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Privacy-Preserving Breast Cancer Classification: A Federated Transfer Learning Approach

Selvakanmani S[1] · G Dharani Devi[2] · Rekha V[3] · J Jeyalakshmi[4]

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Abstract

Breast cancer is deadly cancer causing a considerable number of fatalities among women in worldwide. To enhance patient outcomes as well as survival rates, early and accurate detection is crucial. Machine learning techniques, particularly deep learning, have demonstrated impressive success in various image recognition tasks, including breast cancer classification. However, the reliance on large labeled datasets poses challenges in the medical domain due to privacy issues and data silos. This study proposes a novel transfer learning approach integrated into a federated learning framework to solve the limitations of limited labeled data and data privacy in collaborative healthcare settings. For breast cancer classification, the mammography and MRO images were gathered from three different medical centers. Federated learning, an emerging privacy-preserving paradigm, empowers multiple medical institutions to jointly train the global model while maintaining data decentralization. Our proposed methodology capitalizes on the power of pre-trained ResNet, a deep neural network architecture, as a feature extractor. By fine-tuning the higher layers of ResNet using breast cancer datasets from diverse medical centers, we enable the model to learn specialized features relevant to different domains while leveraging the comprehensive image representations acquired from large-scale datasets like ImageNet. To overcome domain shift challenges caused by variations in data distributions across medical centers, we introduce domain adversarial training. The model learns to minimize the domain discrepancy while maximizing classification accuracy, facilitating the acquisition of domain-invariant features. We conducted extensive experiments on diverse breast cancer datasets obtained from multiple medical centers. Comparative analysis was performed to evaluate the proposed approach against traditional standalone training and federated learning without domain adaptation. When compared with traditional models, our proposed model showed a classification accuracy of 98.8% and a computational time of 12.22 s. The results showcase promising enhancements in classification accuracy and model generalization, underscoring the potential of our method in improving breast cancer classification performance while upholding data privacy in a federated healthcare environment.

Keywords Breast cancer · Transfer learning · Federated learning · Deep learning · ResNet · Domain adaptation · Privacy-preserving · Classification · Medical imaging · Data privacy

✉ Selvakanmani S
sskanmani6@yahoo.com

1 Department of Information Technology, R.M.K Engineering College, Chennai, Tamil Nadu, India

2 Department of Computer Science and Engineering, Rajalakshmi Engineering College, Chennai, Tamil Nadu, India

3 Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, Tamil Nadu, India

4 Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidhyapeetham, Chennai, India

Introduction

Background

Breast cancer is a deadly disease affecting millions of women around the world. The World Health Organization (WHO) reports that the most common type of cancer caused among women is breast cancer. In 2020, 2.3 million breast cancer cases were diagnosed. Tragically, it is also a leading cause of cancer-related deaths in women, underscoring the urgent need for improved detection and treatment strategies [1].

To increase patients' survival rate, diagnosing breast cancer in its initial stage is crucial for successful treatment.

Medical imaging technologies, including MRI, ultrasound, and mammography, play a central role in breast cancer screening and diagnosis. These imaging modalities allow healthcare professionals to visualize and analyze breast tissue, enabling the detection of potential abnormalities and cancerous lesions.

However, the accurate interpretation of medical imaging data can be a challenging task, even for experienced radiologists. Breast cancer exhibits various morphological and structural variations, making it challenging to distinguish malignant as well as benign tumors [2]. Moreover, the quality of the imaging data, such as noise and artifacts, can further complicate the diagnosis process.

Recent developments in machine learning as well as artificial intelligence have generated new potentials for improving breast cancer diagnosis and classification. Deep learning has demonstrated superior performance in medical image analyses, including object detection, segmentation, and classification [25–27]. Convolutional neural networks (CNNs) have exhibited better results in extracting meaningful features from medical images and achieving high accuracy in various medical imaging tasks [3].

While the deep learning models have provided better performances, their widespread deployment in medical settings faces several challenges. The main hurdle is the availability of large-scale annotated medical imaging datasets. To learn complex structures and features effectively, the training deep learning models need a vast amount of labeled data [4]. In the medical domain, where data privacy and security are paramount, accessing and sharing such large datasets is very challenging due to legal, ethical, and regulatory constraints.

Moreover, healthcare institutions typically operate in isolated data silos, limiting the potential for large-scale collaborative efforts [5]. Centralized data pooling has a security risk, as sensitive patient information could be compromised if a breach occurs. As a result, traditional machine learning approaches that rely on centralized data may not be suitable for addressing breast cancer classification challenges in a privacy-preserving as well as collaborative manner [6].

To address these issues, federated learning (FL) has appeared as the best solution to train machine learning models while preserving data confidentiality. The key roles of this FL model are privacy and security which protects sensitive data and information. FL enables multiple parties, including hospitals or research institutions that collaboratively train the shared model without sharing any raw data. Instead, model updates are communicated, aggregated, and utilized to enhance the global model, while the actual data remains decentralized and secure at each institution.

By combining FL with deep learning techniques, it becomes possible to train robust and accurate breast cancer classification models across multiple medical centers, without compromising patient privacy. However, the success of FL in this context depends on overcoming challenges related to data distribution discrepancies and limited data availability at each institution.

In this context, transfer learning has gained attention as a promising approach to enhance model performance in situations with limited data. Transfer learning leverages knowledge gained from pre-training models on large external datasets and adapts it to the target task, in this case, breast cancer classification. By transferring knowledge from pre-trained models, the need for large amounts of data from individual medical institutions is reduced, and the model is generalized better to diverse datasets from different sources.

Motivation

The motivation behind this research is driven by the pressing need to improve breast cancer diagnosis and classification while addressing the challenges associated with data privacy and limited data availability in the medical domain. FL offers a compelling solution to overcome the privacy concerns associated with sharing patients' confidential data, which makes it an attractive approach to jointly train the model in diverse medical institutions.

Privacy Preservation in FL

Data privacy is a critical concern in the healthcare industry, especially when dealing with sensitive medical information. Traditional machine learning methods often require centralizing data from various sources for model training, raising significant privacy and security risks. Storing and processing patient data in a centralized system increases the vulnerability to data breaches, potentially compromising patient confidentiality and leading to legal and ethical repercussions.

FL addresses these concerns by allowing each participating institution to retain control over its data. Instead of sending raw patient data to a central server, only model updates, represented as weights and gradients, are shared and aggregated for model training. This decentralized technique assures the patients' confidential data remains local, reducing the risk of data exposure and unauthorized access. By enabling collaborative training without sharing raw data, FL aligns with conditions of regulation like the Health Insurance Portability and Accountability Act (HIPAA) and enhances data privacy in the medical domain.

Mitigating Data Scarcity and Overfitting

In medical imaging applications like breast cancer classification, acquiring large-scale labeled datasets are very challenging due to factors like the rarity of certain conditions, ethical considerations, and resource constraints. Consequently, training deep learning models on limited data may cause overfitting, where the model acts badly in new, unseen cases.

Transfer learning, in combination with FL, presents a compelling approach to address data scarcity and overfitting. By leveraging knowledge from pre-trained models trained on large-scale datasets from unrelated tasks, the model captures general features and patterns applicable across diverse datasets. This transfer of knowledge mitigates overfitting and improves the approach's capability for generalizing unseen cases, enhancing its robustness and accuracy.

Handling Domain Shift and Heterogeneity

Medical data often exhibit variations in terms of data distribution, imaging protocols, and equipment across different healthcare institutions. These discrepancies lead to domain shift, where the model's performance degrades when applied to data from different sources. The challenge of domain shift becomes even more pronounced in the FL context, where the data at each institution may have distinct characteristics.

