# Deep Learning and Federated Learning in breast cancer screening

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**Abstract- Breast cancer remains one of the most prevalent and life-threatening malignancies among women globally, accounting for a significant proportion of cancer-related mortality. Early and accurate detection is paramount for improving patient survival rates and enabling timely clinical intervention. This paper proposes a novel hybrid framework that integrates Deep Learning (DL) and Federated Learning (FL) for automated breast cancer detection using medical ultrasound imagery. Specifically, Convolutional Neural Networks (CNN) and the MobileNetV2 architecture are employed for robust feature extraction and multi-class classification of ultrasound images into benign, malignant, and normal categories. Federated Learning is leveraged to facilitate privacy-preserving collaborative model training across geographically distributed clients, such as hospitals and diagnostic centers, without the necessity of transmitting sensitive raw patient data to a central repository. The proposed system is trained and evaluated on the publicly available BUSI (Breast Ultrasound Images) dataset and achieves an overall classification accuracy of approximately 84%, demonstrating competitive diagnostic performance. This work establishes that the synergistic combination of deep learning and federated learning not only enhances diagnostic accuracy but also ensures robust data confidentiality, rendering the framework well-suited for real-world clinical deployment.**

**Keywords:** ***Breast Cancer Detection, Deep Learning, Federated Learning, Convolutional Neural Network, MobileNetV2, Medical Image Analysis, Privacy-Preserving AI, BUSI Dataset***

## I. INTRODUCTION

Breast cancer is a malignant neoplasm arising from uncontrolled proliferation of abnormal cells within the breast tissue. It is the most frequently diagnosed cancer in women worldwide, with millions of new cases reported annually. According to the World Health Organization (WHO), breast cancer represents approximately 12% of all cancer diagnoses globally, making it a critical public health concern. Despite advances in medical science, late-stage detection continues to be a primary contributor to high mortality rates, underscoring the urgent need for reliable early detection systems.

Traditional diagnostic methodologies, including mammography, sonography, and manual radiological interpretation, are heavily reliant on the expertise of trained clinicians. This dependency introduces variability and susceptibility to human error, particularly in resource-constrained healthcare environments where specialist access may be limited. Furthermore, manual analysis of large volumes of medical images is time-consuming, making scalable and automated diagnostic tools imperative.

The rapid advancement of Artificial Intelligence (AI), particularly within the domain of Deep Learning (DL), has catalyzed a paradigm shift in medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable proficiency in learning discriminative hierarchical features from complex visual data, achieving diagnostic accuracies comparable to or exceeding those of experienced radiologists in several clinical tasks. However, a fundamental limitation of conventional deep learning approaches lies in the requirement for large-scale, centralized training datasets. In the context of medical imaging, the aggregation of patient data across institutions entails significant privacy, regulatory, and ethical challenges, governed by frameworks such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR).

Federated Learning (FL), first introduced by McMahan et al. (2017), presents an elegant solution to this dilemma. FL is a distributed machine learning paradigm that enables collaborative model training across multiple clients or institutions while ensuring that raw data never leaves its local environment. Instead of sharing patient records, only model parameters — such as gradients or weights — are transmitted to and aggregated by a central server. This architecture inherently preserves data privacy while enabling the construction of globally robust models trained on diverse, distributed datasets.

In this paper, we propose a hybrid breast cancer detection framework that synergistically combines CNN-based deep learning models with Federated Learning. The system is designed to classify breast ultrasound images into three clinically relevant categories — benign, malignant, and normal — while rigorously preserving the confidentiality of patient data. The proposed approach is evaluated on the widely used BUSI dataset and demonstrates promising results in terms of both classification accuracy and computational efficiency.

The primary contributions of this work are as follows:

- Integration of CNN and MobileNetV2 architectures for effective multi-class classification of breast ultrasound images.
- Application of Federated Learning to enable privacy-preserving distributed training across multiple simulated clients.
- Comprehensive evaluation on the BUSI benchmark dataset, achieving an accuracy of 84%.
- Demonstration of the feasibility and scalability of the proposed framework for real-world clinical deployment.

