CNN Based Federated Learning for Breast Cancer Diagnosis Using Ultrasound Images

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***Abstract*—Breast cancer is characterized by uncontrolled cell growth in breast tissue, remains a significant health concern affecting millions annually. Early detection is crucial for reducing mortality rates, necessitating accurate diagnosis of benign and malignant tumors. Manual detection poses challenges, leading to the exploration of machine learning (ML) and Convolutional Neural Networks (CNN) for the automated categorization of breast cancer based on radiological images. However, privacy concerns and limited access to diverse medical data hinder ML's full potential. Federated Learning (FL), a privacy-preserving approach, emerges as a solution by training models directly on edge devices. This paper integrates CNN with FL for the diagnosis of breast cancer through ultrasound images, addressing the limitations of centralized training models. FL ensures controlled access, privacy, and collaboration among healthcare institutions, improving diagnostic model accuracy and robustness while safeguarding patient data. The research motivation stems from the need to enhance breast cancer diagnosis by combining the adeptness of CNNs in complex feature learning and the collaborative capabilities of FL utilizing decentralized data sources. Our Federated Learning based CNN model achieved 98.42% training and 93.33% test accuracy after balancing the dataset. This study shows the potential of this method to increase breast cancer diagnostic efficiency and accuracy, especially when using ultrasound imaging data to gain a more thorough knowledge of breast abnormalities.**

***Index Terms*—Convolutional Neural Network, Federated Learning, breast cancer, ultrasound images.**

I. Introduction

Uncontrolled growth of cells of breast tissue causes breast cancer that is affecting millions of people each year. Genetic mutation or abnormal alteration of cellular genes in leads to uncontrollable cell growth and can disrupt the balance of the regulated cycle of a healthy body [7]. Detecting breast cancer in the pre-mature stage is very crucial since it reduces the mortality rate [5]. In a recent update on the statistics of female breast cancer in the United States, The American Cancer Society revealed a general upward trend in breast cancer incidence rates over the last four decades [15]. Specifically, between 2010 and 2019, there was an annual increase of 0.5% in the incidence rate. The majority of breast cancer diagnoses are reported in women aged 50 years and above, with 91% of breast cancer-related deaths occurring in this age demographic. The risk of fatality due to breast cancer continues to elevate with increasing age. The article includes projections for 2022 about the invasive breast cancer among women, anticipating around 287,850 new cases in the United States. Another separate study investigates disparities in breast cancer molecular subtypes, highlighting differences in rates characterized by HER2 positivity and triple-negative breast cancer among various Asian ethnicities, especially when age is taken into account as a stratifying factor [16]. These results emphasize the significance of acknowledging the diversity within the Asian population to better customize breast cancer care.The benign tumours are curable and are not life-threatening, whereas malignant tumours needs special treatments like radiation therapy or surgery [14]. Detecting breast cancer manually is very challenging and it requires experts due to the human error in differentiating benign and malignant tumors from radio-logical images [5]. For this reason, various ML algorithms have been used to develop different type of models which can diagnosis and classify breast cancer from ultrasound images.

In the past few years, the convergence of privacy considerations and the demand for effective ML models has generated interest in innovative methodologies like FL. Collaborative learning, known as Federated Learning, requires training algorithms across decentralized data samples without sharing the actual data [10]. In contrast to traditional methods, Federated Learning (FL) produces training algorithms on individual edge devices, and the combined model is transmitted to a server without revealing the raw data. This method, focused on preserving privacy, is effective, secure, and allows controlled data access. Unlike conventional machine learning models that face challenges in transmitting raw data and require substantial data volumes, FL offers a solution by training models directly on edge devices. This ensures privacy and facilitates efficient adaptation [11]. Furthermore, Convolutional Neural Networks (CNNs) serve as deep artificial neural networks utilized for diverse visual data applications, including image classification, clustering based on similarity, and object recognition in various scenarios. The essential convolutional layer in CNNs comprises learnable filters characterized by a small receptive field that extends across the depth of the input volume [13].

