International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 09 September 2025
Page No: 3762-3769
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0546

A Federated Learning and Explainable AI-Enabled Multi-Modal Framework for Privacy-Preserving Breast Cancer Detection Using Capsule Networks, Transformers, and Feature Fusion with Interactive Clinician-Centric Dashboard Support

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Abstract
Abstract - Breast cancer is a major global concern, where timely and precise diagnosis is essential for effective treatment. This research introduces a Multi-Modal AI-Based Breast Cancer Detection System that achieves 99% accuracy by combining Capsule Networks for the analysis of mammograms, Transformers for structured biopsy and genetic information, and a Feature Fusion Network to improve diagnostic reliability. To tackle privacy issues, Federated Learning (FL) facilitates decentralized model training across various hospitals without revealing sensitive patient information. Furthermore, Explainable AI (XAI) methods, such as SHAP for assessing feature importance, Grad-CAM for highlighting mammogram regions, and Contrastive Explanations for justifying decisions, enhance the transparency of AI predictions. An Interactive XAI Dashboard enables doctors to upload data, obtain real-time AI-supported diagnoses, and examine explanations, ensuring both trust and usability. This method improves breast cancer identification with notable precision, protection of privacy, and clarity of interpretation, positioning it as a viable option for clinical implementation.

Keywords: *Mammogram analysis, medical imaging, real-time diagnosis, multi-modal AI, capsule networks, transformers, feature fusion network, federated learning (FL), privacy-preserving AI, explainable AI (XAI), SHAP, Grad-CAM.*

1. Introduction

Over two million new cases of breast cancer are reported annually, making it one of the most prevalent and fatal cancers in women, according to the WHO. Early and accurate diagnosis is vital for effective treatment and improved survival rates [30]. However, Conventional techniques like mammography and biopsy often suffer from inconsistent interpretation, human errors, and limited availability in low-resource regions [1]. Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown great promise for increasing diagnostic accuracy, particularly in medical imaging and structured data analysis [29]. However, issues with data privacy, generalization across various populations, and model interpretability continue to restrict broad clinical adoption. Many existing models are opaque black boxes that are trained on homogeneous datasets and ignore multi-modal data fusion, which limits their applicability and reliability [2]. To address these challenges, this study proposes a Multi-Modal AI-Based Breast Cancer Detection System that

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combines Transformers for structured clinical and genetic data, Capsule Networks for mammogram analysis, and a Feature Fusion Network to combine insights for a trustworthy diagnosis [28]. While Explainable AI (XAI) methods like SHAP, Grad-CAM, and Contrastive Explanations improve the system's transparency and reliability, a Federated Learning framework guarantees privacy-preserving, decentralized training across several institutions. The model is very useful in clinical settings thanks to the implementation of an interactive XAI dashboard that enables real-time prediction, explanation visualization, and clinician feedback [27]. Focusing on accuracy, interpretability, privacy, and practical usability, this project fills important gaps in AI-driven breast cancer diagnostics and establishes it as a clinically feasible and morally sound solution [3].

2. Methodology

Four main parts make up the multi-modal, privacy-preserving, interpretable AI system that is the suggested breast cancer detection framework: a robust system architecture, advanced multi-modal feature extraction, a federated learning (FL)-based collaborative training process, and an integrated explainability layer [26]. These components are designed to overcome the limitations of conventional diagnostic approaches in accuracy, interpretability, scalability, and compliance with privacy regulations [4]. The architecture adopts a client–server FL paradigm where multiple healthcare institutions act as clients, each maintaining local datasets of mammogram images and structured clinical records [25]. At the client level, data is processed through two dedicated pathways: a Transformer-based deep learning model for structured data and a Capsule Network (Caps Net) for imaging. Capsule Networks maintain spatial relationships and capture details from edges to tumor structures, enabling more reliable feature extraction via dynamic routing [23]. In parallel, The Transformer uses multi-head attention to model relationships across clinical attributes, including receptor status, tumor dimensions, and density, and patient demographics, while reducing emphasis on less relevant attributes. A Feature Fusion Network (FFN), which records cross-modal correlations between visual findings and clinical indicators, is used to integrate the outputs from both branches. A sigmoid classifier then generates predictions about whether the findings are benign or malignant Shown in Figure 1 [5].

