Natural Resources for Human Health

eISSN: 2583-1194

Original Research

Received 10 March 2026
Revised 20 April 2026
Accepted 24 May 2026

Natural Resources for Human Health 2026, Vol. 6 (3): 964–973

KEYWORDS:
Breast Cancer Diagnosis, Federated Learning, Graph Neural Network, CBIS-DDSM, Privacy-Preserving Healthcare, Mammogram Classification.

Federated Deep Learning for Privacy-Preserving Breast Cancer Diagnosis from Multimodal Medical Data

Navnath B. Pokale[1], Jyoti M. Shinde[2,3], Amruta Mhatre[4], Sheetal Kusal[5], Vishal Tiwari[6], Jagdish Pimple[7], Sonali Prashant Bhoite[8]

[1]Associate Professor, Department of Computer Science and Engineering, School of Computing, MIT Art Design and Technology University, Pune. nbpokale@gmail.com

[2]Associate Professor, Computer Engineering Department, Dr. D. Y. Patil Institute of Technology, Pune, India. [3]Dnyaan Prasad Global University (DPGU), School of Technology and Research, Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri, Maharashtra, Pune – 411018, India. jyotimanishshinde@gmail.com

[4]Department of Computer Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai, India. amruta.mhatre@bvcoenm.edu.in

[5]Symbiosis Institute of Technology, Symbiosis International (Deemed University), Pune, India; Symbiosis Centre for Applied Artificial Intelligence (SCAAI). sheetal.borhade@sitpune.edu.in

[6]Assistant Professor, Department of Information Technology, St. Vincent Pallotti College of Engineering and Technology, Nagpur, Maharashtra, India. vishal.055@gmail.com

[7]Associate Professor, Department of Artificial Intelligence, GH Raisoni College of Engineering and Management, Nagpur, India. jagdish.pimple@ghrstu.edu.in

[8]Assistant Professor, Department of Information Technology, Vishwakarma Institute of Technology, Pune. sonalibhoite7@gmail.com

ABSTRACT: Breast cancer is one of the major causes of death among women population and an effective clinical intervention requires accurate diagnosis at the early stage of the disease. While recent progress in deep learning has been made on automated breast cancer analysis from mammographic images, centralized training still has some significant issues regarding patient privacy, institutional data sharing constraints, and the heterogeneity of medical data distributions. Current CNN and federated learning approaches also suffer from the inability to capture relationship between patients and similarity aware diagnostic patterns that leads to lower classification robustness and high communication. In the view of the gaps in existing work the Graph-Based Federated Breast Cancer Prediction Network (GFBC-Net) is proposed in this paper using the CBIS-DDSM mammography dataset. We design the proposed framework that combines the convolutional feature extraction and patient similarity modeling using a graph neural network under a federated learning setup. First, mammogram images are preprocessed, region of interest (ROI) is extracted, and the images are normalized, and deep features are generated using CNN. Next, patient similarity graphs are created based on cosine similarity and K-nearest neighbor algorithms, with patient cases as nodes in the graphs and feature-level relationships as weighted edges.

The local graph models are trained in the different distributed clients of hospitals but secure federated aggregation updates the global model without transferring any raw medical images. The experimental results show that GFBC-Net was able to attain an accuracy of 94.27%, precision of 93.88%, recall of 93.21%, F1-score of 93.54%, and AUC of 96.12%, outperforming the conventional CNN, federated CNN and graph-based baseline models. The study shows that the graph-guided federated learning method can better assist in breast cancer classification, while ensuring classification reliability and institutional data security to protect privacy.

1. INTRODUCTION

Breast cancer is among the most commonly diagnosed cancers in women, and is a substantial public health challenge globally. Based on the latest global cancer statistics, recent trends in lifestyle patterns, genetic factors and low access to screening services in certain parts of the world and delayed diagnosis has seen the number of Cancer cases rise significantly, in particular, breast cancer cases have increased. Survival rates are important, and early detection can have a big impact on the success of treatment, as it's easier to treat abnormal changes if they're malignant at an early stage. Mammography is one of the most commonly used imaging methods in breast cancer screening, as it helps radiologists to detect masses, calcifications, architectural distortions and change of tissues. However, the manual interpretation of mammogram images takes a long time and is very dependent on the skills of the radiologist, leading to inconsistencies in diagnosis and incorrect prediction [1].