In this work, we used ultrasound pictures to diagnose breast cancer by integrating CNN with federated learning. The traditional centralized model of training is prone to data silos and has a high privacy concerns. By enabling healthcare institutions to pool their ultrasound image datasets, CNN-based federated learning provides a optimistic queue to enhance the accuracy and robustness of breast cancer diagnostic models while ensuring patient privacy. Federated learning, leveraging decentralized data sources for collaborative model creation, enhances deep learning capabilities. Combining CNNs and Federated Learning presents a promising approach to enhance accuracy and efficiency in breast cancer diagnosis. Additionally, utilizing ultrasound image data contributes to a more comprehensive understanding of breast lesions.

II. RELATED WORK

Developed a FL facility that employs transfer learning for extracting features from specific image regions, enhancing preprocessing and data training. Utilized the Synthetic Minority Oversampling Technique (SMOTE) for more uniform data classification and improved diagnostic predictions in disease identification. FeAvg-CNN + MobileNet was implemented in a FL framework to protect client privacy. Experimental results with balanced and imbalanced mammography datasets demonstrated superior classification performance, making the solution viable for AI healthcare applications [1]. Using chest X-ray pictures from many medical facilities, the work presents a collaborative FL framework for COVID-19 screening. Due to its ability to train models without requiring the sharing of patient data, this method overcomes issues with data distributions that are not balanced, independent, or identically distributed. Experimental results show that the proposed framework yields competitive performance compared to models trained with shared data, supporting the adoption of collaborative processes among medical institutions to leverage private data for building effective COVID-19 screening models [2]. In this research, the authors presented a systematical review of FL in medical image analysis in the literature. Following PRISMA guidelines, the study synthesizes data from various articles, providing a comprehensive overview. The results show characteristics of models and federated data, model performance, and standard machine learning comparisons. The paper also discusses open issues, challenges, and offers recommendations for the future direction of FL in medical image analysis, presenting a state-of-the-art summary of FL methods [3]. The author introduced a FL framework for efficient medical image diagnosis utilizing model parameter sharing instead of data sharing to ensure privacy. Tests conducted on a histological dataset of breast cancer yield findings similar to those of centralised learning, confirming the viability and effectiveness of their methodology. In addition to having simple extensibility, the framework includes a task scheduler for load balancing, a distributed computing architecture for efficiency, and encryption methods for privacy. Their experiments demonstrate that state-of-the-art models achieve similar FL performance as centralized learning, affirming the reliability and consistency of the proposed framework [4].

CNN architectures have been emerged as an efficient tool to detect cancer by analyzing large image datasets. The authors observed the results of these models for identifying breast cancer using ultrasound pictures and eight pre-trained models. Besides, the author proposed a shallow CNN model with the fivefold cross validation technique and compared the results of performance metrics with the outcomes of those eight pre-trained models to draw the analysis. Their proposed model was able to outperform all the pre-trained models, achieving 100% accuracy and 1.0 AUC score.This model had a small number of parameters, making it faster to train on images, than other pre-trained models [5]. Alanazi et al. introduced a CNN-based model to automate the detection of breast cancer in women [6]. They used a big dataset of 275,000 whole-slide images to analyze the hostile ductal carcinoma tissue zones from these RGB image patches. The authors implemented various CNN architectures along with several ML algorithms and compared the results to validate the model's outcome thoroughly. Their proposed system achieved an accuracy of 87% while incorporating with CNN, making the experiment a success whereas the same model achieved 78% accuracy with ML Algorithms. Zeimarani et al. explored the application of CNNs for categorizing anomalies in ultrasound images of the breast, addressing the challenge of limited labeled data in medical image analysis [8]. The authors employed a custom-built CNN, regularization techniques and transfer learning with pre-trained models to improve performance. The dataset consisted of 641 cases, where 413 benign and 228 malignant lesions were present. They also used A 5-fold cross-validation in the evaluation process. The proposed CNN architecture included four convolutional layers for distinguishing between benign and malignant lesions. AUC (Area Under the Receiver

