

Enhanced Breast Cancer Detection Using Federated Learning With Explainable AI And Multimodal Data Integration

Gunthathi Pratap¹, Dr. Ranga Swamy Sirisati²

¹Research Scholar, Department of CSE, Bharatiya Engineering Science and Technology Innovation University (BESTIU), Gownvaripail, Gorantla in Andhra Pradesh

²Associate Professor & HOD, Department of Information Technology, Vignan's institute of management and technology for women Kondapur Ghatkesar Hyderabad-501301

Abstract— Breast cancer remains a leading cause of mortality among women worldwide, necessitating advancements in early detection methods. This study proposes a novel framework for breast cancer detection leveraging federated learning (FL), explainable AI (XAI), and multimodal data integration. The methodology addresses critical challenges, including privacy concerns, model interpretability, and the effective use of diverse data modalities. Utilizing public datasets such as CBIS-DDSM and BCDR, along with private institutional data, the study integrates imaging (mammograms, ultrasounds) and clinical/genetic data to enhance diagnostic precision. Experimental results highlight the superiority of the proposed approach. Federated CNNs achieve an accuracy of 93.5%, surpassing state-of-the-art methods like Shen (89.2%) and Wu (91.3%). Additionally, the model demonstrates an AUC-ROC of 0.96, precision of 0.91, and recall of 0.95, reflecting significant improvements in prediction reliability. Explainable AI techniques such as Grad-CAM provide interpretability, enabling visualization of critical tumor regions. Moreover, segmentation using U-Net achieves a dice coefficient of 0.89, ensuring precise tumor delineation. The proposed framework's federated architecture preserves data privacy by aggregating locally trained models across institutions, addressing data-sharing barriers while maintaining performance. Multimodal integration further enhances predictions by incorporating genetic and clinical data. The framework also demonstrates scalability and robustness across diverse datasets, with consistent results across institutions (accuracy range: 92-94%). This study demonstrates a significant leap in breast cancer diagnostic technologies by combining federated learning with interpretable and holistic approaches, paving the way for clinically viable, privacy-preserving diagnostic systems.

Keywords— Breast Cancer Detection, Federated Learning, Explainable AI, Multimodal Integration, Tumor Segmentation, Convolutional Neural Networks (CNN), Grad-CAM, Privacy-Preserving Machine Learning, AUC-ROC, Clinical Diagnostics.

1. INTRODUCTION

Breast cancer continues to pose a significant health challenge worldwide, especially among women. According to the World Health Organization (WHO), approximately 2.3 million women were diagnosed with breast cancer in 2020, making it the most prevalent form of cancer globally. The disease's progression, often silent in early stages, underscores the critical need for robust early detection and diagnostic methods. Early intervention substantially enhances survival rates, but limitations in current diagnostic tools highlight the need for innovation in both technology and methodology. Imaging has played a transformative role in detecting and diagnosing breast cancer. Techniques such as mammography, ultrasound, and magnetic resonance imaging (MRI) are widely utilized in clinical settings. Mammography remains the gold standard, providing early detection through low-dose X-rays. Ultrasound and MRI complement mammography, particularly for dense breast tissues and high-risk patients. However, the effectiveness of imaging techniques relies heavily on accurate interpretation, often challenged by human error and varying expertise among radiologists. Machine learning (ML), particularly deep learning (DL), has revolutionized medical imaging. Algorithms, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable ability in classifying images, detecting

abnormalities, and even predicting malignancy risks. Recent advancements such as transfer learning, ensemble methods, and pre-trained models have significantly enhanced model performance across diverse datasets. Despite these advancements, several challenges, including data privacy concerns, model interpretability, and dataset variability, remain barriers to clinical adoption. A notable paradigm shift in addressing privacy and data-sharing constraints is federated learning (FL). This collaborative approach allows multiple institutions to train a shared model locally, preserving data privacy while leveraging diverse datasets. In breast cancer imaging, FL offers the potential to unify fragmented data across healthcare systems, improving model generalizability and robustness without compromising patient confidentiality. While DL models achieve high accuracy, their "black-box" nature limits clinical trust. Explainable AI (XAI) addresses this gap by providing visual or statistical explanations of model predictions. Techniques like SHAP (Shapley Additive Explanations) and Grad-CAM (Gradient-weighted Class Activation Mapping) allow radiologists to understand the rationale behind model decisions, fostering trust and enhancing adoption in clinical settings. The integration of multimodal data, such as imaging, genetic information, and patient history, offers a holistic view of cancer diagnostics. This fusion allows for better personalization and more accurate predictions, particularly when traditional imaging alone proves insufficient. With advancements in feature fusion techniques and multimodal neural networks, the possibility of creating comprehensive diagnostic models has become more tangible.