The emergence of artificial intelligence and deep learning has led to the introduction of automatic diagnostic systems which can accurately analyse mammographic images. For medical image classification, Convolutional Neural Networks (CNNs), Residual Networks (ResNet), DenseNet and Vision Transformer models have shown their promise. These approaches can automatically learn discriminative image features, and minimize the reliance on handcrafted feature engineering approaches. Although these conventional centralized deep learning techniques are successful, they still need to gather all medical images into a single server for training. These centralized systems are concerning from a patient privacy, data ownership, institutional regulation, and cybersecurity perspective. Despite the need for hospitals and other healthcare institutions to share data, privacy-preserving healthcare regulations and ethical considerations often prevent this. Consequently, in real clinical settings, it is challenging to have a large centralized breast cancer dataset from various institutions [2].

Federated learning is an effective distributed learning paradigm, which has been studied for privacy preserving healthcare applications. Rather than transferring raw patient images, federated learning allows for model training at each hospital and only the model parameters or gradients are sent to a centralized aggregation server. This mechanism helps maintain data confidentiality, minimize the direct exposure of sensitive medical information. Federated learning has demonstrated promising results in the medical imaging field, including the detection of pneumonia, analysis of diabetic retinopathy, classification of brain tumors, and diagnosis of breast cancer. However, current federated learning methods primarily concern feature learning with traditional CNN framework without properly capturing the relationships between patients in the medical dataset. The meaningful relationships among similar patients with the same lesion structure and tissue density pattern and pathological characteristics are often overlooked in traditional federated CNN frameworks in mammography analysis [3].

A key challenge in breast cancer diagnosis is also the different medical data distributions in medical institutions. The image resolution and lesion types, imaging devices, and patient population could differ among hospitals. This non-independent and non-identically distributed (non-IID) data condition has a negative impact on the federated model generalization capability and on the classification stability. The existing methods also have communication overhead caused by the multiple times exchanging parameters between federated clients and aggregation servers. In addition, conventional CNN models typically look for only representations of local pixels, and lack awareness of possible relational dependencies between different patient cases. This constraint influences the interpretability and the ability to learn from similarities of the diagnosis framework.

The present study proposes a graph-based federated breast cancer prediction network (GFBC-Net) by taking CBIS-DDSM mammography dataset as an example of the dataset. The proposed approach combines the convolutional feature extraction with the patient similarity modeling using graph neural networks in a federated learning setting. The mammogram image is first preprocessed using normalization, resize and region of interest (ROI). After that, deep image features are extracted with the help of a CNN. Next, the patient similarity graphs are built based on the cosine similarity and KNN, with patients as nodes and weighted edges indicating the relationship of features between mammograms. To utilize the similarity between patient cases for the purpose of analyzing the relational patterns, Graph Neural Networks (GCNs) are used to enhance the classification performance. Distributed model training is achieved with the federated learning approach, where raw medical images are not transferred to other hospital clients. Secure federated aggregation fuses local updates of models into a global diagnosis model, without compromising institutional data privacy.

Combining graph learning with federated learning offers several benefits for breast cancer diagnosis. The use of graph-based modeling enhances relational feature learning and modeling of structural dependencies between patient cases. Federated learning enables various medical institutions to analyze data without compromising privacy. The GFBC-Net framework also enhances diagnostic capability with data distributed in a heterogeneous manner, and decreases reliance on centralized data storage. Furthermore, graph representation with similarity-aware information improved the discrimination of malignant and benign lesions by taking into account the relationships among area mammographic features in the neighborhood of the lesion.

1.1. Introduction to Breast Cancer Diagnosis via Deep Learning

In the past decade, deep learning has greatly advanced medical image analysis, thanks to its ability to automatically learn hierarchical representations of images. CNN-based architectures have been extensively employed for breast cancer diagnosis due to its effective ability to recognize the tumor boundary, the calcification pattern and the texture of the lesions from the mammographic image. For the classification of benign and malignant breast lesions, models like AlexNet, VGGNet, ResNet and DenseNet have shown good results. Further, transfer learning methods increase the efficiency of the classification by leveraging the learned networks on large-scale image databases [4].