Operating Characteristic Curve) and accuracy were also used to evaluate the results. Outcome findings indicated that the proposed method, initially achieving 85.98% accuracy and 0.94 AUC without regularization, significantly improved to 92.05% accuracy and 0.97 AUC after regularization and fine-tuning. Lastly, the study examined how radiologists' diagnoses and the suggested method compared to a cutting-edge CAD system. The CNN outperformed the CAD system using hand-crafted morphological features and surpassed one radiologist's analysis in accuracy, although precision and specificity levels differed.

III. Dataset

The dataset, sourced from Kaggle in the year 2018, comprises medical images collected from 600 female patients, with a total of 780 images in PNG format, each sized at 500x500 pixels. This dataset included masking image for each ultrasound image data. we removed masking image before performing any other operation. In Figure-1 demonstrated a sample of our without mask image.

A. Data Collection

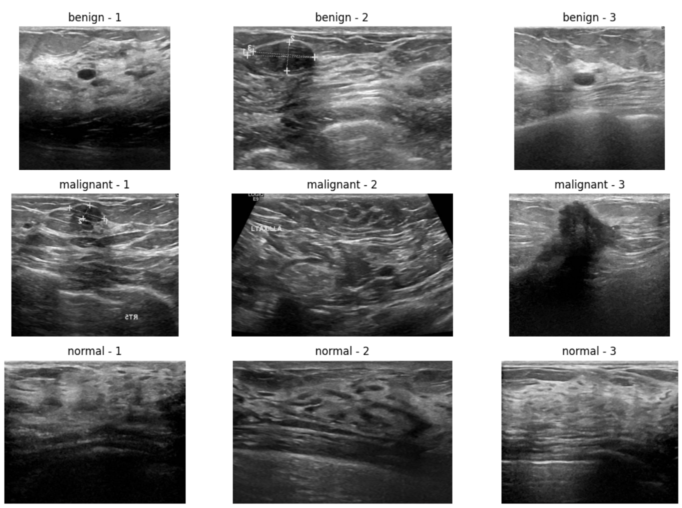

Fig. 1. Sample of the data collection

B. Data Analysis

We utilized the Breast Ultrasound Image Dataset from kaggle in our research, focusing on breast cancer, a prominent cause of female mortality worldwide. Timely detection is imperative for reducing mortality rates, and the dataset specifically explores medical images of breast cancer obtained through ultrasound scans. The dataset classifies images into three categories such as normal, benign, and malignant, highlighting the effectiveness of machine learning, particularly in the areas of categorization, identification, and segmentation of breast cancer when utilized with ultrasound images. The dataset gathered in the year 2018, includes foundational data consisting of breast ultrasound images obtained from a gathering of six hundred women with the age range of 25 through 75 years. Altogether, there are 780 images, where each image has the dimensions of a square of 500 image points and saved in PNG format. Images representing the actual or true state of a given situation is often referred to as Ground Truth (GT) views, that is crucial for training and validation, are carefully provided alongside the original images, categorized into normal (133 files), benign (437 files), and malignant (210 files). In summary, this dataset represents a comprehensive compilation of breast ultrasound images, offering a valuable resource for constructing the machine learning models aimed at refining detection, categorization, and segmentation of breast cancer.