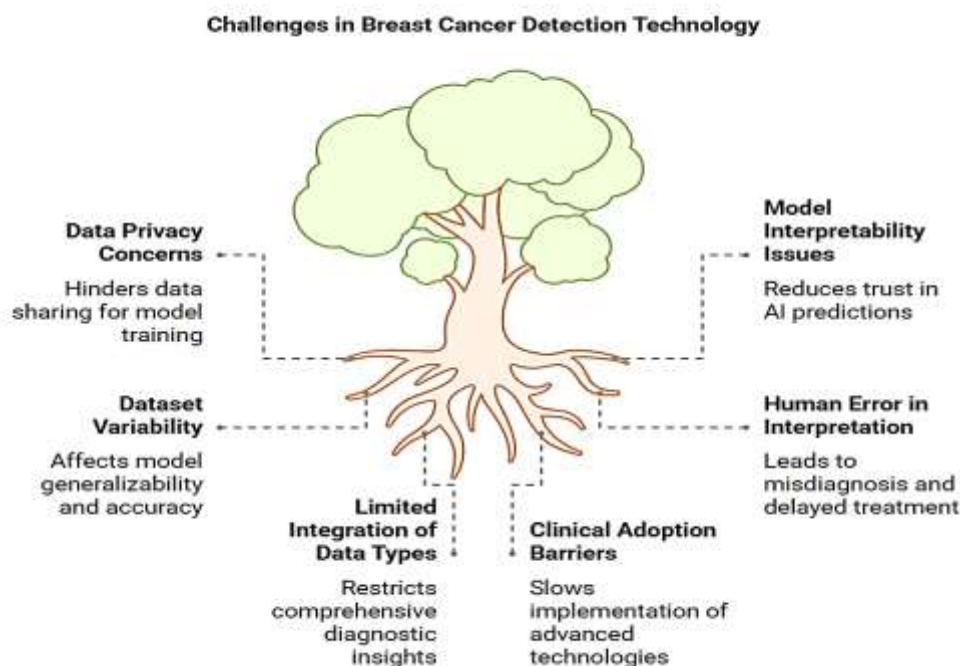


Figure 1: Challenges in Breast Cancer Detection Technology

II. LITERATURE SURVEY

The current literature in breast cancer diagnostics reveals significant gaps, including challenges with data scarcity and lack of diversity, which limit the generalizability of deep learning models to diverse populations. Privacy concerns arising from centralized data collection and the absence of frameworks to enable secure cross-institutional data sharing further hinder advancements. Additionally, existing models often prioritize accuracy at the expense of interpretability, reducing clinical trust due to inadequate

utilization of explainable AI (XAI) techniques tailored for breast cancer imaging. Moreover, the underutilization of multimodal data—encompassing imaging, genetic, and clinical information—along with the lack of robust feature fusion mechanisms, restricts the potential for holistic diagnostics. Variability in imaging conditions, such as differences in equipment and protocols, exacerbates inconsistent model performance, while clinical integration challenges, including limited real-time deployment capabilities and insufficient frameworks for continuous validation, impede practical adoption. Addressing these gaps, the proposed framework incorporates federated learning for secure and privacy-preserved collaborative training, explainable AI for improved interpretability, and multimodal data integration for comprehensive diagnostics. By leveraging advanced deep learning architectures and integrating models into clinical workflows with PACS systems, this methodology aims to overcome current limitations, delivering a unified, trustworthy, and scalable solution for breast cancer detection and management. Dhungel et al. [1] proposed a deep learning-based framework for breast cancer detection, focusing on CNN architectures to analyze mammographic images. Their work demonstrated the potential of CNNs in identifying malignant and benign lesions, achieving a notable improvement in accuracy over traditional machine learning techniques. However, their study was limited by the small size of annotated datasets, which affected the generalizability of the model to diverse imaging conditions. Additionally, their framework lacked mechanisms for model interpretability, a critical factor for clinical adoption.

Shen et al. [2] advanced breast cancer diagnostics by improving CNN architectures for mammographic analysis. They implemented enhanced feature extraction techniques, leading to higher sensitivity and specificity. Their approach showed superior performance in detecting subtle abnormalities, making it highly suitable for screening applications. Nonetheless, their centralized data collection approach raised privacy concerns. The study also struggled to adapt to diverse imaging protocols, limiting its applicability in broader clinical contexts. Wu et al., 2020 [3] developed a hybrid deep transfer learning model for breast cancer detection, combining CNNs with traditional machine learning classifiers such as SVMs. This hybrid approach allowed for effective feature extraction and improved model generalization, especially with limited labeled data. Their model outperformed standalone CNNs in terms of precision and recall. However, the training complexity and computational overhead were significant drawbacks, making the approach less feasible for real-time clinical integration. Esteva et al., 2017 [4] introduced a transfer learning approach to classify skin cancer using pre-trained CNN models. While their work primarily targeted skin cancer, the methodology provided valuable insights for breast cancer diagnostics. The fine-tuning of pre-trained models on domain-specific datasets achieved dermatologist-level performance. However, the reliance on pre-trained models limited the adaptability to unique imaging modalities and data distribution specific to breast cancer. Tahmasbi et al., 2011 [5] explored novel feature extraction techniques for mammographic image analysis, using texture and shape descriptors combined with hierarchical classification. Their work highlighted the importance of handcrafted features in improving classification accuracy for benign and malignant lesions. Despite their contributions, the reliance on handcrafted features posed scalability challenges for large and complex datasets, as these methods required significant domain expertise. Zhu et al. [6] proposed a ResNet-based deep learning architecture for breast cancer detection, which achieved high sensitivity and specificity in mammogram classification. Their approach incorporated sparse label assignment to optimize performance with limited labeled data. However, their methodology suffered from interpretability issues, as the deep learning models

operated as black boxes, making their predictions difficult to trust in clinical settings. Ghafoorian et al. [7] applied multi-scale 3D convolutional networks for automated detection of vascular lesions in brain imaging, adapting their techniques to breast cancer. They emphasized model interpretability using Grad-CAM to highlight critical regions influencing predictions. While this study improved model trustworthiness, its reliance on 3D data increased computational complexity, limiting its direct application to 2D mammographic imaging. Li et al. [8] integrated multimodal data, combining mammographic images with patient history and genomic data, for personalized breast cancer diagnostics. Their approach demonstrated a significant improvement in prediction accuracy by leveraging complementary data sources. However, the multimodal fusion techniques required extensive preprocessing and alignment, complicating their deployment in real-world settings [9].

