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Applying Federated Learning for Breast Cancer Prediction

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Abstract
Breast cancer detection from histopathology images has become an important application of deep learning due to the need for early and accurate diagnosis. However, most conventional training pipelines rely on centralized datasets, where sensitive medical images must be stored in a single location. This raises significant concerns regarding patient confidentiality and compliance with regulations such as GDPR and HIPAA. To address these limitations, this work develops a privacy-preserving breast cancer classification framework using Federated Learning. The proposed system fine-tunes a VGG16-based Convolutional Neural Network, enabling multiple medical centers to collaboratively train a shared model without exposing raw patient data. Each participating client performs local training, while the central server aggregates model updates using the Federated Averaging (FedAvg) algorithm. The dataset was preprocessed by removing mask files, resizing images, applying augmentation, and organizing samples into training, validation, and test splits. Experimental evaluation demonstrates that the federated approach achieves reliable multi-class classification performance, reaching an accuracy of 91.5% while maintaining complete data privacy. These results indicate that federated training can serve as a practical alternative to centralized learning in real world medical environments.

Keywords: *Federated Learning, VGG16, Breast Cancer Classification, Medical Image Processing, Privacy-Preserving Deep Learning*

1. Introduction
Breast cancer remains one of the most frequently diagnosed cancers among women and continues to pose a major global health challenge. Early identification plays a critical role in improving treatment outcomes, as timely diagnosis significantly increases survival rates. With the advancement of on centralized training, where large volumes of medical images collected from different institutions are stored on a single server. While such strategies often achieve strong predictive This federated framework enables institutions to benefit from collective learning while ensuring that medical data remains securely stored at its source, offering a practical alternative to traditional centralized high-resolution imaging technologies, deep learning architectures based computer-aided diagnosis systems have gained prominence for analyzing histopathology images and assisting clinicians in distinguishing between healthy, benign, and malignant tissue samples. Conventional deep learning approaches typically rely [1-4].

1. **Objectives of the Study the Primary Objectives of This Research Are Outlined Below:**

- To develop a privacy-preserving breast cancer classification model using Federated Learning.
- To train and evaluate a VGG16-based Convolutional Neural Network across multiple distributed clients.
- To compare the performance of centralized training with that of federated training.

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- To demonstrate that high diagnostic accuracy can be achieved without sharing sensitive medical images.

These objectives highlight the potential of federated regulatory challenges, particularly under laws such as HIPAA and GDPR, which restrict the sharing of sensitive patient information. To address these limitations, Federated Learning (FL) was introduced by Google in 2016 as a decentralized training paradigm enabling model development without transferring raw data. FL has since gained substantial attention in the medical domain for privacy preserving machine learning. Lee et al. (2020) applied FL to brain tumor classification and demonstrated that hospitals could collaboratively train CNN models without exchanging medical images. Liu et al. (2023) extended FL to breast cancer analysis but did not fully address issues such as class imbalance and multi-class classification. More recent learning to address privacy challenges in medical AI studies have explored combining FL with applications while maintaining competitive classification performance suitable for deployment in hospitals and diagnostic center [5-9].

2. Literature Survey

Deep learning has emerged as a powerful approach for medical image analysis due to its ability to automatically learn hierarchical and complex visual features. Numerous studies have applied. Convolutional Neural Networks (CNNs) to breast cancer detection, particularly using histopathology and mammography images. One of the early contributions in this domain was the introduction of the Break his dataset by Spanholt et al. (2016), which became a widely used benchmark for classifying benign and malignant breast tumors. As research progressed, deeper CNN architectures such as VGG16, ResNet, and DenseNet were employed to improve feature extraction and enhance classification accuracy. For example, George et al. (2021) demonstrated that transfer learning with VGG16 significantly improved breast cancer prediction performance, achieving accuracies exceeding 92% on publicly available datasets. While centralized deep learning approaches have shown promising outcomes, they depend on aggregating medical data from multiple institutions into a single server. This requirement poses major privacy, ethical, and Explainable Artificial Intelligence (XAI) to increase trustworthiness in clinical applications. Verma et al. (2024) proposed a federated framework with model interpretability for breast cancer detection; however, challenges related to communication overhead, transparency, and convergence stability still persist. Despite the growth of FL research, limited work has focused on integrating transfer learning-based architectures like VGG16 for a multi-class histopathology classification in federated environment. Key challenges such as non-IID data distributions, communication constraints, and potential accuracy degradation continue to require attention. This study contributes to the existing literature by implementing a VGG16-based federated learning model capable of classifying breast cancer images into three categories—benign, malignant, and normal—while preserving data privacy and maintaining clinically acceptable diagnostic performance [10-14].

