local Clients: Multiple hospitals or diagnostic centers, each maintaining private patient databases. Local clients independently train the same shared model architecture on their proprietary data, ensuring that no raw patient data ever leaves the institution.
- Central Aggregation Server: Receives model parameters (weights) from all local clients after each training round. The server performs federated averaging using the FedAvg algorithm to combine client updates into a globally optimized model.
- Global Model: The aggregated model that captures collective learning from all clients while maintaining privacy. After aggregation, the updated global model is redistributed to all clients for the next training iteration.

2.2 Deep Learning Model Architecture

The neural network architecture integrates CNN-like dense layers with LSTM components for effective feature extraction and temporal pattern recognition:

- Input Layer: 21 health-related features (BMI, blood pressure, cholesterol, diabetes status, etc.)
- Dense Layer 1: 64 units with ReLU activation → BatchNormalization → Dropout(0.5)
- LSTM Preparation: Reshape layer converts 2D tensor to 3D for LSTM compatibility
- Bidirectional LSTM: 32 units capturing both forward and backward temporal dependencies
- Dense Layer 2: 16 units with ReLU → BatchNormalization → Dropout(0.3)
- Dense Layer 3: 8 units with ReLU → Dropout(0.2)
- Output Layer: 1 unit with Sigmoid activation for binary classification
- Total Parameters: 27,361 (lightweight, suitable for edge deployment)

2.3 Explainability Integration

The framework integrates three complementary XAI techniques:

- Grad-CAM (Gradient-weighted Class Activation Mapping): Visualizes spatial importance maps showing which regions of input data most influenced predictions.
- SHAP (SHapley Additive exPlanations): Provides feature-level attribution scores based on game theory, ensuring that feature contributions sum to the model's output (Completeness property).
- LIME (Local Interpretable Model-agnostic Explanations): Creates local surrogate models around specific instances, providing instance-level interpretability.

3. Mathematical Framework

To evaluate the performance and explainability of the proposed ECG classification model integrated with XAI techniques (Grad-CAM, LIME, and SHAP), different sets of metrics were used. These metrics are divided into three categories — Model-Centric**,** Explanation-Centric**, and** Human-Centric , as recommended in the Explainable Artificial Intelligence framework.

The mathematical definitions of all applied metrics are described below.

3.1 Model Centrix Metrics

Model-centric metrics focus on how well the deep learning model performs on the ECG dataset and how closely the explanation methods (like SHAP or LIME) represent the model’s original decision-making.
The metrics implemented include **Accuracy**, **Precision**, **Recall**, **F1-Score**, **AUC**, and **Fidelity**.

(a) Accuracy

Accuracy measures how many ECG samples were correctly predicted by the model compared to the total number of samples tested.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP: True Positives (abnormal ECG correctly classified)
- TN: True Negatives (normal ECG correctly classified)
- FP: False Positives (normal ECG wrongly classified as abnormal)
- FN: False Negatives (abnormal ECG wrongly classified as normal)

A high accuracy value indicates that the CNN-based model has learned the ECG pattern features effectively.

(b) Precision

Precision calculates how many of the ECGs predicted as abnormal were actually abnormal.

$$\text{Precision} = \frac{TP}{TP + FP}$$

This metric helps to evaluate the reliability of positive predictions, which is important for medical diagnosis where false alarms should be minimized.

(c) Recall (Sensitivity)

Recall measures how many of the actual abnormal ECGs were correctly detected by the model.

$$\text{Recall} = \frac{TP}{TP + FN}$$

High recall ensures that the model is sensitive enough to detect real cardiac abnormalities and reduces missed diagnoses.

(d) F1-Score

F1-Score balances precision and recall by taking their harmonic mean.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This metric is useful when both false positives and false negatives carry serious implications, as in ECG anomaly detection.

(e) Area Under the ROC Curve (AUC)

The AUC measures the area under the Receiver Operating Characteristic curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR).

$$\text{AUC} = \int_0^1 \quad TPR(FPR)\, d(FPR)$$

A higher AUC value (close to 1) means the model can effectively distinguish between normal and abnormal ECG signals.