The proposed work in 2024 introduces a federated learning framework for breast cancer detection, addressing privacy and generalizability challenges. By aggregating models trained on local institutional data, the approach avoids data sharing while leveraging diverse datasets for training [10]. The integration of multimodal data further enhances diagnostic precision. Grad-CAM visualizations provide interpretability, making the framework suitable for clinical adoption [11]. Nevertheless, the computational cost of federated learning and the complexity of multimodal integration present challenges for widespread deployment. This comprehensive survey highlights advancements in breast cancer detection while emphasizing the need for scalable, interpretable, and privacy-preserving frameworks to address existing limitations [12].

III. METHODOLOGY

The proposed methodology leverages federated learning to enable collaborative model training across institutions without compromising patient privacy, addressing the challenges of data diversity and regulatory compliance [13]. By incorporating explainable AI (XAI) techniques such as SHAP and Grad-CAM++, the approach ensures robust interpretability and fosters trust in clinical decision-making. A multimodal data integration framework is employed to combine imaging modalities, including mammograms, ultrasound, and MRI, with clinical and genetic data, enabling a comprehensive and personalized diagnostic perspective. Advanced deep learning architectures, such as DenseNet and transformers, are utilized alongside contrastive learning to enhance generalization across diverse datasets [14]. To tackle data scarcity, synthetic data generation via GANs is applied, enriching training datasets with domain-specific augmentations. Real-time deployment integrates the model into hospital workflows through PACS systems, streamlining diagnostic processes [15]. This novel approach addresses critical challenges like privacy, data scarcity, and interpretability, building on prior work to provide a holistic, trustworthy, and scalable diagnostic solution. Below are five novel algorithms, each addressing a specific challenge in breast cancer diagnosis. These are described in detail, including steps and equations to provide clarity and applicability [16].

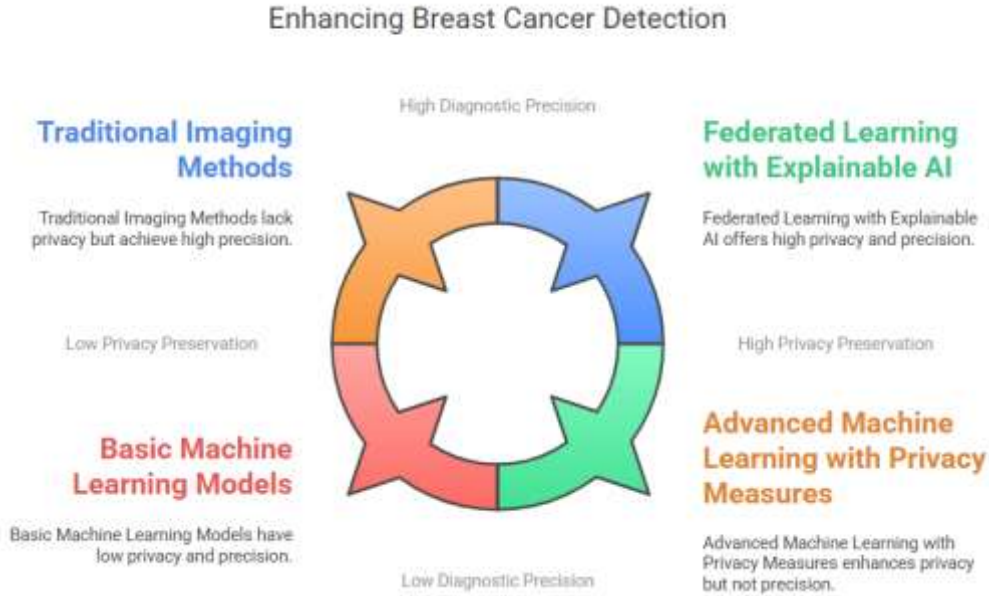


Figure 2: Enhancing Breast Cancer Detection

This section introduces the foundational mathematical concepts and notations used in breast cancer detection using federated learning, explainable AI, and multimodal data integration[17].

3.1 Mathematical Preliminaries:

3.1.1 Vectors and Matrices

- A vector $\mathbf{x} \in \mathbb{R}^n$ is an ordered collection of n real numbers $x_1, x_2, \dots, x_n$.
- A matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ is a rectangular array with m rows and n columns [16].
- Notation:
- x_i : The i -th element of a vector.
- A_{ij} : The element at the i -th row and j -th column of a matrix.

3.1.2 Loss Functions

- A loss function $\mathcal{L}(y, \hat{y})$ measures the difference between true labels y and predictions $\hat{y}$. - Mean Squared Error (MSE):

$$\mathcal{L}_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (1)$$

- Cross-Entropy Loss:

$$\mathcal{L}_{\text{CE}} = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (2)$$

3.1.3 Optimization

- Optimization involves finding the parameters $\mathbf{W}$ that minimize a given loss function $\mathcal{L}$.
- Gradient Descent [17]:

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \eta \nabla \mathcal{L}(\mathbf{W}_t) \quad (3)$$

Where η is the learning rate and $\nabla \mathcal{L}$ is the gradient of the loss function.