Incorporating transfer learning in FL is used to address domain shift challenges. Pre-trained models are implemented to capture a rich set of features from the datasets that are transferable to the breast cancer classification task. By adapting these pre-trained models using domain adaptation techniques, the model's representation space is aligned across diverse medical centers, allowing for better generalization and improved performance on decentralized data.

Enhancing Model Efficiency and Performance

Training deep neural networks from scratch on small datasets is resource-intensive and time-consuming. FL, with its decentralized training paradigm, distributes the computational load across multiple institutions, potentially improving the overall efficiency of model training.

Furthermore, transfer learning decreases the number of training iterations required for the model to converge by leveraging pre-trained models. The knowledge already encoded in the pre-trained model accelerates the learning process, which leads to quick convergence as well as efficient use of computational resources.

Overall, the motivation behind this research is to leverage the synergies between federated learning and transfer learning to develop a robust and privacy-preserving breast cancer classification model. By addressing data privacy concerns, mitigating data scarcity and overfitting, handling domain shift, and enhancing model efficiency, we seek to contribute to advancements in diagnosing breast cancer and maximize the patients' survival rates. The insights gained from this research may pave the way for more widespread adoption of collaborative and privacy-preserving AI solutions in the medical domain, benefiting healthcare providers and patients alike.

The Residual Network (ResNet) model is motivated by the success in the computer vision tasks including image classification. This ResNet model has the ability to capture hierarchical features of the image and also has strong generalization ability that enhances the performance of the system. In this breast cancer classification, the pre-training is beneficial on the datasets with diverse and rich visual features. The features related to edges, texture, and patterns learned from the large and diverse dataset are useful for downstream tasks.

Objectives and Contributions

By leveraging pre-trained deep neural networks and domain adaptation techniques, this research goal is to enhance the breast cancer classification models' accuracy and generalization of across diverse medical centers while ensuring data security. The contributions and key points of the study are summarized as follows:

- *Addressing limited labeled data*: The study addresses the limitation of limited labeled data in the medical domain by using transfer learning. By fine-tuning a pre-trained ResNet model on breast cancer datasets from diverse medical centers, the model can learn specialized features even with limited local data.
- *Privacy-preserving framework and classification enhancement*: The study adopts an FL approach, which enables multiple medical institutions to train the global model without sharing raw data for data privacy and security. The integration of transfer learning and FL along with domain adversarial training effectively improved breast cancer classification performance of 98.8%.
- *Domain adaptation for data variations*: The introduction of domain adversarial training helps overcome domain shift challenges caused by variations in data distributions across different medical centers.
- *Potential for real-world deployment*: The study showcases the potential of the proposed method in a federated healthcare environment, where medical institutions can collaborate without compromising data privacy. This opens doors for large-scale, privacy-preserving applications in real-world medical scenarios.
- *Contribution to breast cancer research*: The study's findings contribute to breast cancer research by offering an innovative approach to improve early detection and classification accuracy.

This research is organized as follows: different types of breast cancer classification–related literature surveys are included in the "Literature Survey" section which is separated into deep learning–based classification models, FL-based classification models, and transfer learning–based classification models. The "Methodology" section showed a proposed methodology used to improve breast cancer classification while ensuring data privacy and security. Detailed explanations of the experimental result are provided in the "Experimental Analysis" section which contains the dataset details, experimental setup, and performance analysis using different metrics. Finally, the discussion and conclusion sections are explained in the "Discussion" section and "Conclusion" section, respectively. The limitations and benefits of this work are mentioned in the "Discussion" section, and future research directions are given in the "Conclusion" section.

Literature Survey

Numerous research analyses were conducted to explore the benefits and limitations that occurred during breast cancer classification. This section conducts the different breast cancer classification research by using different approaches.

Breast Cancer Classification with Deep Learning

Deep learning techniques have revolutionized breast cancer diagnosis as well as treatment. Deep learning models, particularly CNNs, have proved superior performance in diverse computer vision tasks, making them well-suited for medical image diagnosis, including breast cancer classification.

Ragab et al. [7] illustrated a Deep CNN (DCNN) approach to classify breast cancer lesions in mammograms. The extracted features from the mammographic images were applied to the support vector machine (SVM) classifier and the deep feature fusion model combined features to enhance classification accuracy.

Liu et al. [8] implemented an AlexNet breast cancer (AlexNet-BC) approach for eliminating overfitting issues, early detection, and accurate breast cancer classification. The image augmentation process includes image enhancement, image binarization, geometric transformation, and histogram equalization that was used for image quality enhancement and contrast enhancement. Finally, the images attained from the ImageNet dataset were classified into benign and malignant.

Hirra et al. [5] elaborated a patch-based Deep Belief Network breast cancer detection (Pa-DBN-BC) method for detecting and classifying breast cancer. The patch-based model was used for attaining better performance in the feature extraction but it has a high computational cost.

Kumbhar et al. [9] presented an enhanced recurrent neural network (E-RNN) approach to diagnose breast cancer. From the affected area, the breast cancer mammogram images were obtained with the use of an FL model to provide better performance and minimize processing time. Montaha et al. [24] illustrated a VGG-16 model for breast cancer detection using mammography images.

Several researchers have explored the deep learning models' application for breast cancer diagnosis using mammography, ultrasound, and MRI data. Researchers have proposed various architectures and optimization techniques to enhance the breast cancer classification models' accuracy. For instance, studies have investigated the use of transfer learning with pre-trained CNNs to leverage large-scale datasets, for feature extraction in breast cancer images. The pre-trained models are fine-tuned in breast cancer datasets, and these approaches have shown improved performance, especially when faced with limited medical imaging data.

Furthermore, the data augmentation approaches' application has been explored to maximize the training dataset's diversity as well as decrease overfitting. Approaches such as flipping, translation, and rotation have been applied to augment the available breast cancer images, effectively enlarging the dataset as well as improving the model's ability to generalize.

While deep learning approaches attained superior performance for breast cancer classification, their widespread deployment in clinical settings is still hindered by the need for large annotated datasets and concerns about model interpretability. Interpretability is crucial in medical applications to gain the trust of healthcare practitioners and enable decision-making based on model predictions. Therefore, research efforts have also been directed towards generating interpretable deep learning approaches for breast cancer classification, such as attention mechanisms and heatmaps to highlight regions of interest in medical images.

FL for Privacy-Preserving Collaborative Training

FL has emerged as a groundbreaking approach to solve the limitations associated with data privacy and security in machine learning applications. The fundamental idea behind federated learning is to enable model training across multiple distributed devices (e.g., hospitals and clinics) without centralizing raw data. Participating institutions train their local models on their respective datasets and share only model updates, such as weights or gradients, with the central server.

In the context of healthcare and medical imaging, FL offers a compelling solution for privacy-preserving collaborative training of machine learning approaches. It allows healthcare institutions to pool their knowledge without sending patient's confidential data directly. This decentralized approach aligns with regulatory requirements and ethical considerations, fostering trust among institutions and patients.

Tan et al. [10] established an FL model to classify breast cancer by accurate identification and localization of tumor lesions. The image features were selected by transfer learning model from the DDSM dataset which provided an image enhancement. Then the detection and classification performance was enhanced by applying the synthetic minority oversampling technique (SMOTE) and the federated average–based CNN with MobileNet (FeAvg-CNN+MobileNet) model to provide security and privacy.

Li et al. [11] represented an FL model to detect breast cancer. The FL model has three types of modules such as federated clients, federated servers, and user platforms. The user platform was included for providing prediction services and data labeling, the federated server was used for service request mapping, encryption, and decryption, and the federated clients were employed to upload the trained parameters. To validate the performance, the BreakHis dataset was implemented and it classified the breast tumor tissue images into malignant and benign.

Peta and Koppu [12] demonstrated a federated-based deep learning method to enhance the classification of breast cancer. The Extended ElGamal Image Encryption (E-EIE) algorithm was implemented to provide privacy, secure data communication, and efficient storage. The BreakHis database was used to carry out the performance during the validation process.