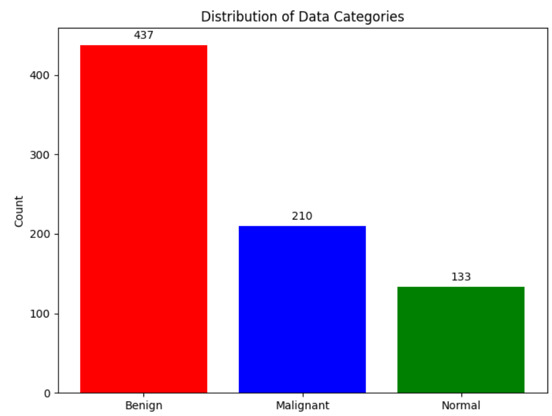

Fig. 2. Dataset Distribution

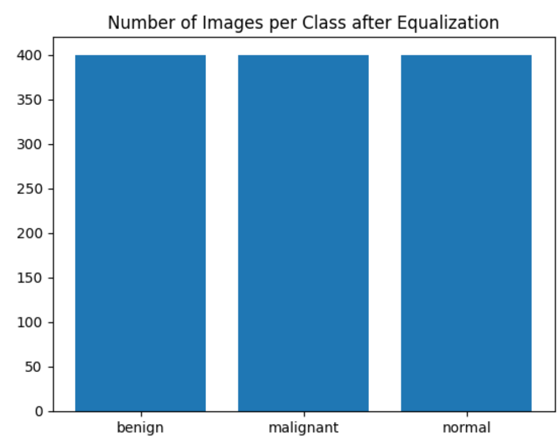

Fig. 3. Dataset Distribution after Augmentation

IV. Methodology

In our approach, we adhere to a series of multiple steps.

A. Steps for Model Architecture

1) Dataset Balancing and Data Pre-processing : The dataset, sourced from Kaggle, forms the foundation of this study. Employing the necessary libraries, data is loaded and transformed through a comprehensive pipeline. But our dataset were imbalanced through the classes. So, we performed some data augmentation technique like- horizontal flip, vertical flip, rotate, resize