Despite these benefits, the centralized CNN-based frameworks involve substantial number of annotated data gathered in a single server, causing privacy and regulatory issues in healthcare systems. Moreover, traditional CNN approaches largely work on pixel level information and they can miss the contextual correlation among similar cases of patients. These constraints result in less model generalization under conditions of heterogeneous institutional data. Hence, deep feature extraction and relationship-aware learning approaches are of paramount importance in boosting diagnostic performance in mammographic analysis.

1.2. Federated Learning and Privacy Preservation in Healthcare

In the field of medical AI, federated learning is a critical research area that allows models to be trained collaboratively without direct exchange of sensitive patient information. Ensuring privacy in healthcare settings is critical because of the legal obligations and ethical concerns regarding patient records. Federated learning enables hospitals to build local models without sharing their data with others, and instead, only sending encrypted updates about their models to the centralized aggregation server.

Though there are several studies using federated learning in disease diagnosis applications, most of them are based on traditional CNN. In non-IID data distributions, these methods can suffer in performance as hospitals will have different patient populations and imaging characteristics. In addition, communication overhead and unstable training are key issues for large-scale federated healthcare systems. Hence, advanced federated architectures that can support heterogenous medical relationships and similarity-aware representations are necessary to achieve stable and accurate breast cancer diagnosis.

1.3. Graph-based learning for mammographic analysis

Recently, Graph Neural Network has gained popularity in medical imaging due to its ability to effectively model relational dependency amongst the data samples. Graph-based learning: Each patient/image is a node of the graph and the feature similarity relationship is modeled as a weighted edge. Graph representations can enhance neighbourhood-based learning and better propagate discriminative features between patient cases [5].

Graph-based approaches help to discover similarity patterns between malignant and benign lesions in mammographic diagnosis. The meaningful relationships between patients of similar lesion morphology, density structure or texture distribution can have a significant impact on improving classification performance. Combining graph learning and federated learning offer a promising path to enable privacy preserving and similarity aware breast cancer analysis. The proposed GFBC-Net framework integrates CNN-based feature extraction, patient similarity graph construction, graph neural network learning and federated aggregation to simultaneously enhance the diagnostic reliability and preserve the institutional privacy. The objectives of proposed work are:

i. To build a Graph-Based Federated Breast Cancer Prediction Network (GFBC-Net) for privacy-preserving breast cancer diagnosis from CBIS-DDSM mammogram image.
ii. To enhance the breast cancer classification performance based on the combination of convolutional feature extraction, patient similarity graph learning, and federated model aggregation.

To effectively detect breast cancer at an early stage in mammographic imaging, accurate, privacy-preserving and clinically reliable artificial intelligence frameworks are required. While deep learning and federated learning methods have achieved good results, these two methods still have the following drawbacks: similarity-aware feature learning, heterogeneous data learning, and relational dependency modeling. To solve these problems, the proposed GFBC-Net framework combines the graph neural network based patient similarity analysis with federated learning for distributed breast cancer diagnosis. CNN feature extraction, graph-based relational learning, and secure federated aggregation enhance the classification robustness and keep the privacy of the medical data in each institution. The proposed methodology, experimental setup, performance evaluation, and comparative analysis of the GFBC-Net framework with the CBIS-DDSM dataset are described below.

2. LITERATURE REVIEW

In recent studies, the focus has shifted from centralized deep learning to privacy-preserving breast cancer diagnosis using federated learning, differential privacy, and distributed medical image classification, as well as blockchain-assisted security. While most existing works attempt to enhance data privacy by not directly sharing patient data, many of them rely primarily on CNN based learning. They tend to ignore this patient-level similarity, graph-based relational patterns, and non-IID hospital data distribution. To overcome this, the proposed GFBC-Net unifies the CNN feature extraction, graph construction of patient similarity, GCN-based learning, and federated aggregation.