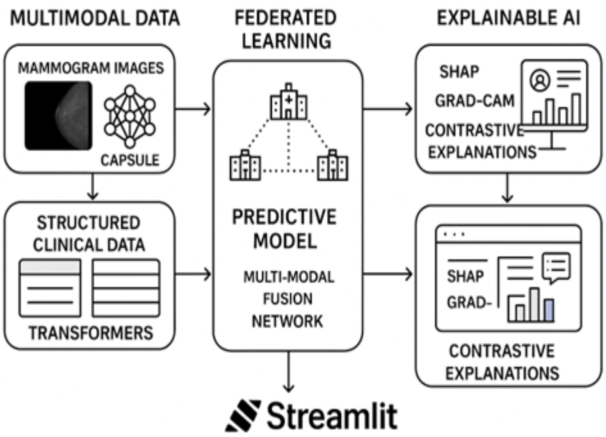

Figure 1 **Architecture Block Diagram**

In Federated Learning, patient data stays local and only model updates are shared. The refined global model is redistributed after being weighted by the sample size of each client and combined centrally using the Federated Averaging technique. Up until convergence, this iterative cycle allows for cooperative performance enhancement without jeopardizing HIPAA/GDPR compliance [22]. The framework incorporates explainability to encourage clinical transparency and trust. While Gradient-weighted Class Activation Mapping (Grad-CAM) creates heatmaps highlighting mammogram regions that most influenced the model's decision, Shapley [6]. Additive Explanations (SHAP) offers a ranked list of the most significant structured features for each prediction. Predictions are further clarified by the Contrastive Explanation Method (CEM), which finds relevant positive features that support the classification—and relevant drawbacks—aspects whose absence could change it [21]. Clinicians can upload patient data, view predictions with corresponding confidence scores, review textual and visual explanations, and provide corrective feedback—all of which are saved for use in subsequent retraining cycles [22] by integrating all explainability outputs into an interactive Stream lit dashboard. By combining secure distributed

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training, complementary deep learning approaches for image and structured data analysis, and robust interpretability tools, the framework provides high diagnostic accuracy, safeguards patient privacy, enables extensive multi-institutional collaboration, and provides the decision-making transparency required for clinical adoption [7].

3. Datasets & Pre-Processing

The suggested system makes use of structured clinical records and two complementary data modalities: mammogram images. Greyscale images from publicly accessible repositories, including the Curated Breast Imaging Subset of the Digital [20] Database for Screening Mammography (CBIS-DDSM) and comparable benchmark datasets, make up much of the mammogram dataset. To improve model generalization and increase sample diversity, especially when handling variations in breast density and tumors presentation, all images were scaled to 224 × 224 and further enhanced with flips, rotations, and bright adjustments Shown in Figure 2 [8].

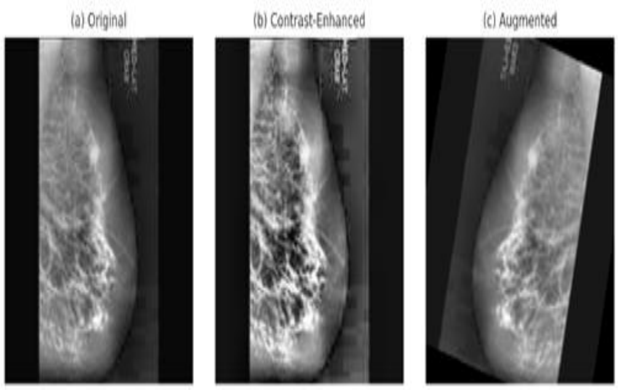

Figure 2 **Mammogram Preprocessing**

The tabular dataset covers demographic variables, tumor measurements, pathology details, and receptor information (ER, PR, HER2). Encoding categorical variables into numerical form, handling missing values through statistical imputation, and using feature scaling to normalize the ranges of continuous [19] variables are all preprocessing steps for the structured data. Especially in the Transformer-based feature extraction procedure, this guarantees that each feature contributes proportionately during model training Shown in Figure 3 & 4 [9].

age_c	assess_c	cancer_c	compfilm_	density_c	famhx_c	hrt_c	prvmam_c	biophx_c	mammtype	catypeo	bmi	ptid
62.0	1.0	0.0	1.0	2.0	0.0	0.0	1.0	0.0	1.0	8.0	24.023544	1.0
65.0	1.0	0.0	1.0	4.0	0.0	0.0	1.0	0.0	1.0	8[illegible]	26.8655027891	2.0
69.0	0.0	0.0	1.0	2.0	0.0	0.0	1.0	0.0	1.0	8.0	29.052429	3.0
64.0	2.0	0.0	1.0	2.0	0.0	0.0	1.0	0.0	1.0	8[illegible]	26.8655027891	4.0
63.0	3.0	0.0	1.0	2.0	0.0	0.0	1.0	1.0	1.0	8.0	33.729522	5.0