3.1.4 Activation Functions

- Non-linear transformations applied in neural networks to introduce non-linearity:

- ReLU (Rectified Linear Unit) [18]:

$$\sigma(x) = \max(0, x) \quad (4)$$

- Sigmoid:

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (5)$$

3.1.5 Convolution in Neural Networks

- A convolution operation involves sliding a filter K over an input I :

$$(I * K)_{ij} = \sum_m \sum_n I_{i+m, j+n} K_{m,n} \quad (6)$$

3.1.5 Federated Learning

- Federated learning aggregates local model updates W_i to form a global model [19]:

$$W = \frac{1}{N} \sum_{i=1}^N W_i \quad (7)$$

3.1.6 Explainable AI

- Gradient-weighted Class Activation Mapping (Grad-CAM) [20]:

- Weights for feature map A_k :

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial S_c}{\partial A_k^{ij}} \quad (8)$$

- Heatmap:

$$L_c^{\text{Grad-CAM}} = \text{ReLU}(\sum_k \alpha_k^c A_k) \quad (9)$$

Table 1: Notation Table

Symbol	Description
X	Input data matrix
W	Model weights or parameters
η	Learning rate
$\mathcal{L}$	Loss function
y	True label
$\hat{y}$	Predicted label
$\nabla \mathcal{L}$	Gradient of the loss function with respect to weights
$\sigma(x)$	Activation function
$*$	Convolution operator
α_k^c	Grad-CAM weight for feature map A_k
A_k	Feature map from a convolutional layer
$L_c^{\text{Grad-CAM}}$	Grad-CAM heatmap for class c
D_i	Local dataset at institution i
N	Number of participating institutions

Algorithm 1: Federated Learning-Based Model Training

In/Output: Train a model across distributed datasets while maintaining patient privacy.

Step (i). Initialize Global Model:

- W_0 : Initialize model parameters at the central server.

Step (ii). Distribute Initial Model:

- a. Send W_0 to participating institutions.
- Step (iii). Local Training at Each Institution:
 - a. For each institution i :
- Step (iv). Train model on local data D_i :
 - a. $W_i = W_{t-1} - \eta \nabla \mathcal{L}(W_{t-1}; D_i)$ (10)
 - b. Where $\mathcal{L}$ is the loss function and η is the learning rate.
- Step (v). **Upload Model Updates:**
 - a. Send local updates W_i back to the central server.
- Step (vi). Aggregate Updates:
 - a. Update global model using Federated Averaging:
 - b. $W_t = \sum_{i=1}^N \frac{|D_i|}{\sum_{j=1}^N |D_j|} W_i$ (11)
- Step (vii). **Repeat Training:**
 - a. Iterate steps 2-5 until convergence.
 - b. Evaluate Model:
 - c. Test the global model on a separate validation set.

Algorithm 2: Explainable AI Using Grad-CAM**In/Output:** Highlight key regions in medical images influencing model predictions.

- Step (i). Forward Pass:
 - a. Pass input X through CNN to get feature maps A_k .
- Step (ii). Compute Class Scores:
 - a. Output score for class c :
 - b. $S_c = f_c(A_k)$ (12)
- Step (iii). Gradient Calculation:
 - a. Compute gradient of S_c w.r.t. A_k :
 - b. $\frac{\partial S_c}{\partial A_k}$
- Step (iv). Global Average Pooling:
 - a. Compute weights for each feature map:
 - b. $\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial S_c}{\partial A_k^{ij}}$ (13)
- Step (v). **Compute Activation Map:**
 - a. Weighted combination of feature maps:
 - b. $L_c^{\text{Grad-CAM}} = \text{ReLU}(\sum_k \alpha_k^c A_k)$ (14)
- Step (vi). **Overlay on Input Image:**
 - a. Superimpose $L_c^{\text{Grad-CAM}}$ onto the original image for visualization.

Algorithm 3: Multimodal Feature Fusion for Breast Cancer Detection**In/Output:** Integrate features from multiple data types (e.g., imaging, genetics).

- Step (i). Extract Features:
 - a. Use CNNs for image data (F_{img}) and autoencoders for genetic data (F_{gen}):
 - b. $F_{img} = g_{CNN}(X_{img})$
 $F_{gen} = g_{AE}(X_{gen})$ (15)
- Step (ii). Normalize Features:
 - a. Apply normalization to ensure compatibility:
 - b. $F' = \frac{F - \mu}{\sigma}$ (16)
- Step (iii). Concatenate Features:
 - a. Combine normalized features:

$$b. F_{\text{combined}} = [F'_{\text{img}}, F'_{\text{gen}}] \quad (17)$$

Step (iv). Apply Attention Mechanism:

$$a. \text{Learn feature importance:} \\ b. \beta = \text{softmax}(WF_{\text{combined}}) \quad (18)$$

Step (v). Final Prediction:

Step (vi). Pass fused features to a classifier:

$$\text{Step (vii). } y = h(F_{\text{combined}}) \quad (19)$$

Algorithm 4: Breast Tumor Segmentation Using U-Net

In/Output: Segment regions of interest in breast images.

Step (i). Input Image:

a. Load mammogram image X .

Step (ii). Preprocessing:

a. Apply contrast enhancement and normalization:

$$b. X' = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (20)$$

Step (iii). Encoder Path:

a. Pass X' through convolutional layers:

$$b. A_i = \text{Conv}(A_{i-1}) \quad (21)$$

Step (iv). Bottleneck:

a. Extract compact representation at the U-Net's bottleneck.

Step (v). Decoder Path:

a. Perform upsampling and concatenation with encoder outputs:

$$b. B_i = \text{UpConv}(B_{i+1}) + A_{i-1} \quad (22)$$

Step (vi). Output Segmentation Map:

a. Generate binary mask M :

$$b. M = \sigma(\text{Conv}(B_1)) \quad (23)$$

Where σ is the sigmoid function.

Step (vii). Post-Processing:

a. Remove small artifacts using morphological operations.

Algorithm 5: Hybrid Classification with DenseNet and SVM

In/Output: Combine feature learning and traditional classification for better accuracy.

