IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 2, April 2026, pp. 1632~1645
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i2.pp1632-1645

Breast cancer detection using residual DenseNets in deep learning

Naganandini Gururajarao, Vishwanath R. Hulipalled
School of Computing and Information Technology, REVA University, Bengaluru, India

Article Info

Article history:

Received Aug 22, 2024
Revised Nov 5, 2025
Accepted Feb 6, 2026

Keywords:

Artificial intelligence
Breast cancer
Convolutional neural network
Dense network
Mammograms
Residual DenseNets

ABSTRACT

Breast cancer, the leading cause of cancer-related deaths among women globally, requires a prompt and precise diagnosis in order to increase survival rates via therapy. There is a possibility of bias and inconsistency in the results of traditional diagnostic procedures like mammography, ultrasound, and histological testing since they rely on the expertise of radiologists and pathologists. There are exciting new opportunities for breast cancer diagnostics to be enhanced by artificial intelligence (AI) and deep learning. The purpose of this research is to examine the feasibility of using convolutional neural networks (CNNs) and residual dense networks (ResDenseNets) used for breast cancer automated detection in medical images. Because of their superior capacity to learn hierarchical features from raw image data, CNNs are ideal for medical image interpretation. By including residual connections, which allow for the training of considerably deeper models, ResDenseNets—an extension of CNNs—mitigate the problem of vanishing gradient in deep networks. ResDenseNet and CNNs considerably enhance the accuracy of breast cancer diagnosis in comparison to conventional approaches, according to the findings. Notably, ResDenseNets outperform other types of networks because they are able to learn intricate and nuanced properties directly from the data.

Corresponding Author:

Naganandini Gururajarao
School of Computing and Information Technology, REVA University
Bengaluru, Karnataka, India
Email: raonaganandini@gmail.com

1. INTRODUCTION

Breast cancer continues to be one of the most common and potentially fatal cancers affecting women worldwide. According to the World Health Organization, breast cancer accounts for a significant proportion of female cancer-related deaths, emphasizing the importance of early detection and accurate diagnosis. Timely identification of malignant tumors significantly improves treatment outcomes and survival rates. Traditional diagnostic techniques such as mammography, ultrasound imaging, and biopsy are widely used in clinical practice; however, these approaches often rely heavily on the expertise of radiologists and pathologists, which can lead to diagnostic variability and delays in treatment decisions [1], [2].

Recent advancements in artificial intelligence (AI) and deep learning have opened new opportunities for improving breast cancer detection and diagnosis. In particular, convolutional neural networks (CNNs) and residual networks (ResNets) have demonstrated remarkable success in medical image analysis due to their ability to automatically extract complex features from imaging data. CNN-based models have been widely adopted in computer vision applications and have shown strong performance in detecting abnormalities in mammograms, ultrasound scans, and histopathology images [3], [4]. ResNet architectures extend traditional

CNN models by introducing residual connections, which help address the vanishing gradient problem and enable the training of much deeper neural networks with improved accuracy and stability [5], [6].

CNNs were originally developed to mimic the hierarchical processing of visual information in the human brain. These networks consist of multiple layers that perform convolution operations, pooling, and nonlinear activation functions to learn features at different levels of abstraction. Through this multi-layered structure, CNNs can effectively capture spatial patterns, textures, and structures in medical images, allowing them to distinguish between normal and cancerous tissues with high precision [7], [8]. The introduction of residual learning in ResNet architectures further enhances deep learning performance by allowing identity mappings between layers, which facilitate efficient gradient propagation during backpropagation and enable deeper networks to be trained without degradation in performance [5].

This study investigates the potential of CNN and ResNet architectures for breast cancer detection using medical imaging datasets. The focus is on applying these deep learning techniques to various imaging modalities, including mammograms, ultrasound images, and histopathology slides. By leveraging the capabilities of these advanced neural network architectures, the proposed models aim to accurately differentiate between malignant and benign breast tissues. Using publicly available datasets and advanced preprocessing techniques, the study demonstrates how deep learning approaches can improve diagnostic accuracy and support clinical decision-making processes [3], [7].