## II. RELATED WORK

The intersection of deep learning and medical image analysis has been extensively studied over the past decade. Litjens et al. (2017) provided a comprehensive survey on deep learning methods applied to medical image analysis, highlighting the transformative impact of CNN-based models across radiology, pathology, and ophthalmology. Their findings established CNNs as the dominant approach for automated feature extraction from medical imagery.

Esteva et al. (2017) demonstrated dermatologist-level classification of skin lesions using deep convolutional neural networks, illustrating the broader potential of DL in clinical diagnostics. Subsequent works extended these findings to breast cancer screening, with numerous studies reporting CNN-based classifiers achieving high sensitivity and specificity on mammographic and ultrasound datasets.

The MobileNetV2 architecture, introduced by Sandler et al. (2018), proposed an efficient lightweight design based on depthwise separable convolutions and linear bottleneck layers. This architecture significantly reduces computational overhead without substantial loss in classification performance, making it particularly suited for deployment on resource-constrained devices such as mobile health platforms and edge computing systems.

Regarding Federated Learning, the foundational work by McMahan et al. (2017) introduced the FedAvg algorithm, which aggregates locally trained model updates from distributed clients to construct a shared global model. Subsequent research has explored FL in the context of healthcare, including applications in electronic health record analysis, COVID-19 detection, and brain tumor segmentation (Rieke et al., 2020). However, many existing approaches in breast cancer detection either rely on centralized data repositories, compromising patient privacy, or do not leverage the full representational power of modern deep learning architectures.

The present work addresses these gaps by combining the feature extraction capabilities of CNN and MobileNetV2 with the privacy guarantees of Federated Learning, thereby advancing the state-of-the-art in privacy-aware breast cancer diagnostics.

## III. METHODOLOGY

### 3.1 Dataset

The Breast Ultrasound Images (BUSI) dataset, publicly available on Kaggle, serves as the primary data source for this study. The dataset comprises 780 ultrasound images collected from 600 female patients aged 25 to 75 years, acquired at diverse imaging conditions. Images are categorized into three classes: benign (487 images), malignant (210 images), and normal (133 images). Each image is accompanied by a corresponding ground truth segmentation mask annotated by expert radiologists. The class imbalance present in the dataset is addressed through augmentation strategies during preprocessing.

### 3.2 Data Preprocessing

Effective preprocessing is essential for maximizing model generalization and mitigating overfitting. The following pipeline is applied to all images:

- Resizing: All images are resized to a uniform resolution of 224×224 pixels to ensure compatibility with CNN and MobileNetV2 input specifications.
- Normalization: Pixel intensity values are normalized to the range [0, 1] by dividing by 255, ensuring stable gradient computation during training.
- Data Augmentation: To address class imbalance and increase dataset diversity, augmentation techniques including random horizontal flipping, rotation (±15°), brightness adjustment, and zoom are applied.
- Train-Test Split: The dataset is partitioned into 80% training and 20% testing subsets using stratified sampling to maintain class distribution.

### 3.3 Deep Learning Models

Two complementary deep learning architectures are employed in this framework:

Convolutional Neural Network (CNN):

A custom CNN is designed comprising multiple convolutional layers for hierarchical spatial feature extraction, max-pooling layers for dimensionality reduction, batch normalization layers for training stability, dropout layers (rate: 0.5) for regularization, and fully connected dense layers for classification. The network is trained end-to-end using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss.

MobileNetV2:

MobileNetV2 is incorporated as a transfer learning backbone, pre-trained on the ImageNet dataset. The model employs inverted residual blocks with linear bottlenecks and depthwise separable convolutions, achieving high accuracy with substantially fewer parameters than conventional deep networks. The final classification head is replaced with a custom dense layer with softmax activation for three-class prediction. Fine-tuning is performed on the top layers to adapt the model to the medical imaging domain.