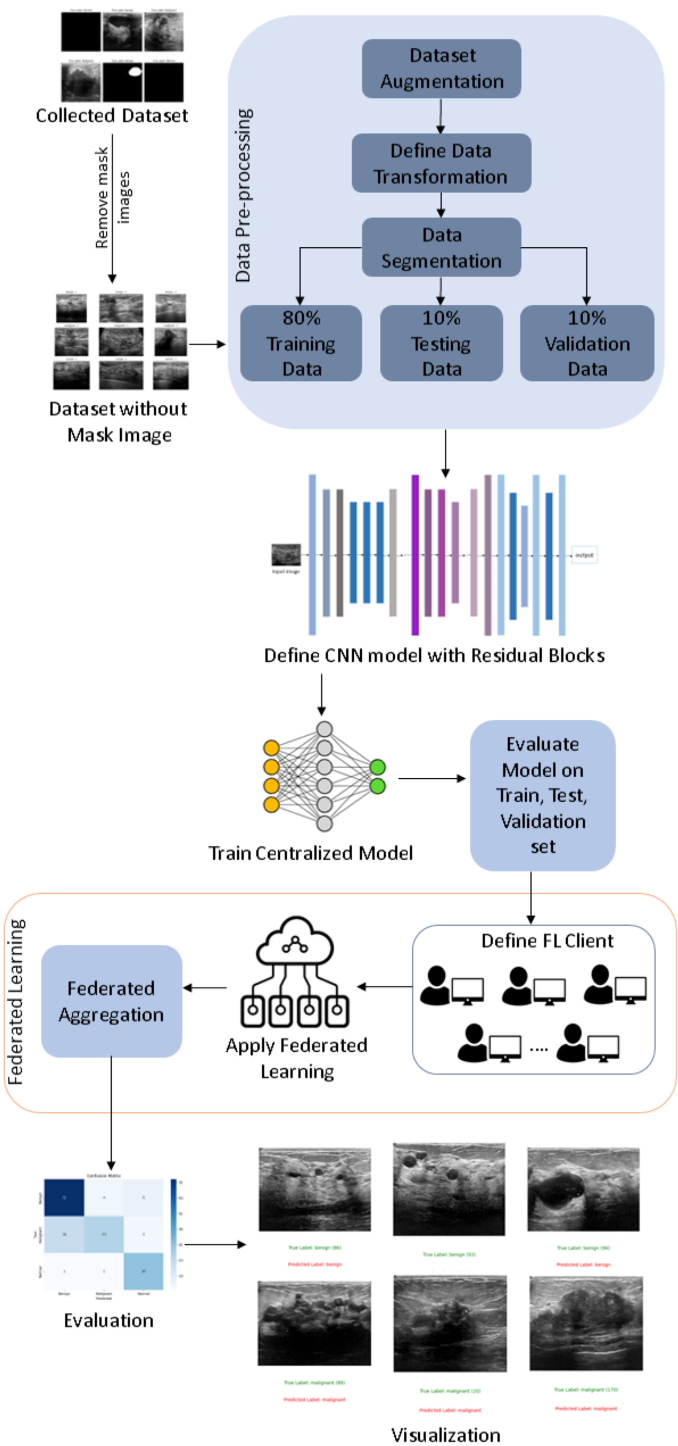

Fig. 4. Workflow Diagram

etc and made more copies of existing data using these techniques. Thus after the data augmentation, we've successfully created a balanced dataset of 3 class each containing 450 ultrasound image data (Figure-3). Afterwards, resizing and normalization operations are applied to ensure uniformity in image dimensions and pixel values. Specifically, the transforms.Compose function orchestrates these operations, culminating in a normalized dataset. Subsequent to image loading, an additional processing step involves denormalizing and reshaping the images for visualization purposes. The dataset is then meticulously split into training (80%), validation (10%), and test (10%) sets, laying the groundwork for subsequent model training and evaluation.

2) Define CNN Model with Residual Block: The model architecture adopted for this study is rooted in a custom Convolutional Neural Network (CNN) enriched with residual blocks. The incorporation of residual blocks is pivotal for facilitating the training of deeper networks, harnessing their capacity to capture intricate features. Each residual block consists of two convolutional layers, complemented by batch normalization and rectified linear unit (ReLU) activations. The final layers, featuring fully connected components, are coupled with ReLU activations and dropout regularization to enhance the model's generalization capabilities.

3) Centralized Training: The initial phase of model training unfolds in a centralized manner on a singular device, be it a CPU or GPU, employing the PyTorch framework. The Adam optimizer is utilized in conjunction with the CrossEntropyLoss function to iteratively adjust model parameters. The centralized training phase provides a foundational understanding of the model's performance on a specific dataset.

4) Federated Learning: The study transitions into a federated learning paradigm, leveraging the Flower framework designed for federated learning scenarios. The custom CNN model assumes the role of the global model, with federated averaging (FedAvg) serving as the strategy for aggregating parameters across multiple clients. This federated approach emphasizes collaboration among decentralized entities, making it particularly suitable for scenarios involving privacy-sensitive data.

5) Evaluation: Model evaluation is a multi-step process. Initially, during centralized training, the model's performance is assessed on the validation set, providing insights into its proficiency in generalizing unseen data. Post-federated learning, the model undergoes evaluation on the test set. The federated accuracy, an aggregate measure of model performance across multiple clients, is visualized over rounds to gauge the collaborative learning process's effectiveness.

6) Visualization: The study places a strong emphasis on visualizing key aspects of the performance of the model. Throughout centralized training, plots depicting training and validation accuracy/loss over epochs offer insights into the learning dynamics. The federated accuracy is visualized over rounds during the federated learning phase, shedding light on the collaborative training's progression. Additional visualizations include a confusion matrix and a classification report, offering a detailed understanding of the model's performance across different classes. The code also features a function for classifying individual images, exemplified by the classification of multiple images, providing a practical demonstration of the model's inference capabilities.