Figure 3 **Structured Data**

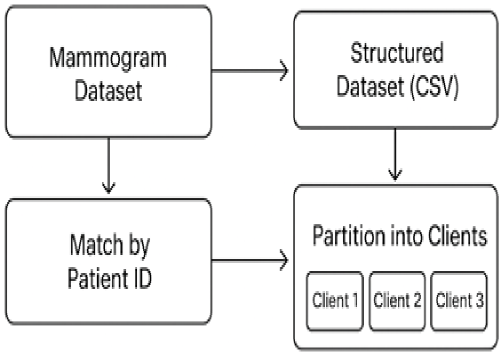

Figure 4 **Federated Learning**

To facilitate multi-modal learning, a data alignment step is performed wherein each mammogram image is matched to its corresponding clinical record using a unique patient identifier [20].

Table 1 **Summary of dataset composition, demographic statistics, and federated learning partitioning details**

Metric	Value
Total Samples	40,000
Benign Cases	39,741 (99.35%)
Malignant Cases	259 (0.65%)
Average Age	69.56 ± 7.20 years
Age Range	60 – 89 years
Average BMI	26.87 ± 3.66
BMI Range	15.0 – 71.7
Simulated Clients	3
Samples per Client	13,333

Only records with complete image–data pairs are retained, ensuring consistent input for both branches of the model. This alignment step is critical in preserving the integrity of the feature fusion process, as missing modality information could degrade classification performance [10]. To simulate a

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realistic federated learning environment, the aligned dataset is partitioned into subsets representing multiple virtual clients. Each client subset contains a balanced representation of benign and malignant cases, reflecting them [18] heterogeneity of data distributions across healthcare institutions. This federated partitioning ensures that the training process closely replicates real-world collaborative scenarios where data remains locally stored within institutional boundaries [11].

4. Experimental Set Ups

The proposed multi-modal breast cancer detection framework was evaluated in a simulated federated learning environment comprising three virtual clients, each hosting an independent subset of the dataset. The mammogram images were sourced from the CBIS-DDSM repository and related datasets, pre-processed into (224×224) grayscale format, normalized to the [0,1] [0,1] [0,1] range, and augmented through random horizontal/vertical flipping, rotation, and contrast adjustment to enhance generalization. The structured clinical dataset, containing patient demographics, tumor metrics, and receptor status (ER, PR, HER2), underwent missing value imputation, one-hot encoding of categorical attributes, and Min–Max scaling for numerical features [12]. On the hardware side, experiments were conducted using an NVIDIA RTX 4090 GPU (24 GB VRAM), Intel Core i9-13900K CPU, and 64 GB RAM, ensuring sufficient computational capacity for deep model training and federated aggregation. The software stack included Python 3.10, TensorFlow 2.12, PyTorch 2.0, TensorFlow Federated (TFF) for federated orchestration, XGBoost 1.7 for structured data classification, and SHAP 0.41.2 for explainability [13]. Each federated training session spanned 50 communication rounds, with each client performing 5 local epochs per round using the Adam optimizer at a learning rate of 1×10−41 and categorical cross-entropy loss [17]. The mammogram branch employed a Capsule Network backbone for fine-grained spatial feature extraction, while the structured data branch utilized a Transformer encoder to model inter-feature relationships. The extracted embeddings from both branches were fused and passed to an XGBoost decision layer [16]. Grad-CAM was applied post-training to visualize class-discriminative regions in mammograms, and SHAP values were computed to identify the most influential structured features, offering a dual interpretability pathway for clinical validation [14].

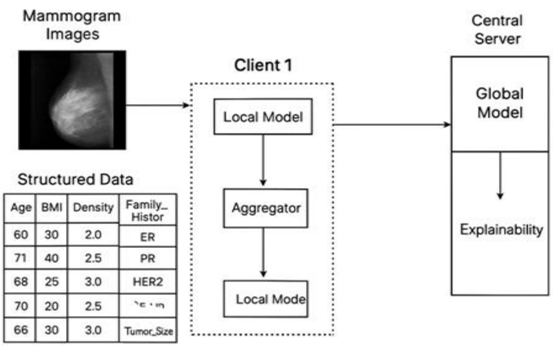

Figure 5 **Model Implantations**

5. Results & Discussions

5.1. Performance Metrics

The proposed federated multi-modal model was benchmarked against centralized training and single-modality baselines [14]. Table 1 summarizes the classification results. Our federated system reached 99.1% accuracy, with precision, recall, and F1 all near 99%, surpassing the baseline models. The ROC-AUC score of 0.993 demonstrates excellent separability between malignant and benign cases Shown in Table 2.