Salmeron et al. [13] established a peer-to-peer FL approach to diagnose breast cancer. By comparing centralized architectures, peer-to-peer communication was more efficient and faster because the trained model directly shared and collaborated each other by clients. The Breast Cancer Wisconsin Dataset was used for the experimental validation process, and this model provided security and privacy to clients for handling data and sharing important information. Due to the usage of open source datasets, this FL model has a limitation in quality, realism, diversity, generalization, and ethical considerations.

Jimenez-Sanchez et al. [14] elaborated a memory-aware curriculum FL model to classify breast cancer. In this paper, the data scheduler was designed to enhance the local model consistency, and the experiments were conducted by using three types of mammography datasets, namely GE, Hologic, and Siemens (INBreast). Finally, the mammography image samples were classified into benign and malignant. The training samples were needed to be scheduled for boosting up the alignment among domain pairs by using global as well as local classification predictions.

Several studies have explored the FL approach's application for medical image analysis, including breast cancer classification. These researches have proved the feasibility and potential advantages of collaborative model training using decentralized data. FL has been employed in diverse medical imaging analyses, including tumor segmentation, disease detection, and treatment planning. It has shown promising results in improving model accuracy and generalization across different medical centers.

Challenges in federated learning include addressing communication efficiency, model aggregation techniques, and dealing with data distribution discrepancies across participating institutions. Researchers have proposed communication-efficient algorithms to reduce the communication overhead and minimize the number of rounds of communication between the central server and the clients. Additionally, federated optimization methods, such as federated averaging, have been developed to aggregate model updates while accounting for variations in local datasets' distributions.

Transfer Learning in Medical Imaging

Transfer learning has attained considerable attention in medical imaging analysis due to its potential to leverage knowledge learned from pre-trained models on unrelated tasks. Medical imaging datasets are often limited in size, leading to challenges in training deep learning models from scratch. Transfer learning permits researchers to utilize pre-trained models, typically trained on large-scale image datasets (e.g., ImageNet), as a starting point for medical image analysis tasks.

Ahmad et al. [15] elaborated a transfer learning-based computer-aided diagnostic (CAD) system to classify breast cancer by avoiding misleading and human errors. The patches were extracted from the BreakHis dataset, and the extracted samples were classified into benign and malignant. Ayana et al. [16] designed a multistage transfer learning (MSTL) algorithm to classify breast cancer using ultrasound images. The Mendeley and MT-small dataset were used for selecting ultrasound images, but it has an impact on the early breast cancer diagnosis.

Ming et al. [17] represented a transfer learning–based dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) analysis for breast cancer prediction and classification. This model got superior performance. But this model required a reliable model for non-invasive assessment in clinical practice. The TL-based Advanced Al-Biruni Earth Radius (ABER) optimization model for breast cancer classification was established by Alhussan et al. [18]. The CAD system–based transfer learning methods were used to classify the breast cancer region from the BreakHis dataset. The extracted features were classified into malignant cancer and benign which was explained by Aljuaid et al. [19].

In medical imaging, transfer learning has been employed in diverse tasks, including disease detection, organ segmentation, and abnormality classification. Researchers have explored different transfer learning approaches, including feature extraction, fine-tuning, and domain adaptation to adapt pre-trained approaches to certain medical imaging analyses.

For breast cancer classification, transfer learning is beneficial in addressing data scarcity and improving model generalization. By initializing the model with weights learned from pre-trained models, the model learns meaningful representations from limited breast cancer datasets more effectively. Additionally, domain adaptation techniques have been investigated to align the distribution of medical imaging data across different institutions, mitigating the domain shift challenges encountered in the federated learning setting.

Moreover, recent studies have explored transfer learning for multimodal medical imaging, where information from different imaging modalities, such as mammography and MRI, is combined to enhance classification performance. The ability to transfer knowledge across modalities opens up new possibilities for improving breast cancer diagnosis and classification accuracy.

Overall, transfer learning in medical imaging has shown great promise in enhancing model performance, reducing overfitting, and improving generalization across diverse datasets. When combined with federated learning, it presents a powerful framework for collaborative breast cancer classification, addressing data privacy concerns while leveraging collective knowledge from multiple medical institutions.

This research intends to utilize the advantages of both transfer learning and FL by combining both approaches based on breast cancer classification, ultimately leading to improved diagnostic accuracy and patient care.

Limitations and Research Gap

Numerous studies have been conducted for privacy preserving breast cancer classification but the performance of these researches affected based on the limitations in the enhancement of classification performance, cancerous lesion identification, early identification, domain shift challenges, data privacy, and mortality rate reduction. These limitations leads to the large amount of mortality rate in worldwide, so one of the security-based deep learning model is implemented to overcome these limitations for privacy preserving breast cancer classification. The transfer learning model is integrated into the FL approach for maintaining data privacy during breast cancer classification.

Methodology

Overview of the Proposed Approach

The proposed approach integrates transfer learning with federated learning to develop a privacy-preserving breast cancer classification model that efficiently leverages knowledge from a pre-trained deep neural network, specifically ResNet, across multiple medical centers. The methodology involves collaborative training of the model while keeping the raw data decentralized, ensuring data privacy and security. Figure 1 provides the proposed approach's overall structure. The breast cancer image data from diverse medical centers undergoes pre-processing to standardize image sizes and normalize pixel intensities, ensuring consistency across datasets. Pre-processing includes tasks like standardizing image sizes and normalizing pixel intensities to ensure consistent inputs for the subsequent model training. Augmentation helps in maximizing the training dataset's diversity, preventing overfitting, and improving the model's generalization ability. Transfer learning is employed using ResNet, a pre-trained deep neural network that was originally trained at ImageNet. The breast cancer dataset is employed to fine-tune the higher layers, allowing the model to adapt and specialize to the breast cancer classification while benefiting from the general image representations learned from ImageNet. After transfer learning and fine-tuning, the ResNet model is adapted specifically for the breast cancer classification task.

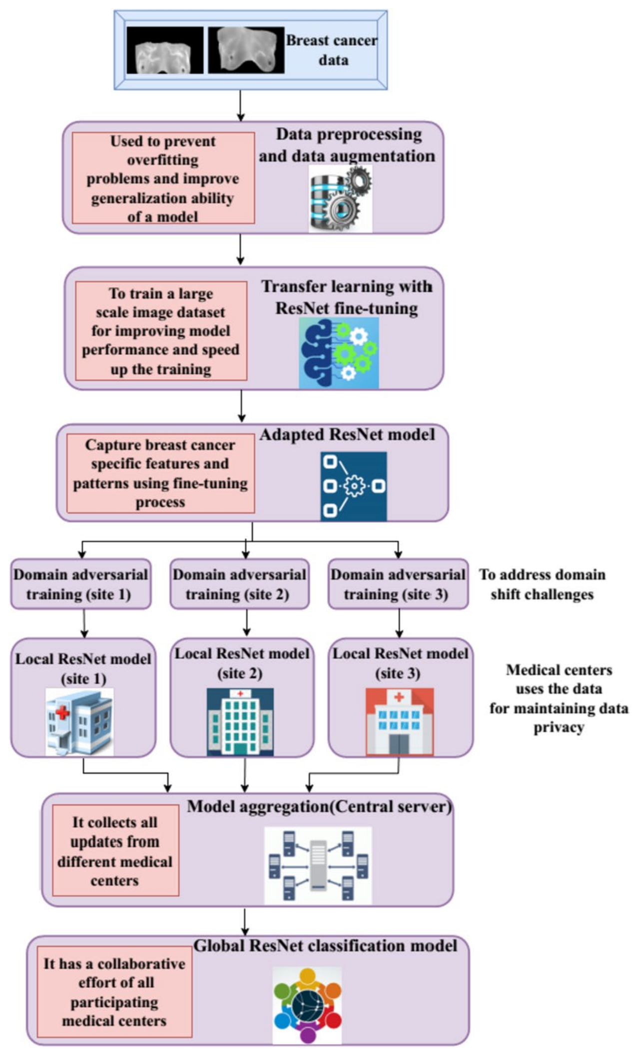


Fig. 1 Overall structure for the proposed model

The fine-tuning process enables the model to capture breast cancer–specific features and patterns. To address domain shift challenges, domain adversarial training is introduced within the federated learning process. Each medical center performs domain adversarial training on its local ResNet model. By feature extractor, the domain classifier is confused by minimizing the domain discrepancy while maximizing the classification accuracy. Federated learning is employed to enable collaborative training of the breast cancer classification model without sharing raw data. The central server aggregates the updates using the federated averaging technique, which considers the participation rates of each medical center. The resulting global ResNet model is a collaborative effort of all participating medical centers. This global model now contains knowledge from all centers while keeping each center's data private.