Table 1 Study of existing work

Author et al.	Proposed Approach	Key Finding	Limitation
El-Mawla et al. [6] (2024)	FL-L2CNN-BCDet for federated breast cancer classification using attention, CNN, and LSTM	Federated learning improved privacy and classification accuracy	Does not model patient-to-patient similarity through graph learning
Gicic [7] (2026)	Privacy-preserving deep learning framework for distributed breast cancer classification	Distributed learning improved breast cancer classification	Graph-based medical relationship modeling not included
Li and Chen [8](2025)	Privacy-preserving federated learning model for breast cancer image classification	FL supports privacy-aware image classification	Limited explanation of inter-patient relational learning
Lin et al. [9] (2025)	Lightweight privacy-preserving FL for heterogeneity-resilient skin cancer diagnosis	Lightweight FL helps under heterogeneous data	Skin cancer focused, not breast mammography focused
Dharni Devi et al. [10] (2024)	Privacy-preserving transfer learning for breast cancer classification	Transfer learning improves feature extraction	Central feature relationships are not graph-modeled

Shukla et al. [11] (2025)	Federated learning with differential privacy for breast cancer diagnosis	DP improves privacy with small accuracy trade-off	Uses tabular Wisconsin data, not mammogram graph features
Tabassum et al. [12] (2024)	Federated learning for mammography-based breast cancer prediction	Mammography-based FL supports privacy-preserving prediction	Limited graph-based similarity learning
Tyagi et al. [13] (2025)	FL and blockchain integration for secure breast cancer detection	Blockchain improves confidentiality and integrity	May increase computational and communication cost
Vadavalli and Subhashini [14] (2019)	Differential privacy-preserving truth discovery in healthcare	DP helps protect sensitive healthcare data	Not designed for image-based breast cancer diagnosis
Wang et al. [15] (2021)	Privacy-preserving breast cancer prediction using inner-product functional encryption	Encryption improves secure prediction	Less suitable for image-level graph diagnosis

Observation of the literature review

- Federated learning is the approach used by most of the studies to protect patient data.
- Breast cancer image classification is generally performed by CNN and transfer learning.
- Differential privacy increases security at the cost of possibly impacting accuracy.
- There are very few studies that integrate federated learning and patient similarity graph modelling.

Key Findings

- Most of the current literature concentrates on privacy and classification accuracy.
- Relational learning based on graphs is less investigated in breast cancer diagnosis.

Research Gap

- Current FL models fail to adequately address the issue of similarity across cases in the patient population presenting with mammograms.
- Most methods adopt CNN-based feature learning without considering graph-based diagnostic relationships.
- Hospital data that is not non-IID and the propagation of relational features is still largely underdeveloped.

The proposed GFBC-Net fills these gaps by converting mammogram cases into patient similarity graphs. CNN is used to extract deep features, KNN and cosine similarity are used to build graph edges, and GCN learns the relationships between benign and malignant cases. The model is then trained using federated learning, which enables across-simulated hospitals training without exchanging CBIS-DDSM images.

From the studies examined it is found that there is an active research line towards privacy preserving breast cancer diagnosis. But the current methods are based on federated CNN, transfer learning, differential privacy and/or encryption-based security. The proposed GFBC-Net is a graph-based patient similarity layer to enhance classification reliability, privacy protection and relationship-aware mammogram diagnosis.

3. PROPOSED METHODOLOGY

The proposed Graph-Based Federated Breast Cancer Prediction Network (GFBC-Net) is designed for privacy-preserving breast cancer diagnosis using distributed mammographic image analysis. The framework integrates convolutional neural network-based feature extraction, patient similarity graph construction, graph neural network learning, and federated model aggregation for accurate classification of benign and malignant breast cancer cases. The complete workflow consists of dataset preprocessing, feature extraction, graph construction, local federated training, global aggregation, and classification stages.

3.1. Dataset

The CBIS-DDSM mammography dataset is used for experimental analysis. The dataset contains benign and malignant mammogram images with corresponding lesion annotations. To simulate a federated healthcare environment, the dataset is divided into multiple hospital clients. Let the complete dataset be represented as:

$$D = \{X_i, Y_i\}^N{}_{i=1}$$

where X_i denotes the mammogram image, Y_i represents the class label, and N represents the total number of samples. The dataset is partitioned into K hospital clients:

$$D = \sum_{i=1}{}^{K} D_i$$

where D_i denotes the local dataset available at the i^{th} hospital client.