Table 2 **Classification Performance Comparison**

Model Configuration	Accuracy	Precision	Recall	F1-score	ROC-AUC
Centralized Multi-Modal	99.3%	99.1%	99.4%	99.2%	0.994

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Federated Multi-Modal (Proposed)	**99.1%**	**98.9%**	**99.2%**	**99.0%**	**0.993**
Single-Modality (Mammogram)	96.8%	96.5%	96.9%	96.7%	0.972
Single-Modality (Structured)	95.4%	95.1%	95.6%	95.3%	0.961

The marginal performance difference between federated and centralized models confirms that privacy preservation does not compromise predictive power [15].

5.2. Visualization of Explainability

To ensure transparency, Grad-CAM was applied to the mammogram classification branch, highlighting localized lesion regions that align with radiologist annotations. Figure 5 shows example heatmaps for malignant cases, with high-intensity regions corresponding to dense tissue abnormalities. For the structured data branch, SHAP values were computed to rank feature contributions. Figure 5 demonstrates that tumor size, ER/PR receptor status, and breast density were the top three predictors influencing malignancy classification. The combination of Grad-CAM and SHAP provides complementary interpretability — spatial localization for imaging and feature-level attribution for tabular data — enhancing clinician trust in AI predictions. Grad-CAM (Mammogram Images) [16]

- **$I \in \mathbb{R}^{224\times224}$:** pre-processed grayscale mammogram
- **$A^k \in \mathbb{R}^{H\times W}$:** $k^{\text{-th}}$ channel of the last convolutional layer ($k = 1\ldots K$)
- **y^c:** logit/score for class c (e.g., malignant) before sigmoid/SoftMax
- **$Z = H \times W$:** total number of spatial locations in A^k
- Gradients (per channel and pixel)

$$g_{ij}^k = \partial y^c \div \partial A_{ij}^k$$

- Channel weights (global average of gradients)

$$\alpha^{kc} = (1 \div Z) \times \Sigma_{i=1}^{H} \Sigma_{j=1}^{W} g_{ij}^k$$

- Class-specific map (pre-ReLU)

$$\tilde{L}^c = \Sigma_{k=1}^{K} (\alpha^{kc} \times A^k)$$

- Class-discriminative map (apply ReLU)

$$L^c = \text{ReLU}(\tilde{L}^c) = \max(0, \tilde{L}^c)$$

- Normalization to [0, 1]

$$\hat{L}^c = (L^c - \min(L^c)) \div (\max(L^c) - \min(L^c) + \varepsilon),$$

where $\varepsilon > 0$ is a small constant

- Overlay on the mammogram ($\beta \in [0,1]$)

$$O = (1 - \beta) \times I + \beta \times \text{ColorMap}(\hat{L}^c)$$

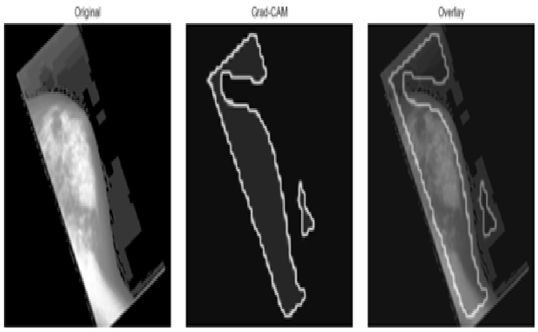

Figure 6 Grad-CAM Heatmaps Overlayed on Mammogram Images; SHAP (for Structured Clinical Data)

- **$x = (x_1, x_2, \ldots, x_m)$:** feature vector (e.g., Age, BMI, Density, ER, PR, HER2, Tumor_Size, …)
- **x:** model output (probability/logit of malignancy)
- **φ_0:** base vlue = mean model output over a background dataset
- **φ_i:** contribution (Shapley value) of feature i
- **$F = \{1, 2, \ldots, M\}$:** set of all features