AI-powered diagnostic systems offer several advantages in breast cancer detection. These systems can reduce the workload of healthcare professionals, minimize human error, and provide consistent and reproducible diagnostic results. Furthermore, deep learning models are capable of identifying subtle patterns within medical images that may be difficult for human observers to detect, thereby improving the chances of early diagnosis and timely treatment [1], [4].

The following sections provide a survey on various AI based breast cancer techniques and an exhaustive account of the approach, everything from gathering and cleaning data to creating models, training procedures, and evaluation tools. The following text showcases the outcomes of our tests, where we have compared the efficiency of CNN and ResNet models. Additionally, we delve into the significance of these findings for clinical practice. In this important area of healthcare, our study's findings highlight the potential effect of AI-powered breast cancer detection and point to potential avenues for further research and development. A major step forward in the fight against breast cancer has been the incorporation of AI into the diagnostic process, which has enhanced diagnostic capabilities and, in the long run, produced better patient outcomes.

2. LITERATURE SURVEY

Kshirsagar *et al.* [9] uses deep learning techniques, specifically MobileNetV2 architecture with transfer learning, to analyze risk factors in breast cancer imaging. The accuracy with which it differentiates between benign and malignant instances suggests promising directions for the development of breast cancer detection systems in the future. However, the study's 0.616 total accuracy score suggests complexity and room for improvement. The model's precision in benign situations is also influenced by societal and cultural factors. The study's generalizability depends on the availability and quality of datasets used, and the study does not address societal and cultural factors that influence access to screening and care, which are essential aspects of early diagnosis.

Ciobotaru *et al.* [10] propose a deep learning-based framework for breast tumor classification using CNNs and transfer learning techniques applied to ultrasound images. The study focuses on multi-instance learning to improve the classification performance of breast tumor images by extracting discriminative features from medical imaging datasets. Experimental results demonstrate that the proposed CNN-based approach improves classification accuracy in distinguishing between benign and malignant breast lesions, highlighting the effectiveness of transfer learning in medical image analysis. However, the study mainly focuses on ultrasound imaging datasets and does not extensively evaluate the model across multiple imaging modalities such as mammography or histopathological images. Additionally, further investigation is required to assess the model’s generalizability and performance in diverse clinical environments with larger and more heterogeneous datasets.

Oyelade *et al.* [11] introduces TwinCNN, an approach for breast cancer image classification from multimodal data streams. It uses modality-based feature learning, binary optimization for feature dimensionality reduction, and a new method for feature fusion. According to the experimental data, multimodal classification outperforms single-modal classification in terms of both classification accuracy and area under the curve (AUC). However, the study's evaluation is based on benchmark datasets, which may limit its generalizability to real-world datasets. The specific performance characteristics and computational requirements of TwinCNN are not extensively discussed, affecting practical implementation.

The purpose of the research [3] was to use a deep learning model (breast cancer convolutional neural network (BCCNN)) to categorize breast tumors into eight groups in order to aid in the early identification and diagnosis of the disease. We used the BCCNN model together with five fine-tuned models to categorize magnetic resonance imaging (MRI) images of breast cancer. With an F1-score of 98.28%, the model was the most accurate. The detection and classification of breast cancer were greatly improved by dataset boosting, preprocessing, and balancing. The great quality of MRI scans at 400X magnification allowed for the highest accuracy. It is unclear how well the model performs in varied patient demographics and real-world clinical situations, since the work relies on a single Kaggle dataset, which may restrict its generalizability to other datasets. Validation of the model's effectiveness in clinical practice and across different imaging modalities requires more investigation. No one knows how well or for how long the suggested methodology will work to increase breast cancer survival rates.

The authors provide a breast cancer detection ensemble classifier [12] that uses deep learning, transfer learning models, and other methods. The approach works admirably on ultrasound datasets and attains a good level of accuracy on the mini digital database for screening (mini-DDSM) dataset. Its adaptability and dependability make it an ideal candidate for multimodal breast cancer diagnosis. The study's results, however, are only applicable to the datasets used to analyze them, therefore their applicability is restricted. Concerns about its therapeutic efficacy arise from the lack of discussion on the interpretability of the deep learning model and the influence of false positives and false negatives on patient outcomes.