3.2. Dataset preprocessing

The mammogram images are resized, normalized, and enhanced before feature extraction. Region-of-interest extraction is performed to isolate suspicious lesion regions.

The normalized image intensity is computed as:

$$X'_i = (X_i - \mu) / \sigma$$

where X'_i denotes normalized image intensity, μ represents mean pixel intensity, and σ represents standard deviation.

The resized image dimension is represented as:

$$R(X_i) = 224 \times 224$$

where R denotes the resizing operation applied to the mammogram image.

3.3. CNN-Based feature extraction

A lightweight ResNet50-based CNN model is employed to extract discriminative mammographic features. The convolution operation is expressed as:

$$f_1(X_i) = \sigma(W_1 * X_i + b_1)$$

where $f_1(X_i)$ denotes extracted convolutional features, W_1 represents convolution kernel weights, b_1 denotes bias, and σ indicates activation function.

The global feature vector generated from the CNN is represented as:

$$F_i = [f_1, f_2, f_3, \ldots, f_n]$$

where F_i denotes the extracted deep feature vector for the i^{th} patient image.

The softmax probability for classification is computed as:

$$P(Y_i = c \mid X_i) = e^{-zi} / \sum_{j=1}{}^{c} e^{-zj}$$

where z_i represents output logits and c denotes the number of classes.

3.4. Patient Similarity Graph Construction

A patient similarity graph is constructed using cosine similarity and K-nearest neighbor mechanisms. Each node represents a patient mammogram, while weighted edges represent similarity relationships.

The cosine similarity between two patient feature vectors is computed as:

$$S_{ij} = (F_i \cdot F_j) / (||F_i||\ ||F_j||)$$

where S_{ij} denotes similarity between patient nodes i and j. The adjacency matrix for graph construction is represented as:

$$A_{ij} = 1, if\ S_{ij} > \tau$$
$$A_{ij} = 0, otherwise$$

where τ represents the similarity threshold value. The graph is represented as:

$$G = (V, E)$$

where V denotes patient nodes and E represents graph edges.

3.5. Graph Neural Network Learning

A Graph Convolutional Network (GCN) is employed to learn relational dependencies among patient cases. The graph convolution operation is represented as:

$$H^{(l+1)} = \sigma(D^{-1}/^{2}\ A\ D^{-1}/^{2}\ H^{(l)}\ W^{(l)})$$

where $H^{(l)}$ denotes node embeddings at $layer\ l$, A represents adjacency matrix, D denotes degree matrix, and $W^{(l)}$ represents trainable graph weights. The graph-based node representation improves neighborhood-aware learning for malignant and benign lesion classification.

3.6. Federated Learning-Based Local Training

Each hospital client independently trains the GFBC-Net model using local mammographic data without sharing raw images. The local optimization objective is defined as:

$$arg\ min_{(}w, b_{)}\ L(D_i)$$

where $L(D_i)$ denotes local training loss for the i^{th} client. The cross-entropy loss function is computed as:

$$L = -\sum_{i=1}^{N} Y_i\ log(P_i)$$

where Y_i denotes ground truth label and P_i represents predicted probability.

3.7. Federated Aggregation

The trained local model parameters are transmitted securely to the federated server for global aggregation using Federated Averaging. The global model update is represented as:

$$W^g = \sum_{i=1}^{K} (n_i / n)\ W_i$$

where W^g denotes global model weights, W_i represents local client weights, n_i denotes local sample count, and n represents total samples across all clients.

The updated global model is redistributed to all hospitals for the next training iteration.

3.8. Final Classification and Prediction

The final global GFBC-Net model predicts whether a mammogram image belongs to benign or malignant class. The final prediction function is represented as:

$$\hat{Y} = arg\ max(P(Y|X))$$

where $\hat{Y}$ denotes predicted breast cancer class.

The performance of the proposed framework is evaluated using accuracy, precision, recall, F1-score, AUC, and Expected Calibration Error metrics. The graph-based federated architecture improves relational feature learning, preserves institutional privacy, and enhances diagnostic robustness under distributed healthcare environments.