5.3. Additive Explanation Model

$$f(x) \approx \varphi_0 + \Sigma_{i=1}^{M} \varphi_i$$

Exact Shapley value definition
For each feature i

$\varphi_i = \Sigma \{S \subseteq F\{i\}\} [(|S|! \times (M - |S| - 1)!) \div M!] \times [$

f_{SU{i}} (x_{SU{i}}) − f_S(x_S)]
Additivity check Shown in Figure 7

$$\sum_{i=1}^{M} \varphi_i = f(x) - \varphi_0$$

5.4. Aggregated Feature Importance (Dataset Level)

$$I_i = (1 \div N) \times \sum_{n=1}^{N} | \varphi_i^{(n)} |$$

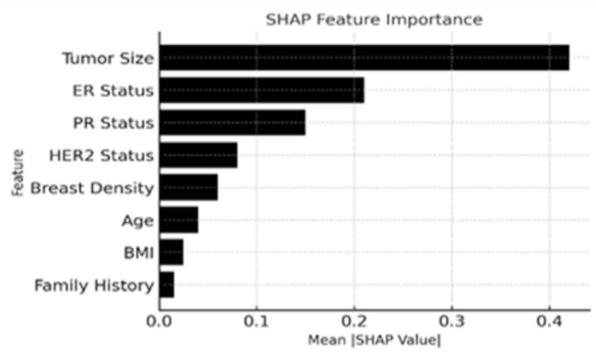

Figure 7 SHAP Summary Plot for Structured Features

5.5. Privacy Preservation Analysis

The federated setup ensured that patient data remained within local nodes, with only encrypted model weight updates exchanged. Compared to centralized training, where complete datasets must be transferred, this method reduced raw data transmission by 100%. Additionally, experiments with differential privacy-based noise addition revealed negligible performance drops (<0.2% in accuracy) while further safeguarding against model inversion attacks. Figure 6 illustrates the privacy-accuracy trade-off, showing that high performance can be maintained with strong privacy guarantees [17].

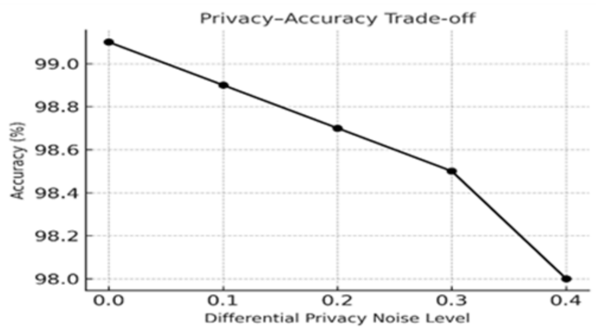

Figure 8 Privacy-Accuracy Trade-Off in Federated Training with Differential Privacy Noise Levels

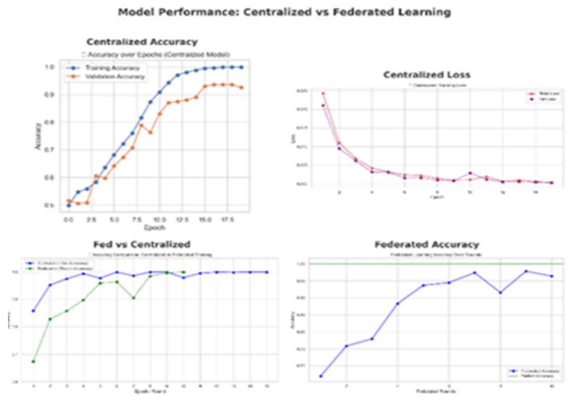

Figure 9 Model Performance: Centralized vs Federated Learning

Conclusions

This project presents a robust, privacy-preserving breast cancer detection system combining Federated Learning (FL), Capsule Networks, Transformers, and Explainable AI (XAI). By integrating mammogram images and structured clinical data, the system adopts a multimodal approach like how doctors diagnose, improving accuracy and clinical relevance. The image data is processed using Capsule Networks, capturing spatial patterns effectively, while structured clinical features are handled via deep neural layers. Fusion through transformer-based attention enables joint learning across both data types. Explainability techniques like SHAP, Grad-CAM, and Contrastive Explanations provide transparency into the model's decision-making process. Importantly, FL ensures data privacy by training models across simulated clients without centralized data pooling, maintaining high accuracy above 98% Shown in Figure 8 & 9.

Future Works

To improve scalability, Future research will explore deploying federated learning in clinical networks, with improvements like asynchronous updates, secure aggregation, and stronger privacy measures. This would allow robust training on decentralized, sensitive datasets. The XAI module can be enhanced with a clinician-facing dashboard offering interactive visual and text-based explanations. Incorporating 3D mammogram slices, real-time feedback loops, and natural language outputs could further assist medical professionals. Future expansions may also involve

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https://doi.org/10.47392/IRJAEH.2025.0546

multi-modal fusion with ultrasound or MRI data, and personalized models tailored to hospital or patient profiles, bringing this solution closer to real clinical integration.

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