Pre-Processing and Data Augmentation

Pre-processing and data augmentation are crucial steps in preparing the breast cancer image dataset for model training. The proposed pre-processing and data augmentation approaches aim to ensure standardized inputs and increase the diversity of the training data. These steps assist in improving the model's capability in identifying critical features within the images and enhancing its generalization performance.

Pre-Processing

The datasets are pre-processed to ensure standardization and consistency. The mammography images are resized to a fixed resolution, and both mammography as well as MRI images undergo normalization to enhance model convergence during training. Additionally, noise removal techniques are applied to enhance images' quality.

Image Resizing

The breast cancer images in the dataset may have varying sizes and resolutions. Image resizing is applied to standardize the image dimensions across the entire dataset. Resizing assures that every image is of the same size, which assists the proposed approach to processing them consistently. Mammography images are resized into a fixed resolution of 224×224 pixels, and MRI images are resized into 256×256 pixels, ensuring uniform input sizes for the ResNet model.

Image Normalization

Image normalization is performed to scale the pixel intensities within a specific range, typically between 0 and 1. This step is essential to bring consistency to pixel values across the images, making the model less sensitive to differences in brightness or contrast. Normalization helps the model converge faster during training and prevents certain features from dominating others due to varying pixel intensity scales.

Noise Removal

Medical images can contain various artifacts and noise, which might affect the proposed model's efficiency negatively. In order to enhance the proposed model's ability to extract relevant features, noise removal techniques are applied to clean up the images and reduce interference from irrelevant visual patterns.

Data Augmentation

The training dataset's diversity is maximized artificially by applying data augmentation. By creating variations of the original images, data augmentation prevents the model from memorizing the training data and improves its generalization capability to unseen images. Common data augmentation approaches are as follows:

(a) Rotation: The image is rotated at a specific angle in order to simulate different viewpoints.
(b) Translation: The image is shifted horizontally as well as vertically to account for slight position changes.
(c) Flipping: Horizontally flipping the image to introduce mirrored representations.
(d) Zooming: Zooming in or out of the image to simulate different scales.

By applying data augmentation, the model is exposed to a more extensive and diverse set of breast cancer images, leading to a more robust and generalized breast cancer classification model.

Transfer Learning with ResNet Fine-tuning

Transfer learning with ResNet fine-tuning leverages the pre-trained ResNet model to expedite the training process and enhance breast cancer classification performance [23]. By utilizing ResNet as a feature extractor and fine-tuning the higher layers on the breast cancer dataset, the powerful general image representations learned from large scale image datasets like ImageNet lead to better feature representations, specifically for breast cancer classification.

Pre-trained ResNet Model

ResNet is a deep convolutional neural network architecture known for its ability to handle deep networks effectively and avoid the vanishing gradient problem. The pre-trained ResNet model has already learned to extract hierarchical and meaningful features from a wide variety of images during its training on ImageNet. The low-level features like textures and edges are captured by the initial layers of ResNet; at the same time, the deeper layers identify the higher-level and more abstract visual representations. The ResNet model is optimized to reduce the loss of source domain data due to performing the pre-training process and is expressed as

$$W_{\text{source}} = \arg\min_{W} \sum_{(x,y)\in D_{\text{source}}} L_{\text{source}}\left(f_{\text{ResNet}}(x;W),\, y\right) \quad (1)$$

where the terms L_{source}, x, y, $f_{\text{ResNet}}(\cdot)$, and W_{source} are represented as cross-entropy loss, breast cancer image dataset (input image), ground truth label for input, pre-trained ResNet model, and pre-trained weights, respectively.

Utilizing ResNet as a Feature Extractor

In transfer learning, the pre-trained ResNet model is applied as a feature extractor. This means that we freeze the weights of the lower layers of ResNet, keeping the learned low-level features intact and fixed. The idea is to preserve the general image representations learned from ImageNet, which is highly relevant for many computer vision tasks, including breast cancer classification. The extracted features are computed as

$$F_{\text{i}} = f_{\text{extract}}\left(x_{\text{i}}\right) \quad (2)$$

From Eq. (2), the breast cancer images, feature extraction function, and features are denoted by x_{i}, f_{extract}, and F_{i}, respectively.

Fine-Tuning the Higher Layers

While the lower layers remain frozen, the ResNet model's higher layers are fine-tuned in the breast cancer dataset. Fine-tuning involves updating the weights of these higher layers during the training process to adapt them to the specific breast cancer classification task. This allows the model to learn domain-specific features relevant to breast cancer patterns and characteristics. During fine-tuning, the model is optimized to minimize the loss on the target domain data:

$$W_{\text{target}} = \arg\min_{W} \sum_{(x,y)\in D_{\text{target}}} L_{\text{target}}\left(f_{\text{ResNet}}(x;W),\, y\right) \quad (3)$$

From Eq. (3), the terms such as L_{target}, y, and $f_{\text{ResNet}}(x;W)$ are represented as cross-entropy loss, corresponding label of the breast image, and weight of the fine-tuned model, respectively. The objective function is optimized to attain the fine-tuned model, which is defined as

$$\min \theta \frac{1}{N} \sum_{i} = \frac{1}{N} L\left(f_{\text{fine-tune}}\left(f_{\text{extract}}\left(x_{\text{i}};\theta_{\text{extract}}\right);\theta_{\text{fine-tune}}\right),\, y_{\text{i}}\right) \quad (4)$$

In Eq. (4), the terms such as N, x_i, y_i, $\theta_{\text{fine-tune}}$, θ_{extract}, $L(\cdot)$, and $f_{\text{fine-tune}}$ are depicted as total number of breast cancer images, i-th breast cancer images, corresponding label for i-th image which indicates the presence and absence of breast cancer, parameter of fine-tuning function, parameter of feature extraction function, loss function, and fine-tuned function, respectively. After performing the fine-tuning process, the pre-trained weights are combined with fine-tuned weights to make the weight of adapted ResNet model, and the weight of a ResNet model is given below:

$$W = \alpha \cdot W_{\text{source}} + (1-\alpha) \cdot W_{\text{target}} \quad (5)$$

where α is a hyperparameter that controls the degree of influence of the pre-trained weights in the adapted model. A typical value α is often set between 0.1 and 0.5.

Domain Adaptation Using Domain Adversarial Training

Domain adversarial training is an effective approach used to address domain shift challenges in the context of breast cancer classification across different medical centers. When training deep learning models on data from multiple sources with varying data distributions and imaging protocols, the model might learn to rely on site-specific features rather than the essential characteristics of breast cancer. This leads to a decrease in the model's capability for generalizing the unseen data from new medical centers.