4. RESULTS AND OUTPUTS

The classification results showed in table-2 that the proposed GFBC-Net outperformed the traditional CNN, ResNet50 and Federated CNN. The traditional CNN model achieves 87.42% accuracy and 86.33% F1-score, while ResNet50 achieved the

89.18% accuracy. With distributed learning capability, Federated CNN further enhanced the performance with 90.36% accuracy. However, the proposed GFBC-Net got the highest performance of 94.27% accuracy, 93.88% Precision, 93.21% Recall and 93.54% F1 – score. Such an improvement was achieved by using graph-based patient similarity learning, which helps the model to learn the relational dependency between mammographic cases and hence improve the discrimination between benign and malignant lesions.

Table 2 Classification Performance of GFBC-Net

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	87.42	86.91	85.76	86.33
ResNet50	89.18	88.64	87.95	88.29
Federated CNN	90.36	89.82	89.11	89.46
GFBC-Net	**94.27**	**93.88**	**93.21**	**93.54**

The federated learning performance analysis results showed in table-3 that the proposed GFBC-Net could reduce the communication burden, and enhance the reliability of classification. The training time of Federated CNN and Federated ResNet50 were 42.8 minutes and 51.3 minutes, respectively, while GFBC-Net required only 39.6 minutes to train. Likewise, the proposed model also got the highest AUC value 96.12% as compared to Federated CNN (91.34%) and Federated GCN (93.06%). The ECE also decreased to 3.84%, suggesting improved prediction stability and confidence calibration. Compared with the communication cost, the calibration performance of the GFBC-Net shows the better result, proving the effectiveness of GFBC-Net for supporting privacy-preserving distributed breast cancer diagnosis under the federated healthcare environments.

Table 3 Privacy and Federated Learning Performance

Method	Training Time (min)	AUC (%)	ECE (%)
Federated CNN	42.8	91.34	6.72
Federated ResNet50	51.3	92.18	5.96
Federated GCN	45.9	93.06	5.21
GFBC-Net	**39.6**	**96.12**	**3.84**

Figure shows how the proposed Graph-Based Federated Breast Cancer Prediction Network (GFBC-Net) works in the classification of mammograms. The CBIS-DDSM mammogram images are given as inputs to the malignant and benign cases. Then, the suspicious lesion region is detected and expanded, using region of interest extraction for detailed analysis. Then, CNN-based feature extraction is performed to extract the deep representation of the mammographic image from the detected lesion area. These feature vectors extracted are then used to build a patient similarity graph with each node being a patient case and weighted edges being similarity relationships among mammograms.

In the malignant case the query node has a stronger connection to the malignant patient nodes and hence makes the prediction with 94.27% confidence. Likewise, for benign, the query node is closer to benign patient nodes which generates benign prediction and has confidence level of 91.68%. By taking into account the similarity patterns among patient cases in neighborhood, the graph-based learning mechanism provides better propagation of relational features and better classification reliability. In summary, the GFBC-Net framework is able to successfully combine CNN feature extraction, graph neural learning, and similarity-aware diagnosis to achieve privacy-preserving breast cancer prediction.