B. *Centralized Training Model Architecture*

The Centralized Training Model Structure consists of a Convolutional Neural Network (CNN) with residual connections.It follows a deep learning paradigm, utilizing convolutional and residual layers where residual connections enable effective training of deep networks by facilitating the flow of gradients for feature extraction. However, the centralized training model consists of several components. The key components are as follows:

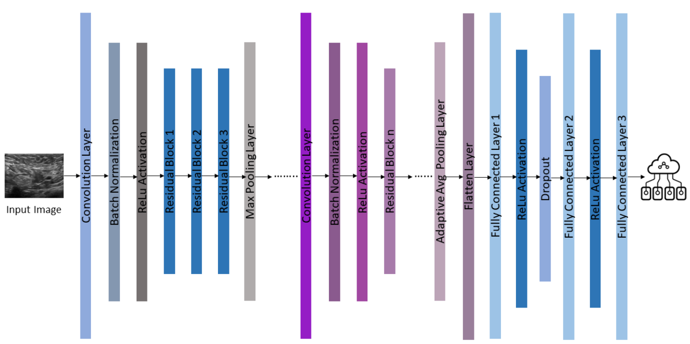

Fig. 5. CNN with Residual Block Model Architecture

1) Input Layer: Input layer accepts input images with three channel color images - Red, Green, Blue (RGB).
2) Convolutional Layers: Multiple convolutional layers with kernel size 3x3 capture hierarchical features. For stable training, batch normalization is used after every convolutional layer. Moreover, Rectified Linear Unit (ReLU) activation functions introduce non-linearity.
3) Residual Blocks: Residual blocks are used to accommodate residual connections. Multiple convolutional layers with batch normalisation and ReLU activation are present in each residual block. Abbreviated route connections handle identity mapping, aiding in mitigating the vanishing gradient problem.Residual blocks contribute to effective feature learning and model depth.
4) Pooling Layer: Max pooling with a 2x2 kernel reduces spatial dimensions, capturing essential features.
5) Fully Connected Layers: The model includes fully connected layers for classification. Output from the last residual block is flattened and connected to fully connected layers.
6) Dropout Layer: Dropout with a rate of 0.5 is introduced for regularization, preventing overfitting during training.
7) Output Layer: The final layer produces logits for three classes. Additionally, the multi-class classification involves the application of the softmax activation function.

C. *CNN based Federated Learning Architecture*

The CNN-based Federated Learning Architecture used in our model involves the collaborative training of a Convolutional Neural Network (CNN) with Residual Layers across multiple decentralized devices while preserving data privacy. It involves several components. The key components are as below :

1) Centralized Model: The initial machine learning model or the centralized training model trained on a central server using a centralized dataset. This model serves as the starting point for federated learning.
2) Clients (Client 1 to Client N): Clients are the individual devices or entities participating in federated learning. Each client holds its own local dataset, maintaining data privacy.
3) Local Models (Local Model 1 to Local Model N): Models trained locally on each client using their respective datasets.These models capture insights specific to each client's data distribution.
4) Local Data (Data 1 to Data N): Datasets held locally on each client device.Raw data remains on the clients to ensure privacy, and only model updates are exchanged.

Workflow of the CNN based Federated Learning model:

1) Centralized Model Training: The federated learning process begins with training a CNN model on a central server using a centralized dataset.
2) Model Distribution to Clients: The trained Centralized Model is distributed to participating clients (Client 1 to Client N) to serve as the starting point for local training.
3) Local Training on Clients: Individual clients autonomously conduct training on their Local Models utilizing their respective Local Data. Training occurs locally, preserving sensitive data on the client devices.
4) Update Exchange: After local training, clients send back their updated Local Models to the central server. Only model updates, not raw data, are exchanged.
5) Model Aggregation: The central server aggregates the received Local Models to update the Global Model. This aggregation process combines knowledge learned by individual clients.
6) Iterative Process: Steps 2-5 are repeated iteratively for multiple rounds of federated learning. The process of

distributing, training, updating, and aggregating continues to refine the model.

7) Centralized Model Training: The federated learning process begins with training a CNN model on a central server using a centralized dataset.
8) Model Distribution to Clients: The trained Centralized Model is distributed to participating clients (Client 1 to Client N) to serve as the starting point for local training.
9) Local Training on Clients: Each client uses its own local data to train its Local Model in an independent manner. Training occurs locally, preserving sensitive data on the client devices.
10) Update Exchange: After local training, clients send back their updated Local Models to the central server. Only model updates, not raw data, are exchanged.
11) Model Aggregation: The Global Model is refreshed by the central server through the assimilation of Local Models it receives. This process of aggregation merges the acquired knowledge from individual clients.
12) Iterative Process: For numerous rounds of federated learning, steps 2 through 5 are repeated iteratively. The process of distributing, training, updating, and aggregating continues to refine the model.