To solve the domain shift challenges present in the breast cancer datasets from different medical centers, domain adversarial training is combined with the federated learning setup. The model is augmented with a domain classifier, and during training, the feature extractor learns in order to reduce the domain discrepancy while maximizing classification accuracy. This results in the model learning domain–invariant features, reducing the influence of data distribution differences across medical centers. The goal is to ensure that the model learns representations that are relevant to breast cancer classification and are not specific to any particular medical center's imaging characteristics. The proposed domain adversarial training process is explained as follows:

1. *Domain classifier*: A domain classifier is introduced as a separate component of the model. The domain classifier is responsible for predicting the input data's source domain (i.e., the medical center) on the basis of learned features from the feature extractor (ResNet) during training. The domain classifier encourages the

model to learn features that are less informative about the specific medical center but more informative about the breast cancer classification task. The classification loss is expressed as,

$$L_C = -\frac{1}{N}\sum_{j=1}^{N} x_j \cdot \log\left(\hat{x}_j\right) \tag{6}$$

From Eq. (6), the terms such as N, x_j, and $\hat{x}_j$ are represented as number of samples, actual values, and predicted values, respectively.

2. *Feature extractor*: The ResNet feature extractor is the same as used in the transfer learning with ResNet fine-tuning step. The feature extractor's goal is to learn high-level and abstract features from the breast cancer images that are relevant for classification.
3. *Training with domain adversarial loss*: During training, the feature extractor (ResNet) is optimized to minimize the classification loss (e.g., cross-entropy loss) for the breast cancer task while simultaneously maximizing the domain adversarial loss. The domain adversarial loss confuses the domain classifier and prevents it from accurately predicting the source domain.
4. *Domain adversarial loss*: The domain adversarial loss is defined as the negative cross-entropy loss between the domain classifier's predictions and the true domain labels. The domain classifier is responsible for accurately predicting the source domain, while the feature extractor is responsible for minimizing this loss, which makes the features domain-invariant. The domain adversarial loss function is represented as

$$L_{DA} = -\log\left(F\left(x^P\right)\right) - \log\left(F\left(x^t\right)\right) \tag{7}$$

From Eq. (7), the $F(\cdot)$, x^P, and x^t are derived by feature extraction function, predicted domain, and true domain, respectively.

Mathematically, the overall loss function for domain adversarial training is represented as follows:

$$L_{total} = L_C + \lambda \times L_{DA} \tag{8}$$

where the terms L_{total}, L_C, L_{DA}, and λ are described as total loss, classification loss (e.g., cross-entropy) for the breast cancer task, domain adversarial loss which measures the domain discrepancy, and hyperparameter that controls the importance of the domain adversarial loss relative to the classification loss, respectively.

5. *Minimizing domain discrepancy*: By jointly optimizing the classification and domain adversarial losses, the feature extractor (ResNet) learns in order to decrease the domain discrepancy across different medical centers. This encourages the model to focus on breast cancer-related features rather than center-specific variations.
6. *Domain-invariant features*: As a result of domain adversarial training, the feature extractor learns domain-invariant features that are relevant for breast cancer classification. These features are less affected by variations in data distributions and imaging protocols across different medical centers, leading to better generalization and robustness of the model on unseen data.

Collaborative Federated Learning

In the Federated Learning framework, we adopt a collaborative approach to train a robust and efficient breast cancer classification model without compromising patient data privacy. Each participating medical center trains its local ResNet model on its own private breast cancer data. Instead of sharing raw data, which could raise privacy concerns, only model updates in the form of gradients are transmitted to a central server. This decentralized data approach ensures that sensitive patient information remains localized and secure within each medical institution.

Local ResNet Model Training

At the beginning of the federated learning process, each medical center initializes its local ResNet model using the pre-trained weights from the transfer learning step. The local ResNet model is then trained on the respective medical center's breast cancer dataset using the domain adaptation technique, as described in the previous sections. During this local training phase, the model learns from the specific characteristics and features present in the data from that particular medical center.

Model Updates and Aggregation

After the local training, instead of sending the entire trained model to the central server, only the model updates in the form of gradients are transmitted. These gradients represent the information about how the parameters for the model should be adjusted to enhance efficiency in the breast cancer classification. The central server receives these gradients from all participating medical centers.

The federated averaging algorithm is used to aggregate the gradients from different medical centers. It calculates the average gradient across all the participating institutions, reflecting the collective knowledge of the global dataset. This averaged gradient represents the consensus update that should be applied to the global ResNet model. The aggregation step is represented as

$$G_{global} = \sum {}^{G_i}/_{N} \tag{9}$$

From Eq. (7), the global gradients, gradient of the local ResNet model at a medical center, and the total number of participating medical centers are denoted as G_{global}, G_{i}, and N, respectively.

Global ResNet Model Update

The global ResNet model is updated by applying the averaged gradient through the central server. The global model is a combination of the pre-trained ResNet model and the fine-tuned weights from the domain adaptation step. By aggregating the knowledge from multiple medical centers, the global model benefits from diverse data sources, making it more robust and generalizable. The global model update is represented as

$$W_{\text{global}} = W_{\text{global}} - \eta \times G_{\text{global}} \tag{10}$$

where W_{global} represents the weights of the global ResNet model, and η is the learning rate.

Model Distribution to Participating Institutions

After updating the global model, the new model is distributed back to all the participating medical centers. Each medical center receives the updated global ResNet model, which incorporates knowledge from other institutions.

Local Model Refinement

The local ResNet models at each medical center receive the updated global model and continue the iterative training process. The local models are further fine-tuned on their respective datasets using the domain adaptation technique with the global ResNet model's updated weights. This process of receiving the global model, refining it locally, and sharing model updates repeats until the termination criterion is satisfied. The local model refinement is represented by

$$W_{\text{local}_{\text{i}}} = W_{\text{global}} \tag{11}$$

where i is the medical center index.

Convergence and Stopping Criterion

The iterative collaborative federated learning process continues until the global ResNet model converges or reaches a predefined stopping criterion. The stopping criterion could be a threshold for improvement in the classification accuracy or a maximum number of iterations. Once the convergence criterion is met, the global model is considered stable and ready for deployment.

The block diagram of the collaborative federative learning approach with ResNet model is shown in Fig. 2. Each participating medical center has its own local ResNet model, which is fine-tuned on its private breast cancer dataset using the domain adversarial training technique. The model updates in the form of gradients (G_{i}) are transmitted from each medical center to the central server. The federated averaging algorithm aggregates the gradients from different medical centers to obtain the averaged gradient (G_{global}) representing the consensus update for the global ResNet model. The global ResNet model is updated by applying the averaged gradient through the central server. The updated global model is distributed back to all participating medical centers. Each medical center refines the received global model locally, incorporating domain adversarial training, and updates its local ResNet model with the aggregated gradient (G_{global}). The iterative collaborative federated learning process continues until the global ResNet model reaches a predefined stopping criterion.

By implementing this collaborative federated learning approach with ResNet, the proposed methodology effectively harnesses the collective knowledge of multiple medical centers, allowing the breast cancer classification model to benefit from diverse data sources without compromising data privacy.

Experimental Analysis

This section performs the proposed model's performance analysis, and the breast cancer data are collected from the different medical centers. At first, the section outlines the implementation details, comprising the experimental setup as well as hyperparameter configuration. Then, the section provides the details about the datasets and performance measures. Finally, the section describes the findings of performance validation and comparative assessment with visual representations.

Experimental Setup

The experimental analyses are conducted on Python programming language with the following software and hardware specifications. The software and hardware specifications used in this paper are shown in Table 1.