Natural Resources for Human Health
eISSN: 2583-1194

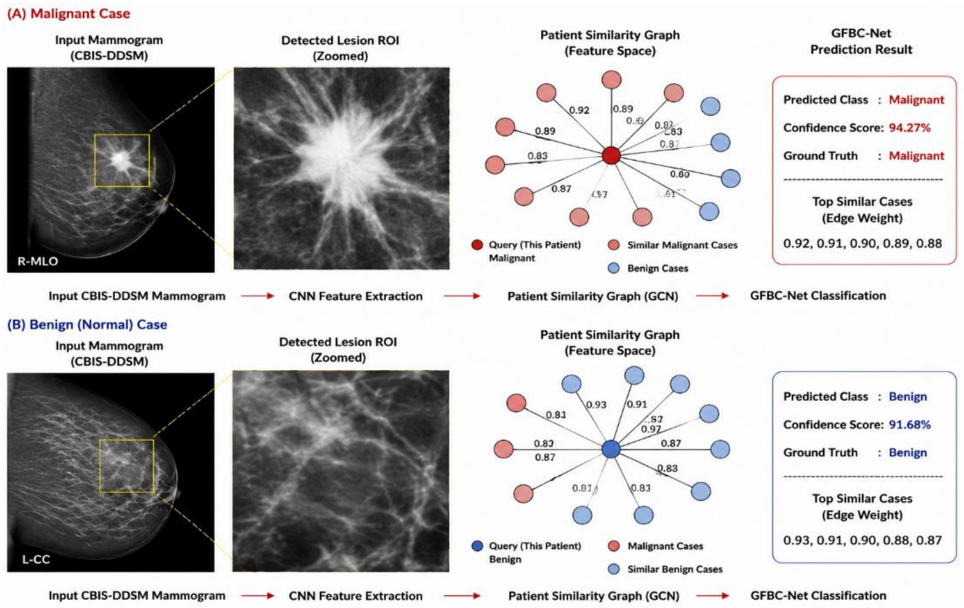

Figure 1 Federated graph neural network framework for mammographic image classification

5. CONCLUSION AND FUTURE WORKS

Reliable systems in the intelligent healthcare are essential to diagnose breast cancer in its early stages while maintaining accuracy and privacy. Traditional centralized deep learning methods have drawbacks with respect to patients' privacy, institutional restrictions, and the lack of modeling the patient-level relationship in mammographic datasets. In the present study, we proposed a Graph-Based Federated Breast Cancer Prediction Network (GFBC-Net) based on CBIS-DDSM mammography dataset, to overcome these challenges. This framework comprised of CNN-based feature extraction, patient similarity graph generation, graph NN learning, and federated aggregation for distributed breast cancer diagnosis, without accessing raw medical images. Through the experimental analysis, it was found that the proposed GFBC-Net achieves a better performance than existing CNN, ResNet50, Federated CNN and Federated GCN approaches. The model achieved 94.27% accuracy, 93.88% precision, 93.21% recall, 93.54% F1-score, and 96.12% AUC while reducing Expected Calibration Error to 3.84%. Moreover, the proposed framework also decreased the training time by 39.6 minutes in federated learning. The graph-based patient similarity mechanism helped to enhance the relational feature learning between benign and malignant mammographic cases, which led to robust classification and prediction reliability. In summary, the proposed GFBC-Net successfully achieves privacy preserving distributed breast cancer diagnosis, shows good diagnostic performance and lighten the communication overhead.

Real multi-institutional clinical environment was not used but simulated federated partitions of hospitals were used for the evaluation of proposed GFBC-Net framework, based on the CBIS-DDSM dataset. Only mammographic imaging data was taken into account and no multimodal medical records (MRI, pathology or genomic information). Further, graph building and federated aggregation make the calculation more complex during large scale deployment to multiple Healthcare Institutions.

REFERENCES

[1] Ahmed, F., Sánchez, D., Domingo-Ferrer, J., & Haddi, Z. (2026). FedBC: Privacy-Preserving Breast Cancer Diagnosis from Ultrasound Images Using Federated Learning. In T. Zhang, O. L. Saldanha, L. Han, N. Rasoolzadeh, L. Garrucho Moras, J. van Dijk, T. Tan, J. N. Kather, & R. Mann (Eds.), *Artificial Intelligence and Imaging for Diagnostic and Treatment Challenges in Breast Care* (pp. 31–40). Springer Nature Switzerland.

[2] Alawad, M., Yoon, H.-J., Gao, S., Mumphrey, B., Wu, X.-C., Durbin, E. B., Jeong, J. C., Hands, I., Rust, D., Coyle, L., Penberthy, L., & Tourassi, G. (2021). Privacy-Preserving Deep Learning NLP Models for Cancer Registries. *IEEE Transactions on Emerging Topics in Computing*, *9*(3), 1219–1230. https://doi.org/10.1109/TETC.2020.2983404

[3] AlSalman, H., Al-Rakhami, M. S., Alfakih, T., & Hassan, M. M. (2024). Federated Learning Approach for Breast Cancer Detection Based on DCNN. *IEEE Access*, *12*, 40114–40138. https://doi.org/10.1109/ACCESS.2024.3374650