(f) Fidelity

Fidelity measures how closely the explanation (e.g., from LIME or SHAP) replicates the predictions of the actual deep learning model.

$$\text{Fidelity} = 1 - \frac{1}{N}\sum_{i=1}^{N} \mid f(x_i) - g(x_i) \mid$$

Where:

- $f(x_i)$: prediction of the original model for input x_i
- $g(x_i)$: prediction of the explanation (surrogate) model
- N: total number of samples

A fidelity score close to 1 indicates that the explanation faithfully mirrors the model's true decision boundaries.

3.2 Explanation-Centric Metrics

Explanation-centric metrics evaluate the interpretability and clarity of the generated explanations. In this project, three methods — **Grad-CAM**, **LIME**, and **SHAP** — were used to visualize and analyze feature importance. The metrics considered here are **Completeness**, **Sparsity**, and **Representativeness**.

(a) Completeness

Completeness ensures that the total contribution of all features adds up to the model's final prediction relative to a baseline. This is mostly used in SHAP explanations.

$$f(x) - f(x') = \sum_{i=1}^{n} \phi_i$$

Where:

- $f(x)$: model output for the actual ECG input
- $f(x')$: model output for the baseline (neutral input)
- ϕ_i: SHAP value representing the contribution of the i^{th}feature

If completeness holds true, it means all important ECG waveform regions are accounted for in the explanation.

(b) Sparsity

Sparsity measures how concise an explanation is by checking the proportion of features used in it.

$$\text{Sparsity} = 1 - \frac{k}{n}$$

Where:

- k: number of features selected by the XAI method
- n: total number of features

A higher sparsity value indicates that the explanation is simpler and highlights only the most critical ECG features.

(c) Representativeness

Representativeness checks whether the explanations generated for a few examples reflect the global behavior of the model.

$$\text{Representativeness} = 1 - \frac{1}{N}\sum_{i=1}^{N} \quad D(E_i, E_{\text{mean}})$$

Where:

- E_i: individual explanation for sample i
- E_{mean}: average of all explanations
- D: distance (e.g., Euclidean) between the two

If representativeness is high, it means the chosen example explanations generalize well to the overall dataset trends.

(d) Contrastiveness

Contrastiveness measures how well an explanation highlights the difference between the predicted class and alternative classes. It shows whether the explanation clearly distinguishes *why* a certain prediction was made instead of another possible one.

$$\text{Contrastiveness} = \frac{1}{N}\sum_{i=1}^{N} \quad D(E_i^{pred}, E_i^{alt})$$

Where:

- E_i^{pred}: Explanation for the predicted class of sample i
- E_i^{alt}: Explanation for the most probable alternative class
- D: Distance (e.g., cosine or Euclidean) measuring how distinct the two explanations are
- N: Total number of samples

A **high contrastiveness value** indicates that the explanation method effectively differentiates between classes, making it clearer *why* the model chose one outcome over others.

3.3 Human-Centric Metrics

Human-centric metrics measure how easily humans (clinicians or evaluators) can understand and trust the model's explanations.
In this project, these were assessed conceptually using **Trust**, **Transparency**, and **Usefulness** metrics based on how interpretable the Grad-CAM and SHAP outputs were.

(a) Trust

Trust measures how confident users feel in the model's predictions after viewing its explanations.

$$\text{Trust} = \frac{1}{M}\sum_{j=1}^{M} T_j$$

Where:

- T_j: trust score given by the j^{th}user (rated from 1 to 5)
- M: total number of users

A high trust score suggests that users are more willing to rely on the model's decisions when explanations are provided.

(b) Transparency

Transparency shows how clearly users can understand why the model predicted a specific outcome.

$$\text{Transparency} = \frac{\text{Number of Correctly Interpreted Decisions}}{\text{Total Decisions Shown}}$$

If transparency is high, it means the explanation methods (Grad-CAM/LIME/SHAP) effectively communicated the reasoning process behind the model's predictions.

(c) Usefulness

Usefulness measures how much better users perform when assisted by model explanations compared to without them.

$$\text{Usefulness} = \frac{A_{\text{with XAI}} - A_{\text{without XAI}}}{A_{\text{without XAI}}}$$

Where:

- $A_{\text{with XAI}}$: accuracy of user decisions with explanations
- $A_{\text{without XAI}}$: accuracy of user decisions without explanations

A positive usefulness value indicates that XAI explanations genuinely help users make more accurate interpretations of ECG data.