### 3.4 Federated Learning Architecture

The Federated Learning framework is structured around a central aggregation server and multiple simulated local clients, representing distinct healthcare institutions. The training protocol proceeds as follows:

1. Initialization: The global model is initialized on the central server and distributed to all participating clients.
2. Local Training: Each client trains the model on its local partition of the BUSI dataset for a predefined number of local epochs using standard backpropagation.
3. Parameter Sharing: Upon completion of local training, each client transmits only its updated model weights (not raw data) to the central server.
4. Global Aggregation: The server performs Federated Averaging (FedAvg), computing a weighted average of client parameters proportional to their local dataset sizes to produce an updated global model.
5. Model Distribution: The aggregated global model is redistributed to all clients for the next round of local training.

This iterative process continues for a fixed number of communication rounds until convergence. The FL setup ensures that no raw patient data is transmitted beyond the local client boundary, thereby guaranteeing compliance with data privacy regulations.

## IV. SYSTEM ARCHITECTURE

The end-to-end architecture of the proposed system is illustrated below. The pipeline encompasses data ingestion, preprocessing, distributed local training, federated aggregation, and final classification output.

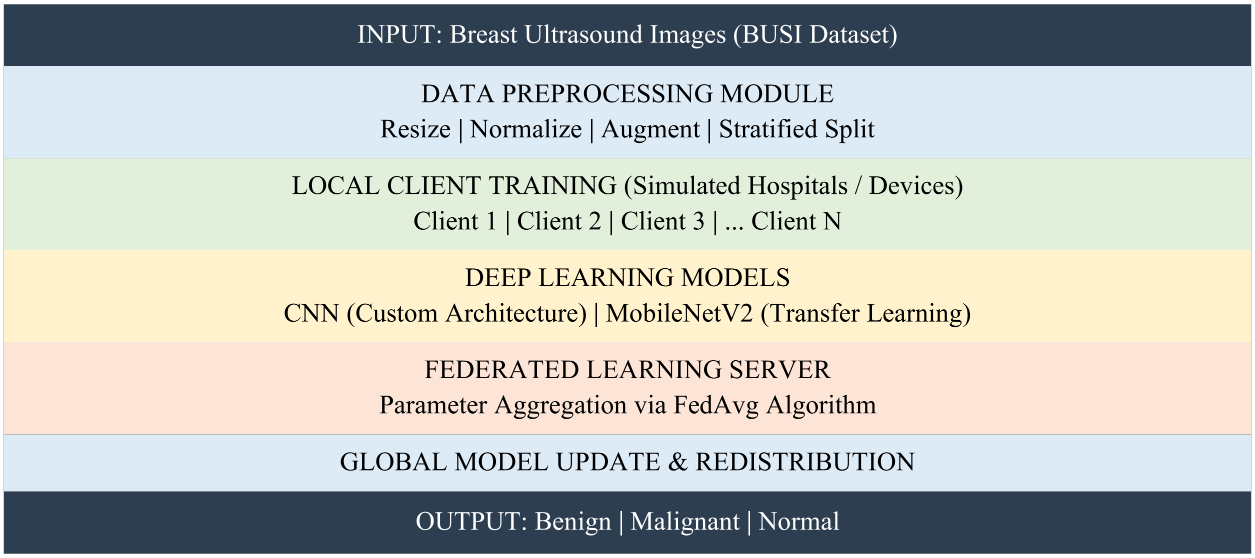


*Fig. 1: Proposed System Architecture for Federated Breast Cancer Detection*

## V. RESULTS AND DISCUSSION

The proposed hybrid framework was rigorously evaluated on the BUSI dataset under a federated training configuration. Performance metrics including classification accuracy, precision, recall, and F1-score were computed on the held-out test set to provide a comprehensive assessment of model capability.