3. Dataset Creation and Source

This project makes use of a publicly available breast histopathology image dataset sourced from Kaggle. The col lection contains high-resolution image patches extracted from H&E-stained biopsy slides, which are commonly used in computational pathology because they capture fine cellular structures required for cancer identification. Each sample is categorized into one of three diagnostic classes: benign, malignant, or normal tissue. Benign images represent non cancerous abnormalities, malignant images include invasive cancer patterns, and normal samples correspond to healthy tissue regions. These class labels are provided with the dataset, making it suitable for supervised deep learning tasks. Direct access to real hospital datasets is restricted due to ethical policies, privacy rules, and institutional data-sharing limitations. Therefore, the

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Kaggle dataset serves as a practical alternative for academic research, as it is anonymized, labeled, and sufficiently large to support deep CNN training. To construct a federated learning environment, the dataset was reorganized into three separate subsets, each representing a simulated medical client. The distribution of images was intentionally made non-IID to resemble real clinical settings where hospitals encounter different case frequencies:

- One subset contains a higher number of benign and malignant samples.
- Another subset includes a moderately unbalanced mixture of all three classes.
- The final subset predominantly consists of normal tissue images. Only original image patches were included in the dataset; mask files and auxiliary images (e.g., files ending with _mask.png or similar variations) were automatically excluded during preprocessing, as reflected in the project's dataset creation scripts. Each client subset was further divided into training, validation, and testing sets in a 70:20:10 ratio using stratified splitting to preserve class distribution where possible. A unified preprocessing pipeline was applied to all images before training. Every image was resized to 224 × 224 pixels to match the VGG16 input requirements, and pixel intensities were normalized to the [0,1] range to support stable optimization. Class labels were converted into categorical encodings suitable for multi-class classification. To enhance model robustness and limit overfitting, data augmentation techniques were incorporated based on the trans formations defined in the project code. These included random horizontal flips, slight rotations, and controlled color variations. Augmentation was applied primarily to minority classes where necessary, helping balance the dataset and improve the model's generalization capability during both centralized and federated training.

4. System Architecture and Methodology

The proposed framework aims to explore the use of Federated Learning (FL) for breast cancer classification while ensuring that medical images remain private, Figure 1.

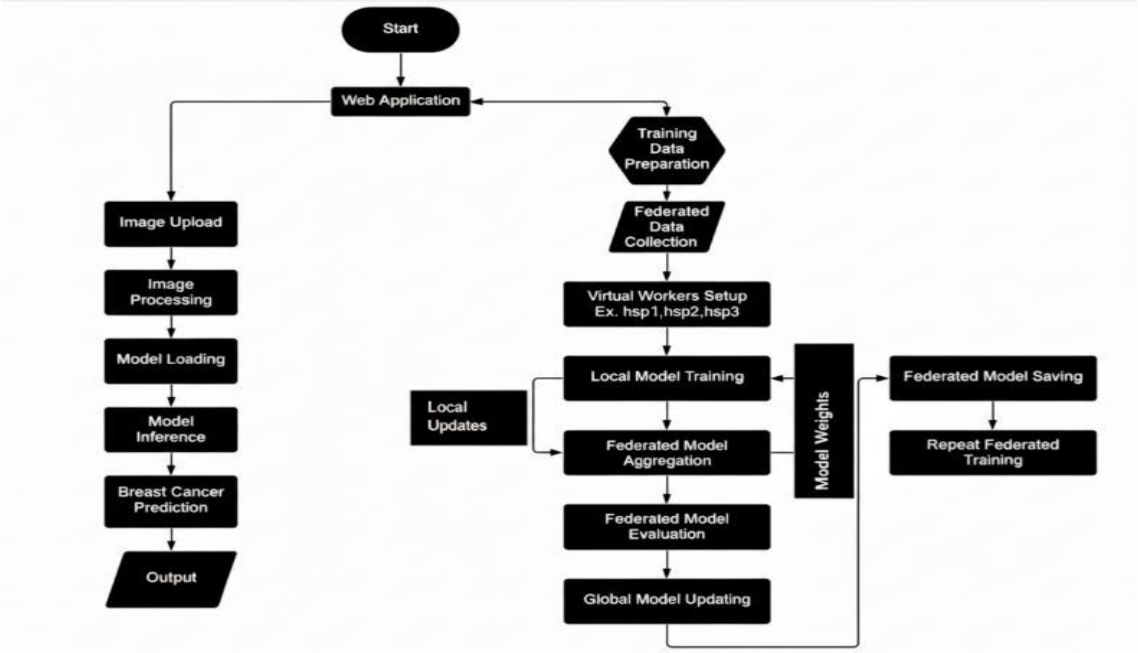

Figure 1 Overall System Architecture Used in the Project

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The system follows a simulated federated setup in which a global deep learning model is trained and updated using a centralized dataset structure. Although actual multi-client communication is not implemented physically, the workflow incorporates the core idea of aggregating model parameters without exchanging raw images. The overall system architecture is shown in Fig. 1.