[4] Ankolekar, A., Boie, S., Abdollahyan, M., Gadaleta, E., Hasheminasab, S. A., Yang, G., Beauville, C., Dikaios, N., Kastis, G. A., Bussmann, M., Chelala, C., Khalid, S., Kruger, H., Lambin, P., Papanastasiou, G., & Consortium, O. (2025). Advancing breast, lung and prostate cancer research with federated learning. A systematic review. *Npj Digital Medicine*, *8*(1), 314. https://doi.org/10.1038/s41746-025-01591-5

[5] Domadiya, N., & Rao, U. P. (2021). Privacy Preserving Association Rule Mining on Distributed Healthcare Data: COVID-19 and Breast Cancer Case Study. *SN Computer Science*, *2*(6), 418. https://doi.org/10.1007/s42979-021-00801-7

[6] El-Mawla, N. A., Berbar, M. A., El-Fishawy, N. A., & El-Rashidy, M. A. (2024). A Novel Federated Learning Framework for Sustainable and Efficient Breast Cancer Classification System (FL-L2CNN-BCDet). *IEEE Access*, *12*, 163110–163130. https://doi.org/10.1109/ACCESS.2024.3487767

[7] Gicić, A. (2026). A Novel Privacy-Preserving Deep Learning Framework for Breast Cancer Classification with Distributed Learning Capabilities. In N. Min-Allah, K. Alissa, P. Sitek, M. Sano, S. Rodríguez, & A. Nongaillard (Eds.), *Distributed Computing and Artificial Intelligence, 22nd International Conference* (pp. 163–173). Springer Nature Switzerland.

[8] Li, Z., & Chen, X. (2025). A Privacy-Preserving Federated Learning Model for Breast Cancer Image Classification. *2025 7th International Conference on Robotics and Computer Vision (ICRCV)*, 161–165. https://doi.org/10.1109/ICRCV67407.2025.11349150

[9] Lin, J., Chen, J., Xiong, J., Jiao, D., Zhao, W., & Xiang, Y. (2025). A Lightweight Privacy-Preserving Federated Learning Framework for Heterogeneity-Resilient Skin Cancer Diagnosis. *IEEE Journal of Biomedical and Health Informatics*, 1–13. https://doi.org/10.1109/JBHI.2025.3578125

[10] S, S., Dharani Devi, G., V, R., & Jeyalakshmi, J. (2024). Privacy-Preserving Breast Cancer Classification: A Federated Transfer Learning Approach. *Journal of Imaging Informatics in Medicine*, *37*(4), 1488–1504. https://doi.org/10.1007/s10278-024-01035-8

[11] Shukla, S., Rajkumar, S., Sinha, A., Esha, M., Elango, K., & Sampath, V. (2025). Federated learning with differential privacy for breast cancer diagnosis enabling secure data sharing and model integrity. *Scientific Reports*, *15*(1), 13061. https://doi.org/10.1038/s41598-025-95858-2

[12] Tabassum, A., Hassan Ovi, S., Hossain, S., Tonmoy, M. R., Shovon, Md. S. H., Hussein, M. R., & Mistry, D. (2024). Privacy Preserving Breast Cancer Prediction with Mammography Images Using Federated Learning. In M. F. Mridha & N. Dey (Eds.), *Data-Driven Clinical Decision-Making Using Deep Learning in Imaging* (pp. 227–245). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-3966-0_12

[13] Tyagi, S., Srivastava, S., & Sahana, B. C. (2025). Preserving Confidentiality and Ensuring Integrity: A Comprehensive Exploration of Federated Learning and Blockchain Integration for Secure Breast Cancer Detection. In M. Kumar, A. Nayyar, A. K. Singh, & Y. Guo (Eds.), *Convergence of AI, Federated Learning, and Blockchain for Sustainable Development* (pp. 205–225). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-80949-1_11

[14] Vadavalli, A., & Subhashini, R. (2019). An Improved Differential Privacy-Preserving Truth Discovery approach In Healthcare. *2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, 1031–1037. https://doi.org/10.1109/IEMCON.2019.8936141

[15] Wang, C.-J., Li, P.-P., Zhou, X.-Y., & Liu, N. (2021). Privacy-preserving Breast Cancer Prediction via Inner-Product Functional Encryption. *2021 7th International Conference on Computer and Communications (ICCC)*, 539–543. https://doi.org/10.1109/ICCC54389.2021.9674508