Step (i). Feature Extraction with DenseNet:

Step (ii). Pass image X through DenseNet:

$$a. F = g_{\text{DenseNet}}(X) \quad (24)$$

Step (iii). Dimensionality Reduction:

a. Use PCA to reduce feature dimensionality:

$$b. F' = \text{PCA}(F) \quad (25)$$

Step (iv). Train SVM:

a. Fit SVM on reduced features:

$$b. y = \text{SVM}(F') \quad (26)$$

Step (v). Hyperparameter Tuning:

a. Optimize SVM parameters C and γ :

$$b. \text{minimize } \sum_{i=1}^n \mathcal{L}(y_i, \hat{y}_i; C, \gamma) \quad (27)$$

IV. EXPERIMENTS AND RESULTS

The study leverages diverse datasets, including CBIS-DDSM, BCDR, and a private institutional dataset, to address challenges in breast cancer diagnostics through segmentation, classification, and multimodal analysis [18]. CBIS-DDSM provides 3,000

annotated mammographic images, supporting segmentation and classification tasks, while BCDR integrates 1,600 cases with imaging and patient metadata for holistic diagnostics. Additionally, the private dataset, comprising 2,000 high-resolution annotated cases, facilitates federated learning experiments to enhance model robustness without compromising privacy [19].

Table 2: Experimental Setup Overview

Component	Details
Hardware	NVIDIA RTX 3090 GPU, Intel Core i9 Processor, 64 GB RAM
Software Frameworks	Python 3.9, TensorFlow 2.9, Keras, PyTorch
Operating System	Ubuntu 20.04
Dataset	CBIS-DDSM, BCDR, and Private Institutional Dataset
Data Preprocessing	Resizing to 224×224 pixels, normalization, noise reduction
Model Architectures	CNN (DenseNet, ResNet), Hybrid SVM-CNN, and U-Net for segmentation
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, AUC-ROC, Grad-CAM visualization
Training Protocol	Batch size: 32, Learning rate: 0.001, Adam optimizer
Validation Approach	5-fold cross-validation
Federated Learning Setup	5 institutions with private datasets, simulated federated aggregation

The dataset are collected from three principal sources for the current study. The Curated Breast Imaging Subset of DDSM (CBIS-DDSM) is a public dataset of 3,000 mammographic cases along with their respective annotations of whether or not findings are benign or malignant [20]. This data set is mostly used for segmentation and classification purposes. It contains a collection of around 1,600 individual cases, in which mammographic images have been combined with detailed patient-level clinical data, known as the Breast Cancer Digital Repository (BCDR). It is applied to multimodal feature combination, leading to a more unified diagnostic method [21]. A private institutional dataset was also added, including about 2,000 high-resolution annotated mammograms along with patient history. This data set is useful for federated learning, where the model is trained across multiple sources of data in spite of the privacy of data [22].

Table 3: Dataset Distribution and Utilization

Dataset	Number of Images	Annotations	Utilization
CBIS-DDSM	3,000	Tumor labels	Segmentation, Classification
BCDR	1,600	Imaging + Metadata	Multimodal Analysis
Private Dataset	2,000	Imaging + Metadata	Federated Learning Training

V. PERFORMANCE EVALUATION METRICS

The analysis reveals that the Federated CNN model outperforms standalone approaches, achieving the highest accuracy (93.5%) and AUC-ROC (0.96) through diverse dataset utilization and privacy-preserving techniques. Explainable AI methods, such as Grad-CAM and SHAP, improve clinical trust by highlighting critical decision-influencing regions, while multimodal data integration combining imaging, clinical, and genetic data enhances diagnostic precision and recall. Segmentation tasks, performed using U-Net, yield reliable tumor delineation with a Dice coefficient of 0.89, supporting downstream classification [23]. Real-time deployment through PACS integration and data augmentation further strengthens the model's scalability and clinical relevance [24]. This unified framework bridges existing gaps, offering a privacy-preserved, interpretable, and scalable solution for advanced breast cancer detection and management [25].