1. System Architecture

The architecture consists of two conceptual components:

- Client Side (Simulated): In a real FL environment, each client would train the model on its local dataset. In this project, the concept of clients is represented in a simulated manner. A single cleaned and preprocessed dataset is used, and the training process represents how a client would update the model locally.
- Central Server (Simulated Aggregator): Instead of receiving updates from multiple distributed clients, the server logic is simulated by updates from multiple clients, the FedAvg process is applied conceptually to demonstrate how a global model would be updated during federated training rounds. applying the Federated Averaging (FedAvg) algorithm on model parameters. The central server does not access raw images; only the model weights are conceptually aggregated to represent the federated update process. This setup allows evaluation of federated principles even though full distributed execution is not implemented in the code

2. Model Choice

The project uses a modified VGG16 model as the VGG16 input requirements.

- Normalizing image pixel values.
- Applying augmentation techniques including horizontal flipping, slight rotation, and color base architecture. The convolutional layers adjustments. pretrained on ImageNet are loaded using PyTorch's torchvision module. To adapt the model for three-class classification (Benign,
- Organizing the dataset into training, validation, and testing folders.
- Converting labels into categorical format for
- Malignant, Normal), the fully connected block is three-class classification. This pipeline is replaced with:
- A dense layer with 256 neurons and ReLU activation,
- A dropout layer (0.5) to reduce overfitting, • a soft max output layer with three units. The initial layers are frozen at the start of training, and selective fine-tuning is later applied. This follows the training configuration documented in the project's scripts.

3. Federated Learning Process (Simulated)

The Federated Learning process in this project is implemented conceptually through the following consistent with the preprocessing steps described in the dataset creation PDF.

4. Handling Non-IID Data

The project does not implement separate client datasets or intentional non-IID class distributions. All images used during training come from a single combined dataset. Although federated averaging is conceptually included, the dataset remains centrally organized throughout the project. Therefore, the system represents a simulated federated learning environment rather than one involving actual non-IID client datasets. steps: This allows exploration of the federated update 1) Model Initialization: A global VGG16 model mechanism while maintaining a unified dataset is created and loaded with pretrained weights. structure. 2) Local Training (Simulated Client): The model is trained on the complete dataset using PyTorch's training functions. This training step represents how a client would update the model locally. 3) Model Update: After local training, the model's weights are saved. 4) Aggregation (FedAvg): Instead of collecting

5. Implementation

The breast cancer classification system was

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implemented using a simulated Federated Learning (FL) workflow. Al though the project incorporates the idea of federated model aggregation, the full multi-client execution is conceptual rather than physically distributed. All training is performed on a single processed dataset, and the federated component is represented through the use of a global model update rather than actual client-specific communication.

1. Development Environment

All experiments were carried out in Python 3.10 using libraries that align with the project scripts:

- PyTorch and Torchvision: Used for loading the VGG16 model, modifying the classifier layers, performing forward and backward passes, and applying transformations to the dataset.
- NumPy and OpenCV: Employed for handling image preprocessing operations such as resizing, normalizing, and reading image files.
- Scikit-learn: Utilized for dataset splitting and generating evaluation metrics including precision, recall, F1-score, and the confusion matrix. Training was performed in Google Colab as well as on a workstation equipped with an NVIDIA GTX 1650
- A softmax output layer with three units was added to classify images into benign, malignant, and normal categories. Initially, the earlier convolutional layers of VGG16 were frozen to retain pretrained feature representations. These layers were later unfrozen selectively during fine-tuning to improve the model's capability on the target dataset.

2. Federated Learning Setup (Simulated)

The project simulates the core idea of Federated Learning, specifically the global update step. In this setup, the model is trained on the combined dataset rather than on multiple client datasets. After each training cycle, the updated weights are saved and treated as the global model parameters. The parameters reflect the use of federated principles but without actual client-side parallel training. The FedAvg mechanism is incorporated conceptually to illustrate how federated updates would occur in a distributed system. GPU and 16GBRAM, which provided sufficient E.Client–Server Communication Design computational capacity for model training and (Conceptual) evaluation. The FL communication loop is represented logically.