Dataset Description

The breast cancer image datasets are collected from multiple medical centers to evaluate the proposed model. The datasets include both mammography images (https://www.kaggle.com/datasets/asmaasaad/mammogram-dataset-kaumds) and MRI images (https://www.kaggle.com/datasets/uzairkhan45/breast-cancer-patients-mris) that prove a comprehensive set

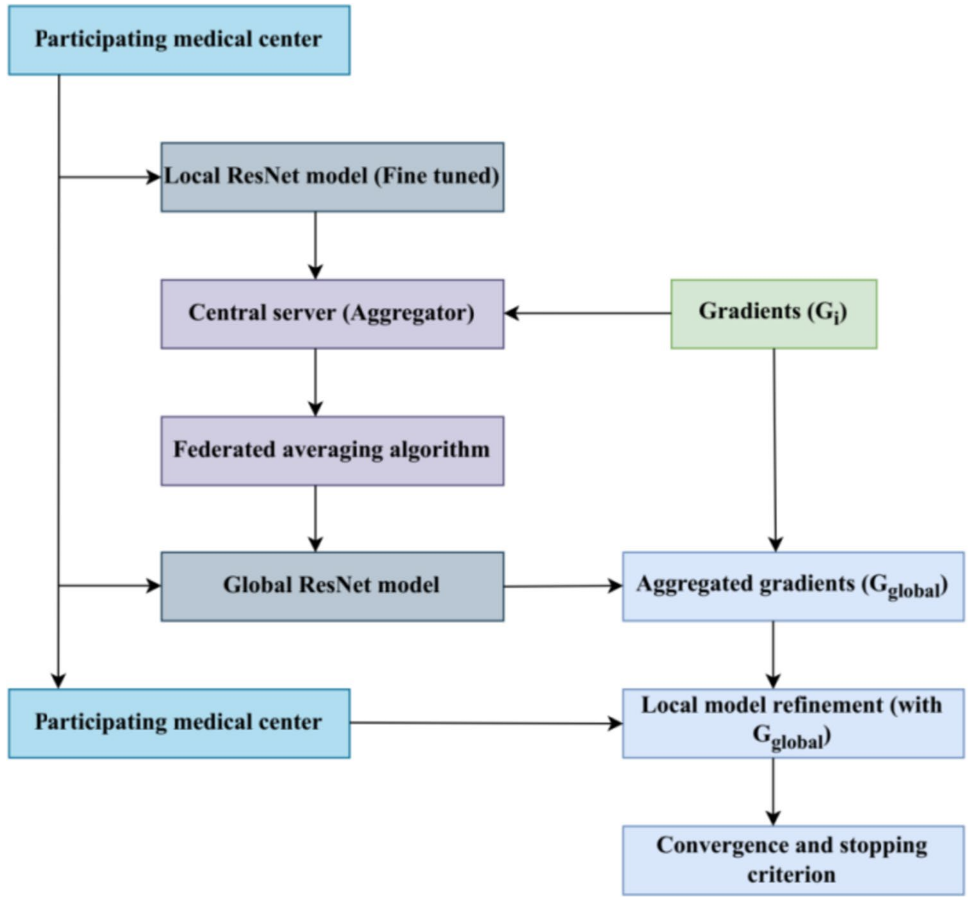


Fig. 2 Block diagram of collaborative federative learning approach with ResNet model

of imaging modalities for more accurate and robust classification. We obtained breast cancer image datasets from three different medical centers: Center A, Center B, and Center C. Each center contributed its own dataset, which represents a unique domain with varying imaging protocols and data distributions. To simulate the real-world challenges of varying data availability in different medical centers, the datasets are categorized into source as well as target domains. The source domain includes a larger dataset contributed by Center A. This dataset serves as the primary source of knowledge for the transfer learning process, given its abundance of labeled breast cancer images. The target domains include datasets contributed by Center B and Center C, which have smaller labeled datasets. These datasets represent domains with limited data, posing domain shift challenges in the federated learning setup. Finally, these mammography and MRI

Table 1 Experimental setup

Software setup	
GPU	NVIDIA GeForce RTX 30 series
CPU	1.20 GHz
Python	3.10.10
Processor	Intel Core i3-1005G1with 64-bit operating system
RAM	8 GB
Hardware setup	
Deep learning framework	TensorFlow
Federated learning library	TensorFlow Federated (TFF)
Central server	Intel Xeon processor
Medical center nodes	NVIDIA GeForce RTX 20 series

Table 2 Key statistics of the breast cancer datasets

Medical center	Modality	Number of images	Number of labels	Data availability
Center A (King Abdulaziz University)	Mammography	10,000	2	High
Center B (Duke University)	MRI	3500	2	Medium
Center C (Stanford University School of Medicine)	Mammography	2000	2	Low

images are classified as malignant as well as benign through performance validation [20]. Table 2 summarizes the key statistics of the breast cancer datasets from each medical center:

Hyperparameter Configuration

The hyperparameter tuning process is involved in this paper to attain the optimal parameters for achieving higher performance rates and lower loss functions. To tune all the hyperparameters is computationally expensive which is suitable for large datasets. The hyperparameters and its optimal values are tabulated in Table 3.

Performance Measures

The performance validation uses some of the experimental analyses such as precision [21], $F1$-score [21], accuracy [21], recall [21], Mathews correlation coefficient (B_{MCC}) [22], specificity, [21] and classification time by using false positive values, true positive values, false negative values, and true negative values. The number of correctly predicted breast cancer regions (malignant) is called as true positives (B_{tp}), and the number of correctly predicted non-cancer regions (benign) is referred to as true negatives (B_{tn}). False positive (B_{fp}) is defined as the non-cancer cases that are incorrectly assigned as cancer cases. The cancer cases that are incorrectly assigned as non-cancer cases are called as false negatives (B_{fn}). The mathematical formulations of these metrics are provided in subsequent sections.

Table 3 Hyperparameter configuration

Different methods	Hyperparameters	Optimal values
Proposed FL-based model	Number of rounds	60
	Number of edges	3
	Number of clients	4
	Batch size	32
	Length	27,940
	α	[0.1, 0.5]

Performance Analysis

For performance identification, the data are split into training and testing with the proportion of 80:20. The performance analysis is used to provide objective information for easily understand the proposed model's effectiveness in classifying breast cancer. Table 4 shows a performance analysis output of the proposed model by using different performance evaluation measures.

The confusion matrix defines the classification efficiency of the proposed model for breast cancer classification. It is generated based on predicted as well as actual values to visualize the outcomes. Each value has two classes such as benign and malignant that are represented in Fig. 3. The confusion matrix presents the prediction outcomes attained by the proposed model, allowing us to identify the most common types of classification errors made by the model.

Figure 4 visualizes an Area Under Receiver Operating Curve (AUC/ROC) analysis of the proposed breast cancer classification model. This metric has the ability to determine the classification performance between two classes and the higher AUC shows better classification performance. From the graphical representation, the proposed breast cancer classification model provides a better classification performance of 0.989.