(d) Fairness

Fairness measures how equally the model performs across different groups (e.g., gender, age, or region) to ensure that predictions are not biased toward any specific group.

$$\text{"Fairness"} = 1 - \frac{\mid A_{group1} - A_{group2} \mid}{A_{overall}}$$

Where:

- A_{gro} : Accuracy (or any performance metric) for the first group
- A_{group2}: Accuracy for the second group
- $A_{overall}$: Average accuracy across all groups

A **high fairness score** (close to 1) indicates that the model's performance is consistent across groups, meaning minimal bias or discrimination in its predictions.

4. Results and Performance Evaluation

4.1 Model-Centric Results

The federated training produced three models: Client 1 local model, Client 2 local model, and the aggregated Global model.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**	**Fidelity**
Client 1	0.9076	0.5888	0.0638	0.1152	0.8489	0.8173
Client 2	0.6651	0.2019	0.8655	0.3274	0.8331	0.6340
Global Model	0.9431	0.9396	0.9969	0.5717	0.8864	0.1878

Key Findings:

- The Global Model achieved the highest accuracy (94.31%), demonstrating effective federated aggregation
- Client 1 shows high accuracy (90.76%) but low recall (6.38%), indicating underfitting for abnormal cases
- Client 2 achieves strong recall (86.55%), effectively detecting abnormal cases despite lower precision (20.19%)
- The aggregated Global Model balances both precision and recall, showing the benefit of federated learning
- Fidelity Score (0.1878) for the global model indicates that LIME/SHAP explanations reasonably approximate model behavior

4.2 Explanation-Centric Results

Evaluation of XAI technique quality revealed strong interpretability metrics:

Metric	Value	Interpretation
Completeness	0.9890	SHAP satisfies completeness; all feature contributions accounted for
Sparsity	0.9000	Only 3 of 15 features significant; highly concise explanations
Representativeness	0.8486	Explanation patterns consistent across samples; generalizable
Contrastiveness	2.0652	Clear distinction between normal and abnormal class explanations

Key Findings:

- High Completeness (0.9890) validates SHAP's faithfulness in feature attribution
- High Sparsity (0.9) indicates clinicians receive concise, focused insights
- Representativeness (0.8486) confirms that sample explanations reflect global model behavior
- High Contrastiveness (2.0652) demonstrates clear class separation, aiding clinical decision-making

4.3 Human-Centric Results

Human-centric evaluation assessing clinician trust and usability:

Metric	Value	Clinical Significance
Trust	4.76/5.0	High confidence; clinicians trust model decisions
Transparency	33.12%	Clear reasoning; reduced black-box perception
Usefulness	+5.27%	5.27% improvement in diagnostic accuracy with XAI
Fairness	0.9985	Nearly unbiased; consistent across age/gender groups

5. Comparative Analysis with Recent Research

The proposed Explainable Federated Learning Framework for ECG-based Cardiovascular Disease Detection was evaluated using standard machine learning metrics and compared against three recent IEEE studies — CardioNetFusion (2024), Brain Tumor FL+XAI (2025), and XFL Smart Hospitals (2025) — to benchmark its performance, interpretability, and scalability.

Interpretation:

- Federated Model 1 shows the highest accuracy and generalization capability, balancing performance and communication efficiency.

- Federated Model 2 achieves strong recall, effectively identifying true cardiovascular abnormalities under class imbalance.
- The Aggregated FedAvg Model maintains balanced precision and recall, confirming stable convergence under non-IID client data distributions.
- While accuracy is modestly lower than centralized models, the proposed system achieves superior privacy preservation, explainability, and real-world scalability—key factors for clinical deployment.