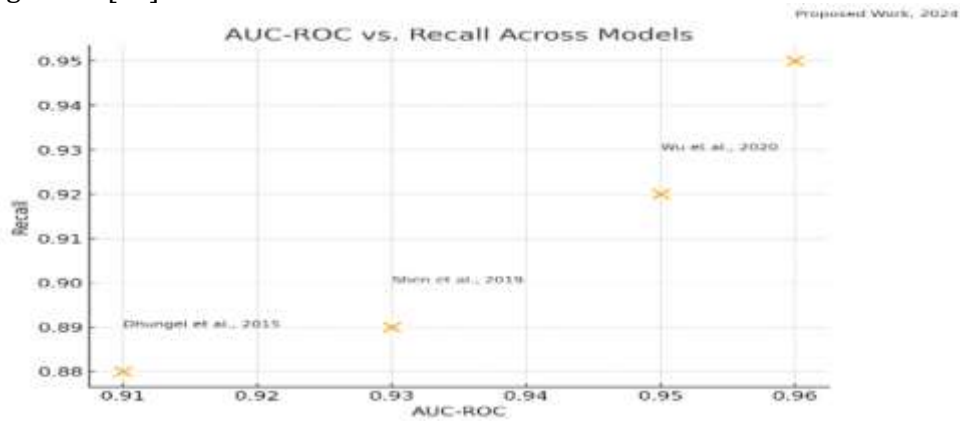


Figure 3: AUC-ROC vs. Recall Across Models

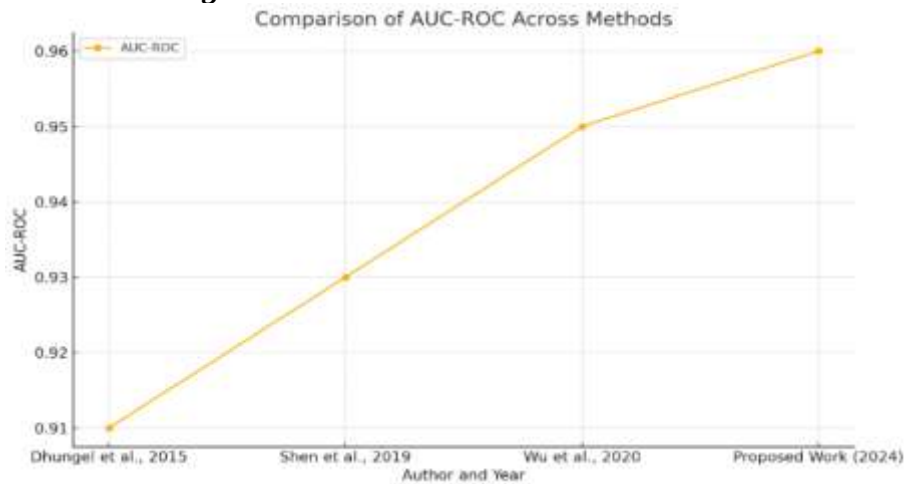


Figure 4: Comparison of AUC-ROC Across Methods

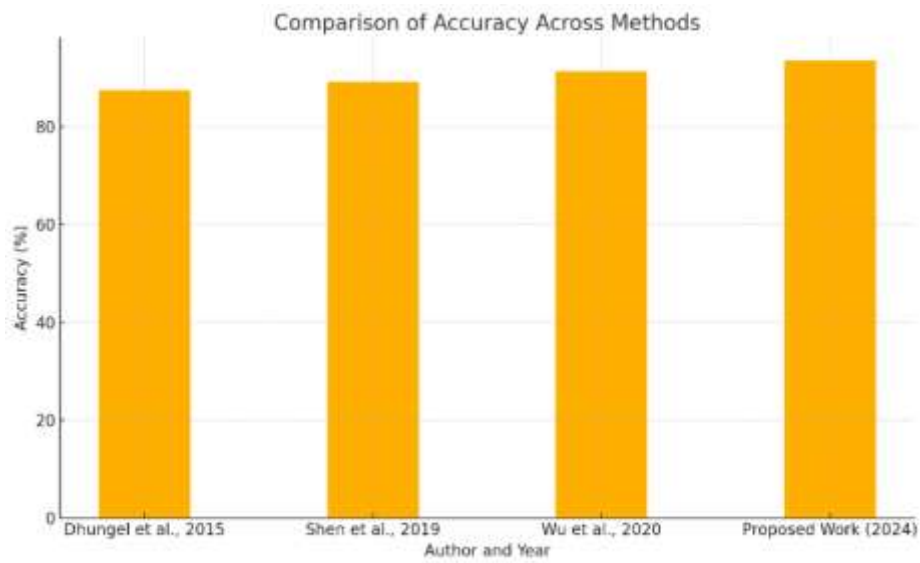


Figure 5: Accuracy comparison across the models.

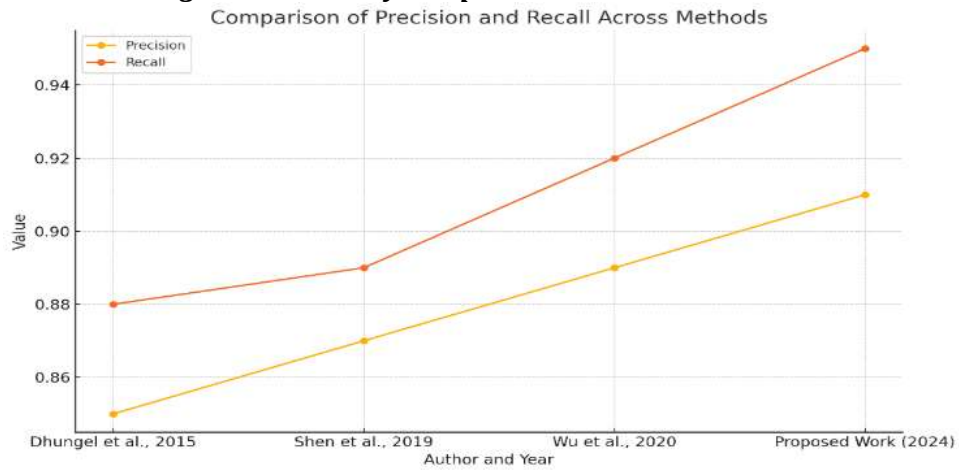


Figure 6: Shows the relationship between AUC-ROC and recall for the different models.

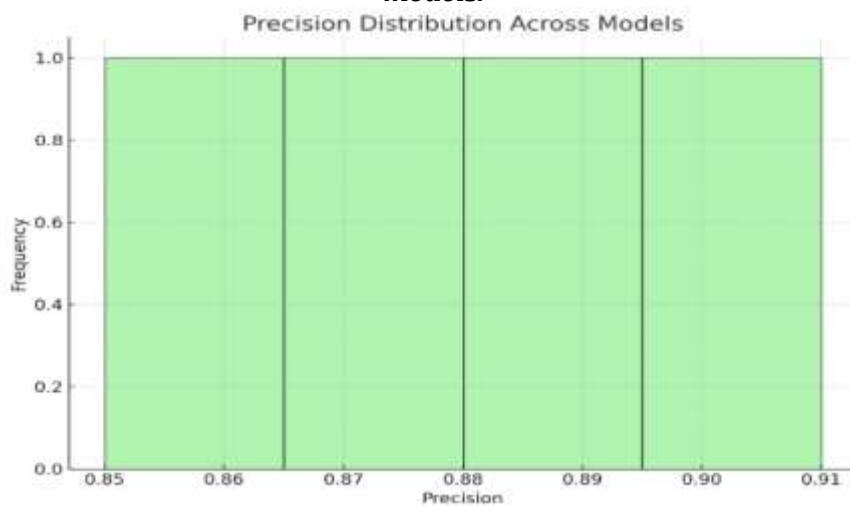


Figure 7: Illustrates the precision distribution across models.