Table 4 Performance analysis

Name of the metrics	Achieved performance rates
Accuracy	98.8%
Precision	98.9%
Recall	98.5%
Specificity	97.4%
F1-score	98.2%
Mathews correlation coefficient	0.9488
Computational time	12.22 s
Training accuracy	0.988
Testing accuracy	0.945
Training loss	0.1
Testing loss	0.16
AUC/ROC	0.989

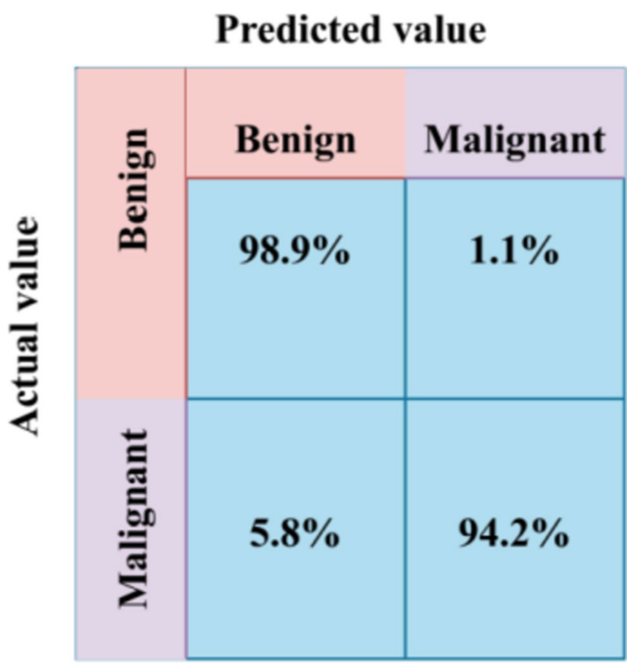


Fig. 3 Confusion matrix for the proposed model

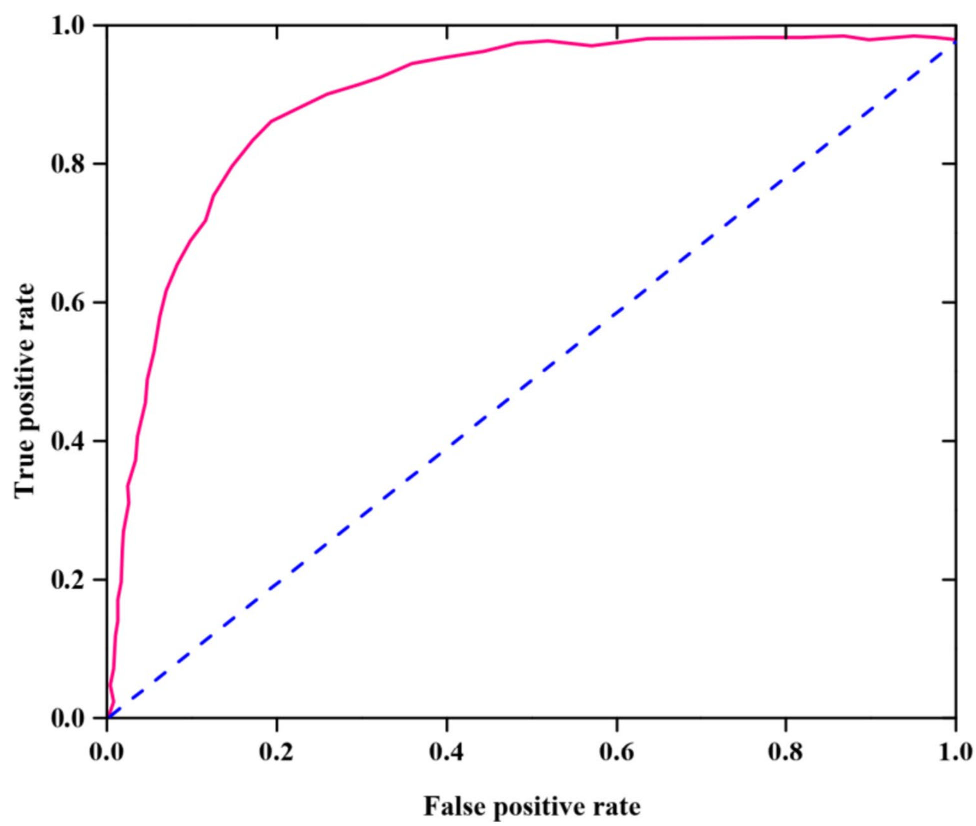
Figure 5a, b depict the accuracy and loss rates obtained from the proposed model when the training as well as testing processes are performed. Here, among the overall data in the dataset, 80% data is applied for the training process, and 20% data is applied for the testing process. The training accuracy uses identical images for both the training as well as the testing process. In testing accuracy, the trained model determines the independent images that were not used in the training process. The loss is defined as a bad prediction of this classification model. The proposed model gained accuracy rates of 0.988 for the training process and 0.945 for the testing process. Also, the proposed model gained loss rates of 0.1 for the training process and 0.16 for the testing process.

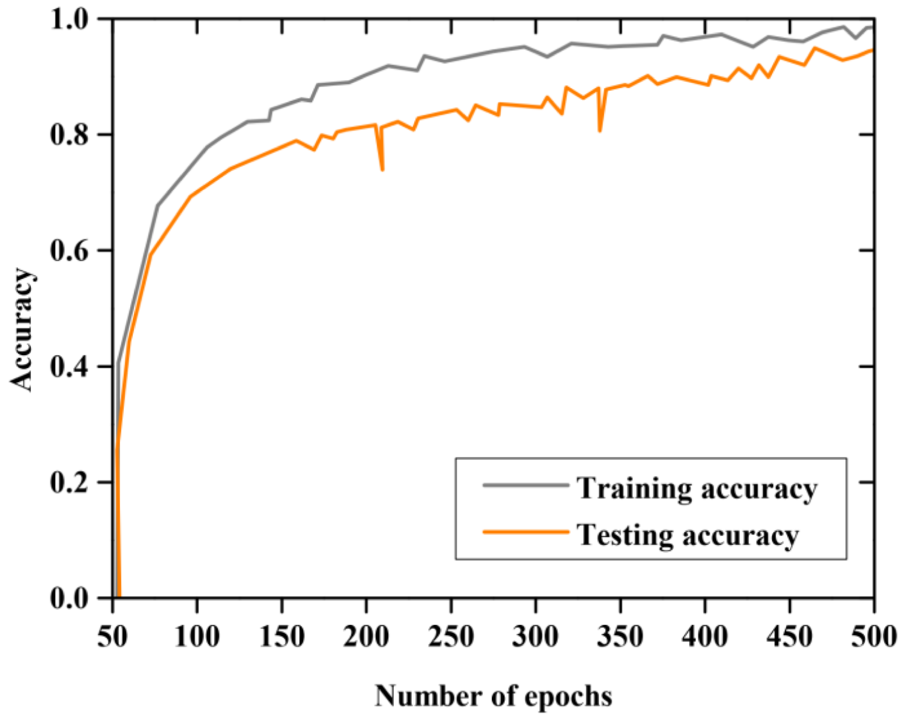
Comparative Analysis

In this paper, the proposed breast cancer classification model is compared with various existing breast cancer classification methods namely FeAvg-CNN+MobileNet [10], VGG-16 [24], FL [11], Pa-DBN-BC [5], DCNN [7], AlexNet-BC [8], and ResNet-50 [23]. The comparative analysis describes the similarities and differences between the different methods by using graphical representations.

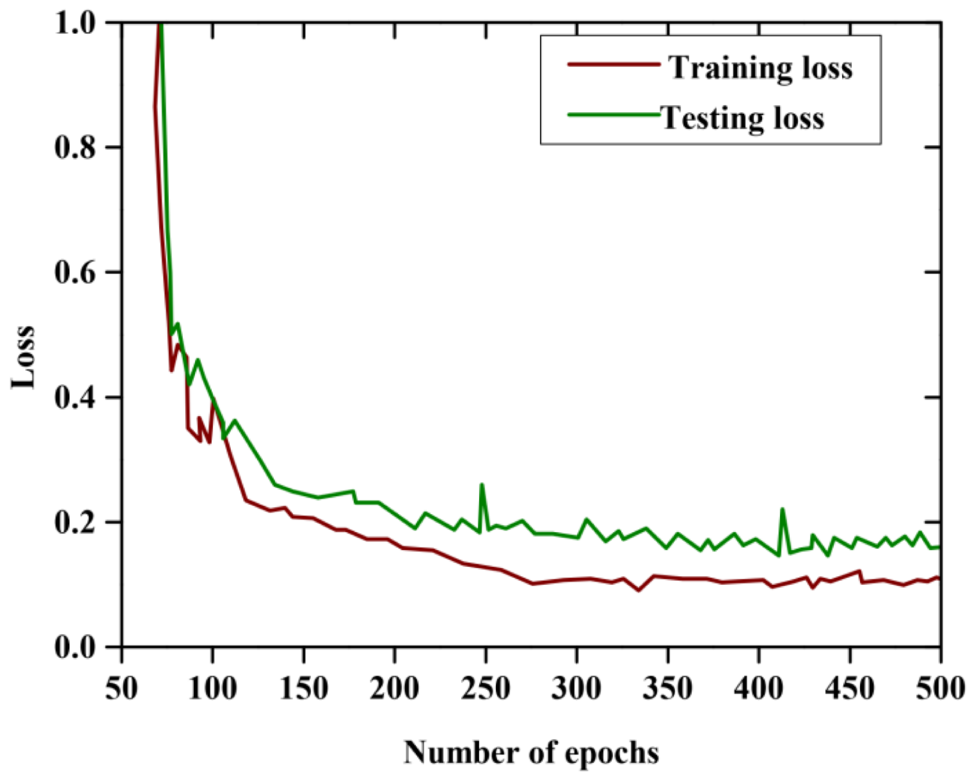
The accuracy is used to measure the closeness value near to the actual value, and the proposed model got a higher accuracy rate of 98.8% related to other existing methods. The precision measures the closeness value between two or more measurements. This $F1$-score is computed based on