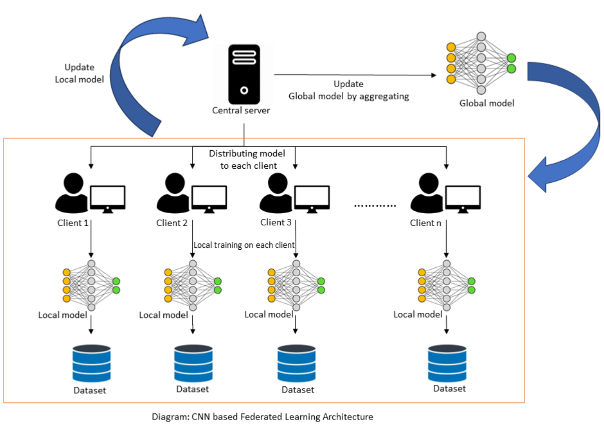

Fig. 6. CNN based Federated Learning architecture

V. Result Analysis

A. Centralized Training Performance

In the initial phase of centralized training, the custom CNN model with residual blocks showcases its ability to learn intricate patterns within the breast cancer dataset. Over 50 epochs, the training accuracy steadily climbs to an impressive 98.43% and final test accuracy becomes 93.33% indicating the model's capacity to discern subtle features and adapt to the complexities of the data. This ascent in accuracy is coupled with a substantial reduction in training and testing loss, final training loss is 0.0052 and testing loss is 0.0500 . These results emphasize the robust learning capabilities of the model during centralized training.

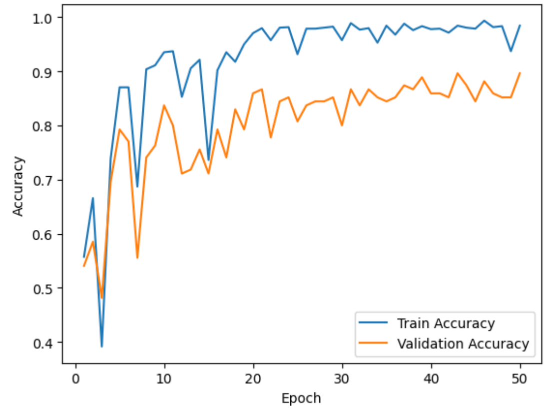

Fig. 7. Train-Test Accuracy Graph

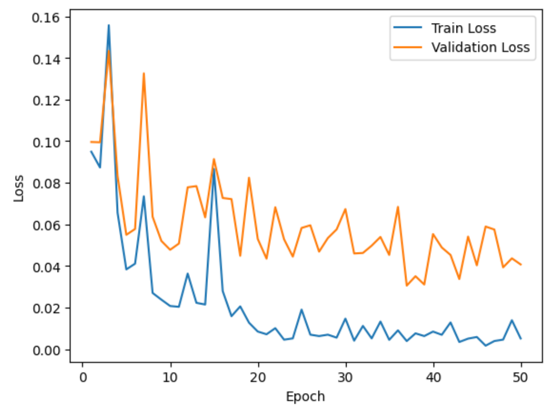

Fig. 8. Train-Test Loss Graph

B. Federated Learning Performance

Transitioning to the federated learning paradigm, the collaborative approach yields compelling outcomes. The final federated training accuracy reaches an outstanding 98.42%, underscoring the model's ability to generalize across diverse datasets distributed across multiple clients. The corresponding loss is notably low, standing at 0.0052. This collective learning strategy demonstrates the model's adaptability in a decentralized setting, showcasing its potential for applications in scenarios where data privacy and distribution are paramount.