Using mammograms and ultrasound pictures, Muduli *et al.* [13] introduce a CNN model for automated breast cancer categorization. Automatic feature extraction with minimum parameters is made possible by the model's four convolutional layers and fully linked layer. It outperforms current methods, achieving high accuracies on various datasets through data augmentation to mitigate overfitting and enhance generalization. However, the paper does not discuss potential drawbacks or limitations, such as performance on diverse demographics or image quality variations, and does not mention potential computational requirements or efficiency limitations, which could be crucial for real-world healthcare deployment.

To automate breast cancer prediction, Abdar *et al.* [14] employs a layered ensemble method that combines machine learning (ML) and data mining approaches. When it came to distinguishing between benign and malignant breast cancers, the two-layer nested ensemble classifiers, SV-BayesNet-3-MetaClassifier and SV-naïve Bayes-3-MetaClassifier, performed better. With an accuracy of 98.07%, these models blew away single classifiers and the majority of prior work in experiments conducted on the Wisconsin diagnostic breast cancer (WDBC) dataset using the k-fold cross validation approach. However, the study's findings are based on the WDBC dataset and their generalizability to other datasets is still unknown. The complex nature of ensemble models may limit transparency and interpretability, posing challenges for clinical adoption and trust. The potential presence of biases in the selected classification algorithms requires careful consideration, especially for marginalized populations. Comparison with previous works may be limited by variations in experimental setups, data preprocessing, and evaluation metrics.

A novel data mining approach for precise breast cancer prediction utilizing support vector machines (SVMs) and artificial neural networks (ANNs) on Wisconsin breast cancer dataset (WBCD) is presented [15]. The confidence-weighted voting-boosting artificial neural networks support vector machine (CWV-BANNSVM) model, a combination of ANNs and SVMs, improved performance to 100% using ensemble techniques. The model's performance evaluation relies on specific metrics, potentially overlooking other aspects. The generalizability of the model beyond the WBCD dataset may be limited, and the focus on high accuracy scores may not translate to clinical applicability or real-world effectiveness. The study also lacks extensive discussion on feature selection and data preprocessing techniques, interpretability, and scalability and computational efficiency for large-scale breast cancer prediction applications.

Using the BreakHis dataset and deep neural networks, Aljuaid *et al.* [7] demonstrates a computer-aided diagnostic approach for breast cancer categorization. The approach uses ResNet, Inception-V3Net, and ShuffleNet to produce high average accuracies for binary and multi-class classification. Additional research is needed to see whether the suggested strategy can be applied to other datasets and real-world clinical contexts, since the findings might be impacted by the content and quality of the BreakHis dataset. Crucial in medical diagnosis, the research fails to provide light on the interpretability of conclusions made by deep learning algorithms. Training data that contains biases might affect how well the model performs in the actual world. The suggested method's resilience and reliability across multiple demographics and imaging modalities must be evaluated via external validation on varied and bigger datasets.

In order to automate the multi-classification of breast cancer histological pictures on the BreakHis dataset, Sharma and Mehra [16] contrasts hand-crafted features with transfer learning using pre-trained networks. Regardless of the magnification level, transfer learning consistently beats baseline techniques and created features. When it came to magnification-dependent picture categorization, VGG16 with linear SVM was the most accurate. The two most difficult types of cancer to detect at various magnifications are fibro-adenoma and mucous carcinoma. However, the study's focus on a specific dataset may limit its generalizability. It also did not consider other types of deep learning architectures, the impact of data imbalance within different classes on classification performance, the interpretability of the models, potential biases in the dataset or model predictions, and the scalability and computational resources required for implementing the proposed models.

Using a combination of transfer learning and pre-trained CNN architectures such as ResNet, VGGNet, and GoogLeNet, a novel deep learning framework for cytology image detection and breast cancer classification is presented [4]. The framework classifies cells as either benign or malignant by extracting information from pictures and applying them across a fully linked layer. When compared to existing deep learning architectures, the framework achieves better results in identifying and categorizing breast cancers in experiments conducted on common benchmark datasets. There is a lack of discussion of the computing resources needed for implementation, the interpretability of the model's decision-making process, precise false positive and false negative rates, and more in the paper. The article could benefit from discussing potential biases in benchmark datasets and the steps taken to mitigate them. Additionally, the framework's scalability and adaptability to varying imaging conditions and equipment should be explored to ensure its robustness across different healthcare settings.