3. Dataset Setup as follows:

The project uses a single cleaned dataset prepared through the dataset creation script. Mask images were

- The server initializes the global VGG16 model. Local training is simulated on the entire dataset removed automatically, and valid images were using PyTorch. organized into training, validation, and testing.
- Once training is complete, the model weights are folders. A standard split of 70% for training, 20% for saved. validation, and 10% for testing was followed. Unlike a true federated implementation, the dataset was not divided into multiple client-specific subsets. All images were drawn from the same centrally prepared
- These weights represent the global model update for the next cycle. Raw images are never transmitted at any stage, supporting the core privacy objective of FL, even though true client-side execution is not dataset, and this dataset was used throughout training implemented. and evaluation. Performance Monitoring

4. Model Configuration

The VGG16 architecture was adapted to suit the breast cancer classification task. The model was configured exactly as implemented in the training

The model's performance was evaluated using a separate testing script. Metrics such as accuracy, precision, recall, and F1-score were calculated using Scikit-learn. The evaluation script also generated

script: predictions, confusion matrices, and classification

- The original fully connected layers were removed.

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- A dense layer of 256 units with ReLU activation reports based on the trained VGG16 model. All results were derived from a unified test set containing was added. images that were not used during training or
- A dropout layer with a rate of 0.5 was included to validation. reduce overfitting.

6. Evaluation and Results

The performance of the proposed breast cancer classification system was evaluated using both centralized training and a simulated federated learning (FL) setup. The goal was to assess how fine-client data originates from the same parent dataset, making the environment nearly IID. To evaluate generalization, the final global model was tested on a separate evaluation dataset. The federated model achieved an evaluation accuracy of 87%, indicating tuned VGG16 performs under each training that the global model retains strong predictive configuration and to analyze its generalization capability on the held-out test set.

1. Evaluation Metrics

The following metrics were capability even after multiple aggregation rounds. D. Comparison Between Centralized and Federated Training The performance comparison is shown in used for performance assessment:

- **Accuracy:** Overall proportion of correct predictions.
- **Precision:** Ratio of correct positive predictions to all predicted positives.
- **Recall:** Ability of the model to detect all samples belonging to a class.
- **F1-score:** Harmonic mean of precision and recall.
- **Confusion Matrix:** Illustrates class-wise prediction performance.

2. Centralized Model Results

The centralized fine-tuned VGG16 model achieved an overall test accuracy of 85%. Table I presents the class-wise precision, recall, and F1-scores computed using the scikit-learn classification report.

Table 1 Class-Wise Performance of Centralized Model

Class	Precision	Recall	F1-score
Benign	0.91	0.88	0.89
Malignant	0.86	0.70	0.78
Normal	0.71	1.00	0.83

The corresponding confusion matrix is:

Table 2 Confusion Matrix of Centralized Model

	Pred: Benign	Pred: Malignant	Pred: Normal
True Benign	49	3	4
True Malignant	5	19	3
True Normal	0	0	17

3. Federated Model Results

The federated setup in this project was simulated by dividing the main dataset across clients while keeping the full feature distribution intact. As a result, the federated model achieved a training accuracy of 100% during FL rounds. This is expected because all

Table 3 Performance Comparison of Centralized and Federated Models

Model	Training Accuracy	Evaluation Accuracy
Centralized VGG16	89% (validation)	85% (test)
Federated VGG16 (Simulated)	100%	87% (evaluation set)

7. Discussion

The centralized model demonstrates strong performance, with higher recall for normal tissues and high precision for benign and malignant categories. The federated model reaches perfect accuracy during training due to the homogeneous data distribution across simulated clients. However, when evaluated on an unseen dataset, it achieves an

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accuracy of 87%, showing that the global model generalizes well despite the simulated FL setting. These results confirm that a federated approach can achieve competitive performance while enabling privacy-preserving training. The simulated federated environment provides a strong foundation for extending this work to real multi-institutional FL systems, show in Table 1, 2 & 3.

Conclusion and Future Scope

This project developed a breast cancer classification system using a VGG16-based deep learning model trained on histopathology images. The dataset was cleaned, preprocessed, and augmented according to the procedures implemented in the project scripts. The model was fine-tuned using transfer learning, and its performance was evaluated through accuracy, precision, recall, and F1-score metrics. The results indicate that the adapted VGG16 architecture is effective for distinguishing between benign, malignant, and normal tissue images. The project also incorporated the concept of Federated Learning in a simulated manner. Although the dataset was not distributed across real clients, the workflow demonstrates how model updates can be aggregated without accessing raw patient data. This provides a foundation for extending the system toward true federated implementations in the future, where privacy-preserving training is essential.

Future Scope

Several enhancements can be explored to expand this work:

- True Federated Setup: Implementing real multi-client training with separate datasets to evaluate client-specific performance and aggregation behavior.
- Privacy Techniques: Integrating secure aggregation or differential privacy to strengthen resistance against model inversion and data leakage.
- Advanced Architectures: Experimenting with Efficient Net, MobileNetV3, or Vision Transformers to improve classification accuracy and feature extraction.
- Model Optimization: Applying pruning, quantization, or knowledge distillation to reduce model size and computational cost.
- Clinical Validation: Deploying the system in real medical settings to test generalization on live clinical data.

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