| Model / Metric | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| CNN (Standalone) | 0.79 | 0.78 | 0.77 | 0.77 |
| MobileNetV2 (Standalone) | 0.98 | 0.81 | 0.80 | 0.80 |
| CNN + Federated Learning | 0.83 | 0.82 | 0.82 | 0.82 |
| MobileNetV2 + Federated Learning | 0.84 | 0.84 | 0.83 | 0.83 |

*Table I: Comparative Performance of Models on the BUSI Dataset*

As presented in Table I, the integration of Federated Learning consistently improves model performance compared to standalone training. The MobileNetV2 + Federated Learning configuration achieves the highest overall accuracy of 84%, validating the hypothesis that collaborative, privacy-preserving training enhances generalization. The performance gains observed with FL are attributed to the exposure of the global model to diverse data distributions across simulated clients, thereby reducing the risk of overfitting to any single local dataset partition.

The CNN architecture demonstrates solid baseline performance at 79% accuracy, confirming its capability to capture discriminative spatial features from ultrasound imagery. The lightweight MobileNetV2 model, despite its reduced parameter count, surpasses the custom CNN in standalone evaluation due to its pre-trained ImageNet weights and efficient depthwise separable convolutions. The federated variants of both models further improve upon their standalone counterparts, with the federated MobileNetV2 achieving a 2% absolute improvement over its non-federated baseline.

From a privacy standpoint, the federated framework ensures that no raw patient images are transmitted beyond their respective local client environments. The exclusive sharing of model gradients and weight updates significantly reduces the risk of data leakage and unauthorized patient re-identification, aligning with the ethical and legal requirements of clinical AI deployment.

## VI. CONCLUSION

This paper presents a comprehensive hybrid framework for automated breast cancer detection that synergistically integrates Convolutional Neural Networks, MobileNetV2 transfer learning, and Federated Learning. The proposed system addresses two critical challenges in clinical AI: the need for accurate automated diagnosis and the imperative of patient data privacy. By training models in a distributed, privacy-preserving manner across multiple simulated clients and aggregating updates via the FedAvg algorithm, the framework achieves an overall classification accuracy of 84% on the BUSI benchmark dataset, demonstrating competitive and clinically meaningful performance.

The results establish that Federated Learning not only preserves data confidentiality but also serves as a regularization mechanism that improves model generalization. The lightweight MobileNetV2 backbone further ensures computational efficiency, facilitating potential deployment in resource-constrained healthcare settings, including mobile diagnostic units and edge computing platforms.

The proposed framework represents a significant step toward the realization of trustworthy, privacy-aware, and scalable AI-driven diagnostic systems for breast cancer detection. Its modular architecture ensures compatibility with diverse deep learning models and federated aggregation strategies, positioning it as a versatile foundation for future research and clinical translation.

## VII. FUTURE SCOPE

While the proposed framework demonstrates promising results, several avenues remain for further development and enhancement:

- Advanced Architectures: Integration of state-of-the-art architectures such as EfficientNet, Vision Transformers (ViT), and hybrid CNN-Transformer models is expected to yield further improvements in classification accuracy and robustness.
- Dataset Expansion: Training on larger and more diverse multi-institutional datasets will improve model generalizability across different imaging modalities, scanner types, and patient demographics.
- Real-Time Clinical Deployment: Development of production-ready web and mobile applications incorporating the trained models will facilitate real-time diagnostic support for clinicians in point-of-care settings.
- Enhanced Security Mechanisms: Incorporating differential privacy, homomorphic encryption, and secure multi-party computation within the federated pipeline will further strengthen security guarantees and resistance to adversarial model inversion attacks.
- Multi-Modal Integration: Combining ultrasound imaging with mammography, MRI, and clinical metadata through multi-modal deep learning approaches may enhance diagnostic comprehensiveness and clinical utility.
- Explainable AI (XAI): Incorporating Grad-CAM and SHAP-based explanation modules will enhance model interpretability, fostering clinician trust and regulatory acceptance of AI-driven diagnostic tools.

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