In order to improve early diagnosis of breast cancer, Alruwaili and Gouda [5] investigates the use of deep learning models in mammography. We utilize transfer learning to distinguish between benign and malignant instances, and we apply several augmentation procedures to enhance the amount of pictures and minimize overfitting. Using ResNet50, the suggested system obtains an accuracy of 89.5% on the mammographic image analysis society (MIAS) dataset, whereas neural architecture search network-mobile (NasNet-Mobile) achieves an accuracy of 70%. However, the findings are limited to specific datasets and models, and may not generalize to other datasets or architectures. The performance evaluation is based on accuracy alone, and further validation on larger datasets is needed. The study also lacks insights into the interpretability of deep learning models, which is crucial for medical professionals' trust. The computational requirements and infrastructure for deploying these models in clinical settings are not addressed, limiting the practical applicability of the proposed system.

A novel breast cancer mass classification model based on deep convolutional neural networks (DCNNs) and transfer learning from pre-trained models such as GoogleNet and AlexNet is introduced [17]. With better accuracy and AUC ratings than GoogleNet, the model performed well on mammography datasets. While the study's findings are promising, there are a few caveats to keep in mind before implementing them in resource-constrained settings. These include the study's narrow emphasis on mammographic datasets, the need for additional validation on larger datasets, and the computational resources needed to train and test these deep models.

The survey from [1] examines the use of CNNs in mammography, highlighting their strengths, limitations, and performance in analyzing mammogram images. Insights into CNN architecture, popular publically accessible mammograms repositories, and methods for enhancing the accuracy of diagnoses are presented. In addition to helping with database selection, the study goes over other methods for improving CNN performance, such as transfer learning, data augmentation, batch normalization, and dropout. However, it may not cover the latest developments in deep learning for mammography, omitting detailed comparative analysis, and overlooking proprietary or specialized datasets. The survey's limitations section may not fully explore practical constraints and resource demands of implementing CNN-based solutions in real-world clinical settings.

To improve the accuracy of digital mammography in the diagnosis of breast cancer, a multiscale all convolutional neural network (MA-CNN) was created [8]. The model accurately classifies mammogram images as normal, malignant, or benign, improving classification accuracy through multiscale filters. It achieves an overall sensitivity of 96% and a 0.99 AUC, demonstrating its effectiveness in early diagnosis. The feature learning capabilities of CNNs enhance classification accuracy, aiding in proper clinical treatments and improving survival rates. Nevertheless, MA-CNN's efficacy could be affected by a number of factors, including the variety and quality of the training dataset, the intricacy of the deep learning algorithms, the availability of accessible advanced imaging and computational resources, and the necessity of ongoing updates and maintenance to accommodate changing clinical practices and developments in breast cancer diagnosis. For the purpose of identifying breast lesions using digital X-ray mammograms, a computer-aided detection (CAD) system based on deep learning has been created [18]. For detection, the system employs you only look once (YOLO); for segmentation, it employs full-resolution convolutional network (FrCN); and for classification, it employs CNN, ResNet-50, and InceptionResNet-V2. At the detection, segmentation, and classification phases, the INbreast database outperformed traditional deep learning techniques. The system has potential to assist radiologists in accurately diagnosing breast lesions. However, its effectiveness in real-world clinical settings requires further validation, and its performance metrics may not capture all aspects of clinical relevance.

In order to identify and classify breast lesions, Al-antari *et al.* [2] presents and assesses a CAD system that is integrated and uses deep learning. For mammograms from the DDSM and INbreast datasets, the YOLO detector achieved excellent detection accuracies and F1-scores. When it came to identifying breast lesions, classification models such as CNN, ResNet-50, and InceptionResNet-V2 shown encouraging accuracy. The YOLO detector improved classification models' diagnostic capabilities, which may have aided in the creation of a reliable CAD system for the detection of breast cancer. The research only employed DDSM and INbreast as datasets, thus how well it does on bigger and more diverse datasets is unclear. No one addressed the computing efficiency or resource needs of implementing such a deep learning system in actual healthcare environments. The impact of false positives and false negatives on clinical decision-making was not thoroughly analyzed, raising concerns about the system's reliability in a real-world setting.