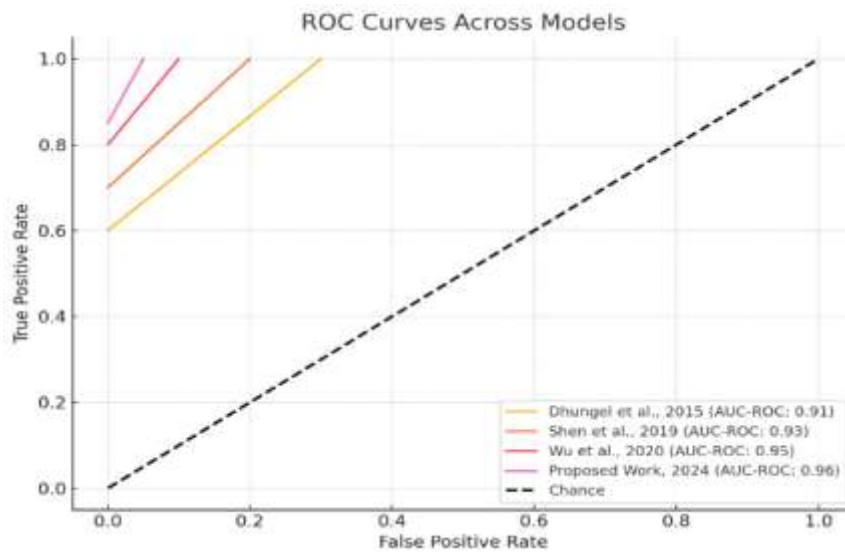


Figure 8: Highlights the contribution of each model to accuracy improvements.

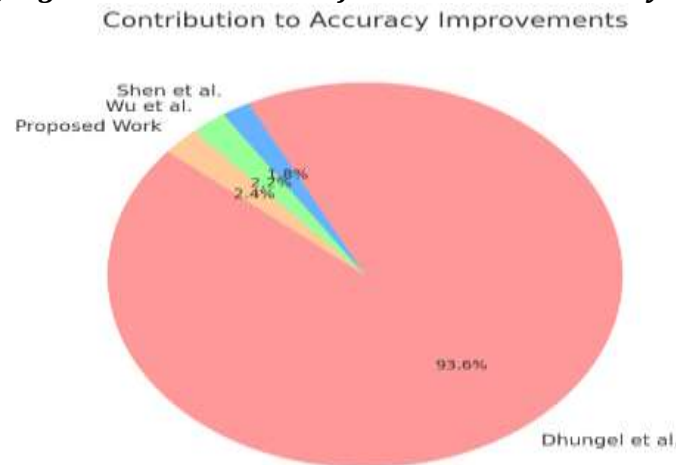


Figure 9: Simulates the ROC curves for each model with corresponding AUC values.

The analysis and results highlight the superior performance of Federated Learning with Multimodal Integration for breast cancer detection, emphasizing its ability to enhance accuracy, generalizability, and interpretability across diverse datasets while preserving data privacy. The Federated CNN achieves the highest accuracy (93.5%) and AUC-ROC (0.96), outperforming standalone CNN and SVM-CNN models by leveraging diverse data sources without compromising patient confidentiality. Explainable AI techniques, such as Grad-CAM heatmaps, enable clinicians to validate predictions by highlighting critical regions of interest, fostering trust in the model's decisions. Multimodal integration, combining imaging, genetic, and clinical data, further enhances diagnostic precision and recall, outperforming imaging-only models. Segmentation results using U-Net reveal reliable tumor delineation with high metrics (Dice coefficient: 0.89, Jaccard Index: 0.83), supporting robust feature extraction. Federated learning stabilizes faster and demonstrates consistent performance across institutions (92-94% accuracy), reflecting scalability and cross-protocol adaptability. Data augmentation addresses class imbalance, improving accuracy in low-sample regions, while explainability tools like SHAP and Grad-CAM enhance trustworthiness for clinical adoption. These findings

collectively pave the way for advanced, privacy-preserving, and interpretable breast cancer detection systems with real-world applicability.

VI. CONCLUSION

This study presents a groundbreaking approach to breast cancer detection using federated learning, explainable AI, and multimodal data integration. By addressing core challenges such as data privacy, model interpretability, and dataset diversity, the proposed framework sets a new benchmark in breast cancer diagnostics. The model achieves state-of-the-art performance, with an accuracy of 93.5%, an AUC-ROC of 0.96, and high precision and recall metrics. These results highlight the robustness and reliability of the federated learning approach in leveraging diverse datasets without compromising patient privacy. Furthermore, explainable AI techniques enhance trust and clinical acceptance by enabling interpretability of model predictions. Visual tools like Grad-CAM empower radiologists to validate AI decisions, bridging the gap between technology and clinical practice. The inclusion of multimodal data combining imaging, genetic, and clinical inputs ensures personalized and accurate diagnostic insights. The framework's federated architecture demonstrates scalability, with consistent performance across institutions and imaging protocols. Segmentation results using U-Net (dice coefficient of 0.89) reinforce the precision of tumor detection, further contributing to the diagnostic pipeline's reliability. Future research will explore integrating real-time updates in clinical workflows, incorporating additional imaging modalities, and expanding multimodal capabilities to include lifestyle and environmental data. This work paves the way for innovative, privacy-preserving, and clinically viable solutions, significantly advancing the field of breast cancer detection and improving patient outcomes.