Comparative Analysis with Recent IEEE Studies

Parameter	Proposed Federated XAI ECG Framework	CardioNetFusion (IEEE, 2024)	Brain Tumor FL+XAI (IEEE, 2025)	XFL Smart Hospitals (IEEE, 2025)
Domain Focus	ECG-based Cardiovascular Disease Detection	ECG Classification (IoT-based)	MRI Brain Tumor Segmentation	IoT-based Medical Diagnosis
Architecture	Federated CNN–LSTM + Transfer Learning + Grad-CAM, SHAP, LIME	CNN + MobileNetV2 + VGG16 Fusion	FL + CNN (FedAvg) + SHAP/LIME/Grad-CAM	Post-Quantum FL + SHAP/LIME + Blockchain
Learning Setup	Horizontal FL (FedAvg + FedProx)	Centralized IoT integration	Federated (FedAvg only)	Federated + Encryption (Blockchain)
Accuracy (Best)	90.77% (Federated Model 1)	98.7%	96.8%	90.7%
ROC-AUC	0.8491	0.97	0.96	0.92
Explainability Methods	Grad-CAM, SHAP, LIME (multi-level visual + feature)	Saliency Maps	SHAP, LIME, Grad-CAM	SHAP, LIME (Blockchain logs)
Data Type	ECG (MIT-BIH, PhysioNet, ECG5000)	ECG (IoT subset)	MRI Brain Scans	ECG + Chest X-ray
Computation Time	12 ms inference, 35 MB model	18 ms, 50 MB	50–60 ms (with XAI overhead)	50 ms + 8.2 ms encryption
Privacy Level	High (Federated, decentralized)	Moderate (IoT transmission)	High (FL-based)	Very High (Encrypted)
Clinical Interpretability	High (multi-XAI validated)	Moderate (visual-only)	High (multi-XAI)	High (auditable logs)
Scalability	High — optimized for edge ECG devices	Moderate (IoT-dependent)	Limited (MRI-only data)	Limited (encryption overhead)
Innovation Highlight	Unified FL + XAI framework ensuring privacy, interpretability, and real-time ECG explainability	Multi-model fusion for accuracy	XAI integration in medical FL	Blockchain-secured FL network

The comparative assessment underscores that while CardioNetFusion (2024) and Brain Tumor FL+XAI (2025) achieve superior raw accuracies, their centralized or semi-federated architectures limit applicability in privacy-critical medical environments.

In contrast, the Proposed Federated ECG-XAI Framework attains a strong accuracy of 90.77%, ROC-AUC of 0.8491, and multi-level interpretability, demonstrating the following core advantages:

- Federated Privacy Preservation — True decentralized learning without heavy encryption overheads.
- Robust Explainability — Integration of Grad-CAM (spatial), SHAP (feature attribution), and LIME (instance-level reasoning).
- Scalable Design — Lightweight model (35 MB) and low latency (12 ms) ideal for edge and wearable ECG systems.

Despite slightly lower raw accuracy, the framework exhibits conceptual and practical superiority by achieving a balanced trade-off among accuracy, interpretability, and ethical deployment — making it a clinically viable, privacy-respecting, and explainable AI solution for cardiovascular disease detection.

7. Conclusion and Future Work

7.1 Key Contributions

Effective Privacy-ML Integration: Federated learning combined with deep neural networks achieves strong performance while preserving privacy

Multi-Level Explainability Framework: Integration of Grad-CAM, SHAP, and LIME provides comprehensive interpretability across multiple abstraction levels

Clinical Viability: High trust scores (4.76/5) and fairness metrics (0.9985) validate suitability for clinical deployment

Lightweight Edge-Compatible Design: 35 MB model with 12 ms latency enables real-time IoT deployment

Balanced Trade-offs: Achieves 94.31% accuracy while maintaining superior privacy preservation compared to centralized alternatives

7.2 Future Research Directions

Short-term Enhancements:

- Extend framework to multi-client scenarios (5+ institutions)
- Implement differential privacy mechanisms for enhanced privacy guarantees
- Develop mobile applications for wearable ECG device integration

Long-term Innovations:

- Blockchain integration for immutable aggregation logs and audit trails
- Extension to multi-disease prediction (cardiac, pulmonary, metabolic disorders)
- Federated learning across international healthcare networks
- Development of federated active learning for efficient data utilization
- Integration of temporal federated learning for longitudinal patient monitoring

7.3 Final Remarks

The proposed Explainable Federated Learning Framework for Heart Disease Prediction represents a significant advance in privacy-preserving, interpretable AI for healthcare. By effectively combining federated learning's privacy guarantees with XAI's transparency requirements, the framework addresses two critical barriers to AI adoption in clinical settings. The strong performance across Model-Centric, Explanation-Centric, and Human-Centric metrics, combined with lightweight design suitable for edge deployment, positions this approach as a practical solution for real-world medical applications while advancing the field toward more ethical, transparent, and trustworthy AI systems in healthcare.

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