C. Federated Test Set Evaluation

The federated test set evaluation further solidifies the model's real-world applicability. With a test loss of 0.0499 and an accuracy of 93.33%, the model demonstrates robust generalization, affirming its efficacy in scenarios beyond the training distribution. These results indicate that the federated learning approach not only maintains but enhances the model's performance in comparison to centralized training, making it a promising solution for scenarios involving distributed data sources.

	Precision	Recall	F1-Score	Support
Benign	0.90	0.93	0.91	46
Malignant	0.96	0.89	0.92	54
Normal	0.95	1.00	0.97	35
Accuracy			0.93	135
Macro Average	0.93	0.94	0.94	135
Weighted	0.93	0.93	0.93	135

TABLE I
CLASSIFICATION REPORT FOR THE MODEL

D. Classification Report and Confusion Matrix Analysis

The comprehensive classification report provides detailed insights into the model's performance across distinct classes. With high recall, precision, and F1-score metrics, the model exhibits proficiency in distinguishing between benign, malignant, and normal cases. The confusion matrix further elucidates the model's nuanced performance, revealing its true positive, true negative, false positive, and false negative predictions for each class. This detailed analysis underlines the model's discriminating abilities and its potential utility in practical medical applications, particularly in the diagnosis of breast cancer.

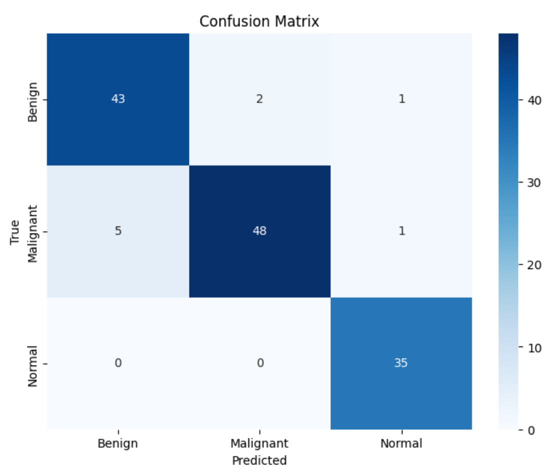

Fig. 9. Confusion Matrix for the Model

VI. CONCLUSION

The integration of CNN and federated learning (FL) for identifying breast cancer through ultrasound images presents a hopeful resolution to the issues associated with centralized storage of medical data. Leveraging the strengths of CNNs for intricate feature analysis and FL for collaborative learning from decentralized datasets, this approach aims to enhance diagnostic accuracy. Through meticulous dataset handling, model training, and result analysis, the combined model demonstrates potential for improved breast cancer diagnosis. The emphasis on large-scale deployment, integration with clinical workflows, and multi-model fusion underscores its practical applicability and holistic diagnostic capabilities.

VII. FUTURE WORK

The future direction of this research entails enhancing the convolutional neural network (CNN) by introducing greater complexity, achieved through the augmentation of network depth via the addition of more convolutional layers or residual blocks. It is crucial to note that this augmentation necessitates careful initialization and regularization to mitigate the risk of overfitting. Another avenue involves expanding the network width, achieved by incorporating more filters into each convolutional layer. This allows the model to concurrently capture a greater array of distinct patterns, potentially bolstering its representational capacity.

Looking beyond the breast cancer dataset, the model showcases substantial potential for widespread applications across various sectors. In the realm of healthcare, its applicability extends to tasks such as medical image analysis and clinical data analysis. The model's versatility further enables its utilization in finance, including applications like fraud detection and credit scoring. In smart cities, the model can contribute to activities such as traffic management and environmental monitoring. Additionally, it proves valuable in manufacturing for tasks like quality control and predictive maintenance, in telecommunications for network optimization and predicting customer churn, and in agriculture for predicting crop diseases and weather forecasting. The overarching goal of the research is to highlight the model's adaptability and demonstrate its efficacy across diverse domains, surpassing its initial focus on healthcare.

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