Early diagnosis is vital for breast cancer [19], a serious worldwide health concern. The categorization of breast cancer using a deep ensemble transfer learning/neural networks classifier has shown encouraging outcomes. The system pre-processes mammogram images, extracts features using an ensemble model, and then uses a neural network for classification. It achieved an 88% accuracy and an AUC of 0.88, demonstrating its potential. However, the system's performance is based on existing data should not generalize or diverse datasets. Further validation and validation are needed to ensure its effectiveness in clinical settings and patient outcomes. The system's accessibility in resource-constrained healthcare settings may be limited by computational resources and time. Continual updates and maintenance are necessary to ensure accuracy and relevance. Ethical considerations regarding patient privacy and consent and system integration are also crucial.

Thanks to recent developments in medical technology, a more rapid and accurate method of diagnosing breast cancer is now required [20]. Researchers developed a computer-monitored diagnostic system that uses histology pictures via the use of ML and image processing. The study focused on invasive ductal carcinoma, using CNNs like VGG19. The results showed a significant improvement in F1-score and accuracy, with the DenseNet model achieving an accuracy of 86.97%. However, the study's generalizability to other types of breast cancer and the reliance on pre-trained CNN architectures may limit its adaptability. Further validation and testing in clinical trials are needed to assess the system's real-world applicability and reliability. Ethical considerations such as patient privacy, data security, and integration with existing healthcare systems need to be addressed before practical implementation.

Using thermography and deep learning models for categorization, Emam *et al.* [21] talks about how important it is to identify breast cancer early. With a classification accuracy of 99.97% on the test set, it presents the improved DenseNet model (Lévy flight and random opposition-based learning-improved coati optimization algorithm-DenseNet121-breast cancer (LFR-COA-DenseNet121-BC)). The model's effectiveness was evaluated in real-world medical scenarios, showcasing its efficacy in breast cancer classification. However, the article lacks detailed insight into the specific challenges faced by CNNs with hyperparameters, the nature of abnormalities detected by thermography, and the correlation with breast cancer. The comparison with established models and algorithms could benefit from a more in-depth analysis, including potential biases or limitations. Future studies should address the interpretability of the DenseNet model and the practical feasibility of implementing the LFR-COA algorithm in clinical settings.

An intelligent method for analyzing breast cancer images has been created [22] employing ML models for transfer learning and ensemble stacking. The system incorporates transfer learning models like as Inception V3, VGG19, and VGG16, as well as ensemble multi-layer perceptron (MLP) and SVM models, for the purpose of evaluating ultrasound breast cancer pictures. With accuracy value of 0.858 and an AUC of 0.947, the suggested technique (Inception V3+Stacking) surpasses current breast cancer diagnostic methods. Data gathering, pre-processing, transfer learning, ML model ensemble stacking, and performance assessment are all part of the system. The results may need more testing and confirmation on bigger datasets to represent clinical use in the real world. Important for building confidence and acceptability in healthcare settings, the research does not address the question of AI/ML models' interpretability. The findings are not specifically addressed in terms of their transferability to other healthcare contexts or geographical areas. Research on healthcare AI and ML systems can benefit from addressing possible privacy, security, and ethical issues.

Boudouh and Bouakkaz [23] developed a model for detecting breast tumors by combining data from three different databases using pre-processing filters, transfer learning, data augmentation, and global pooling methods. After undergoing testing and modification, two of the seven pre-trained CNNs—ResNet50V2 and InceptionV3—achieved the best accuracy rates. Breast tumor identification was successfully accomplished using the strategy, which began with filter selection and continued with database gathering and model fine-tuning. The research also used the dataset to find appropriate hyper-parameters for each model. The study's limitations include an inability to generalize the results due to the lack of attention given to the unique difficulties of each database. The research doesn't provide light on the computing resources needed for real-world clinical situations, and the model's performance may change depending on the variety and quality of the data acquired.