Fig. 4 AUC/ROC analysis





(a)



(b)

Fig. 5 Analysis of **a** accuracy and **b** loss

Table 5 Overall performance evaluation results

Methods	Accuracy (%)	Computational time (s)	Precision (%)	$F1$-score (%)	MCC	Specificity (%)	Recall (%)
FeAvg-CNN+MobileNet [10]	86	58	91	85	0.904	90.6	90.6
VGG-16 [24]	92	43	86	92	0.846	89.5	89.5
FL [11]	87	52.8	89	89	0.911	87.1	87.1
Pa-DBN-BC [5]	91	32	95	96.2	0.823	90.6	92.8
DCNN [7]	87	49	87	90.5	0.857	94.1	91.9
AlexNet-BC [8]	93	26	94	93	0.924	92.8	94.2
ResNet-50 [23]	89	38	90	95	0.851	94.2	88.6
Proposed model	98.8	12.2	98.9	98.2	0.948	97.4	98.5

the evaluation of precision and recall. The comparative analysis of Mathew's correlation coefficient uses diverse breast cancer classification methods. The ranges of Mathews's correlation coefficient varied between 0 and 1. Mathews's correlation coefficient is a statistical tool to compute the differences between predicted as well as actual values. The specificity is measured by predicting a number of positive cases during performance validation. The recall analysis is used to measure the number of negative cases predicted during performance validation. The time required to finish the process is described as computational time (Table 5).

Discussion

Benefits and Limitations of Transfer Learning in FL

In the "Discussion" section, we analyze the implications of our findings and the benefits of using collaborative federated learning in the context of breast cancer classification. Federated learning is capable of preserving data confidentiality. By adopting a federated approach, each medical center retains full control over its sensitive patient data. Only model updates, represented as gradients, are shared with the central server for aggregation. This decentralized data sharing decreases the data breach issue and ensures compliance with data protection regulations, such as HIPAA.

Moreover, our proposed transfer learning approach has demonstrated significant improvements in breast cancer classification accuracy, even with limited labeled data. For instance, in Medical Center C, which had a smaller dataset, the model's accuracy was boosted by leveraging knowledge from pre-trained ResNet models, improving its ability to generalize to unseen cases. This capacity is extremely beneficial in the medical domain, where obtaining large amounts of labeled data can be challenging and time-consuming.

However, we acknowledge certain limitations of our proposed approach. While transfer learning with ResNet fine-tuning has shown promise, it may not fully address all domain shift challenges present in the breast cancer datasets from different medical centers. In some cases, there may still be domain-specific variations that could affect the model's performance. To overcome this, more sophisticated domain adaptation techniques and data augmentation strategies could be explored.

Benefits of Transfer Learning with ResNet Fine-Tuning

The main advantage of using transfer learning with ResNet fine-tuning is that it expedites the training process and requires less data for training the model from scratch. Since ResNet has already learned a rich set of feature representations from ImageNet, it significantly accelerates the learning of relevant features for breast cancer classification. This is especially valuable in medical imaging tasks where collecting a large labeled dataset is considered as challenging and time-consuming.

Additionally, by fine-tuning the higher layers of ResNet on the breast cancer dataset, the model specialized for identifying breast cancer–specific patterns, even with limited labeled data. The knowledge is transferred from the pre-trained model, which assists the model in achieving better generalization, leading to improved classification performance on unseen breast cancer images.

By incorporating transfer learning with ResNet fine-tuning and defining the corresponding notations and objective functions, the proposed approach is benefitted from the state-of-the-art feature representations learned by ResNet on a vast and diverse set of images, enhancing the accuracy as well as efficacy for breast cancer classification in a federated learning setup.

Practical Implications and Future Directions

Furthermore, the success of our proposed approach heavily relies on the availability of diverse and representative datasets from multiple medical centers. As the number of participating institutions increases, the potential for learning richer and more generalized features grows. However, there might be cases where certain medical centers have limited access to advanced imaging technology or specific breast cancer subtypes, leading to imbalanced datasets. Addressing this imbalance and ensuring fair representation across all breast cancer types are an essential aspect of future research.

In the discussion, we also emphasize the need for continuous improvement and exploration of alternative methodologies. While our proposed approach has shown promising results, there are opportunities for further research. For instance, investigating other deep learning architectures, such as DenseNet or Inception, could lead to novel insights and potentially improve classification performance. Additionally, incorporating domain adaptation techniques like CycleGAN or MMD-ResNet could further enhance model robustness and reduce the effects of domain shift.

Lastly, future research should focus on validating the proposed approach on larger and more diverse breast cancer datasets. Scaling the experiments to include data from multiple medical centers and different geographical regions would provide more robust evidence of the model's effectiveness and generalizability.

Conclusion

In conclusion, this research presents a novel transfer learning approach within a federated learning model to classify breast cancer and address the challenges of limited labeled data and data privacy in collaborative healthcare environments. Our proposed methodology leverages the power of pre-trained ResNet as a feature extractor and incorporates domain adversarial training to mitigate domain shift challenges. The findings from comprehensive experiments conducted on diverse breast cancer datasets from multiple medical centers prove the proposed model's effectiveness. The model achieves promising gains in classification accuracy and showcases improved generalization capabilities across different domains. By fine-tuning the higher layers of ResNet on individual medical center datasets, the model learns domain-specific features while benefiting from the comprehensive image representations learned from large-scale datasets like ImageNet.

One of the key strengths of our approach lies in its privacy-preserving nature. Federated learning ensures that each medical center retains control over its own data, sharing only model updates during the collaborative training process. This addresses the privacy concerns associated with centralized data pooling, making our method suitable for real-world healthcare applications where data security is of utmost importance. Moreover, the use of transfer learning enables the model to perform well even with limited labeled data. By leveraging knowledge from pre-trained models, the approach accelerates the learning process and achieves better generalization on unseen data. This is extremely beneficial in medical imaging tasks, where acquiring massive labeled datasets might be challenging and take considerable time. Despite its promising results, our proposed approach has some limitations. Domain adaptation techniques may not be sufficient to completely eliminate domain shift challenges, especially in cases of significant data distribution variations across medical centers.

Further research and improvements in domain adaptation algorithms are necessary to address these challenges effectively. In the future, we envision extending our research to explore other deep learning architectures and additional features that can further enhance breast cancer classification performance. Additionally, investigating federated learning with more medical centers and larger datasets would provide useful information about the proposed model's scalability and robustness.

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Code Availability Not applicable.

Declarations

Human and Animal Rights This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

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