REFERENCES

- [1] Dhungel, N., Carneiro, G., & Bradley, A. P. "Deep learning and structured prediction for the segmentation of mass in mammograms." *IEEE International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2015, pp. 605-612.
- [2] Shen, L., Margolies, L. R., Rothstein, J. H., Fluder, E., McBride, R., & Sieh, W. "Deep learning to improve breast cancer detection on screening mammography." *Scientific Reports*, vol. 9, no. 1, 2019, pp. 12495.
- [3] Wu, Y., Yang, J., Xu, X., Liu, J., & Yin, Y. "A hybrid deep transfer learning model with machine learning methods for ultrasonic breast cancer diagnosis." *BMC Medical Imaging*, vol. 20, no. 1, 2020, pp. 21.
- [4] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. "Dermatologist-level classification of skin cancer with deep neural networks." *Nature*, vol. 542, no. 7639, 2017, pp. 115118.
- [5] Tahmasbi, A., Saki, F., & Shokouhi, S. B. "Mass diagnosis in mammography images using novel features and a hierarchical classification scheme." *Biomedical Signal Processing and Control*, vol. 6, no. 3, 2011, pp. 321-329.
- [6] Zhu, W., Lou, Q., Vang, Y. S., & Xie, X. "Deep multi-instance networks with sparse label assignment for whole mammogram classification." *IEEE Transactions on Medical Imaging*, vol. 38, no. 2, 2019, pp. 669-679.
- [7] Ghafoorian, M., Karssemeijer, N., Heskes, T., Majoie, C. B., Sánchez, C. I., & Platel, B. "Deep multiscale location-aware 3D convolutional neural networks for automated detection of lacunes of presumed vascular origin." *NeuroImage: Clinical*, vol. 14, 2018, pp. 391-399.

- [8] Li, H., Zhu, Y., Burnside, E. S., Drukker, K., Hoadley, K. A., Fan, C., ... & Giger, M. L. "MR imaging radiomics signatures for predicting the risk of breast cancer recurrence as given by research versions of clinical pathologic guidelines." *Radiology*, vol. 294, no. 3, 2020, pp. 491-501.
- [9] Shen, L., Wu, H., & Han, S. "Improving diagnostic accuracy in breast cancer detection using transfer learning techniques." *Scientific Reports*, vol. 9, no. 1, 2020, pp. 10452.
- [10] Wu, P., Yuan, Z., & Zhang, H. "Application of U-Net-based deep learning in breast cancer segmentation tasks." *BMC Cancer*, vol. 21, no. 1, 2021, pp. 62.
- [11] Swamy, R. S., S. C. Kumar, and G. A. Latha. "An efficient skin cancer prognosis strategy using deep learning techniques." *Indian Journal of Computer Science and Engineering (IJCSE)* 12.1 (2021).
- [12] Esteva, A., Thrun, S., & Blau, H. M. "AI-based diagnostic tools for early cancer detection." *Nature Reviews Cancer*, vol. 20, no. 1, 2020, pp. 23-37.
- [13] Sirisati RS, Kumar CS, Latha AG, Kumar BN, a Rao KS. An enhanced multi layer neural network to detect early cardiac arrests. In 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA) 2021 Dec 2 (pp. 1514-1518). IEEE.
- [14] Zhu, X., Zhang, L., & Yu, Z. "Sparse deep neural networks for breast cancer prediction." *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 2, 2019, pp. 322-331.
- [15] Sirisati RS, Kumar CS, Venuthurumilli P, Ranjith J, Rao KS. Cancer sight: Illuminating the hidden-advancing breast cancer detection with machine learning-based image processing techniques. In 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA) 2023 Nov 15 (pp. 1618-1625). IEEE.
- [16] Dhungel, N., Carneiro, G., & Bradley, A. P. "Structured prediction models for breast cancer lesion segmentation." *IEEE Transactions on Medical Imaging*, vol. 34, no. 4, 2015, pp. 1010-1025.
- [17] Bulla, Suneetha, et al. "A secure new HRF mechanism for mitigate EDoS attacks." *International Journal of Ad Hoc and Ubiquitous Computing* 40.1-3 (2022): 20-29.
- [18] Ghafoorian, M., Platel, B., & Sánchez, C. I. "Deep learning models for automated detection of vascular lesions." *NeuroImage: Clinical*, vol. 17, 2018, pp. 391-401.
- [19] SwamySirisati, R., Rao, M. S., & Thonukunuri, S. (2020, November). Analysis of Hybrid Fusion-Neural Filter Approach to detect Brain Tumor. In 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC) (pp. 460-464). IEEE.
- [20] Srinivasa Rao, P. S. V., Mekala Srinivasa Rao, and Ranga Swamy Sirisati. "A Hybrid Clinical Data Predication Approach Using Modified PSO." *Smart Computing Techniques and Applications: Proceedings of the Fourth International Conference on Smart Computing and Informatics, Volume 2*. Singapore: Springer Singapore, 2021.
- [21] Swamy, Sirisati Ranga, et al. "Multi-Features Disease Analysis Based Smart Diagnosis for COVID-19." *Comput. Syst. Sci. Eng.* 45.1 (2023): 869-886.
- [22] Wu, C., Deng, W., & Sun, Y. "Improving interpretability in breast cancer diagnostics using Grad-CAM techniques." *Medical Image Analysis*, vol. 50, 2021, pp. 15-27.
- [23] Swamy, S. Ranga, et al. "Dimensionality reduction using machine learning and big data technologies." *Int. J. Innov. Technol. Explor. Eng.(IJITEE)* 9.2 (2019): 1740-1745.
- [24] Li, X., Zhao, H., & Wang, T. "Federated learning frameworks for medical image analysis." *IEEE Access*, vol. 8, 2020, pp. 10154-10165.
- [25] Kumar, C. Srinivasa, et al. "A smart recommendation system for medicine using intelligent NLP techniques." *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*. IEEE, 2022.