A number of recent research [6] have shown that CAD systems built using deep learning techniques based on transfer learning are effective in detecting and analyzing diseases at an early stage. In order to save time, deep learning-based computer vision jobs generally make use of pre-trained models. With an accuracy of 84.07%, Xception outperformed six other transfer learning models used to classify tumors in research using the BreakHis dataset. Balanced accuracy (BAC), a new metric introduced by DarkNet53, achieved the maximum accuracy of 87.17%. The study's overarching goal is to provide doctors with more accurate illness classification tools. But it doesn't look at things like possible biases, limits, generalizability, ethical issues, interpretability, scalability, or actual therapeutic use. The models' efficacy may not reflect their actual performance in the real world if they do not use augmentation and preprocessing approaches.

Early breast cancer identification from ultrasound pictures may be achieved with the use of transfer learning models like MobileNetV2, ResNet50, and VGG16 when paired with long short-term memory (LSTM) [24]. The efficiency of the suggested technique using VGG16 was shown by its high Matthews correlation coefficient (MCC), Kappa coefficient, and AUC, as well as its remarkable F1-score of 99.0%. A strong performance over numerous validation sets was shown by an average F1-score of 96%, which was achieved by cross-validation using the k-fold approach. To improve the visibility of the model's decision-making process, visualization tools such as gradient-weighted class activation mapping (Grad-CAM) and interpretability tools like local interpretable model-agnostic explanations (LIME) were used. Bootstrapping and the normal approximation interval confidence intervals proved that the procedure was consistent and reliable when estimating performance. The method's applicability to other datasets or clinical contexts may be limited, nevertheless, due to the study's possible absence of external validation. The clinical relevance and effect on patient outcomes need more research.

Using three DCNN architectures—VGG-16, Xception, and DenseNet201—a proposed AI system based on transfer learning [25] can identify breast cancer from histopathology pictures. With a 99.42% and 99.12% accuracy rate, respectively, the system outperforms state-of-the-art approaches. Some limitations of the study include the absence of research into the system's use in actual clinical settings, consideration of regulatory and ethical considerations, and further validation on varied datasets. New developments in AI and picture analysis may be beyond the system's flexibility since it uses pre-trained base models. It is also important to recognize and resolve any issues that may arise with the AI-based categorization system's interpretability, repeatability, and transparency.

3. METHOD

The proposed work for this is breast cancer detection using CNNs and residual dense networks (ResDenseNets). It includes the steps like data collection, data preprocessing, training and building a CNN and ResDenseNets models, and finally performance evaluation. The overall system architecture is shown in Figure 1.

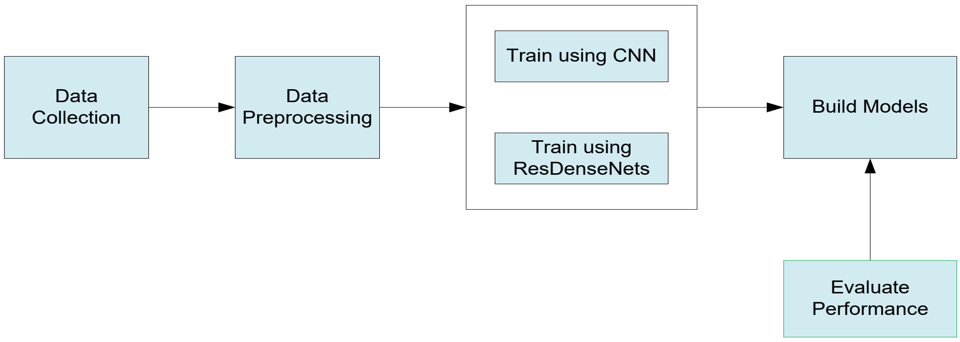

Figure 1. System architecture

3.1. Data collection

The datasets used in this study include publicly available repositories such as DDSM, BreakHis, and MIAS, which are widely adopted in breast cancer research for evaluating deep learning models [1], [7], [17]. These datasets contain mammograms, ultrasound images, and histopathological slides, enabling comprehensive analysis across multiple imaging modalities. The data collection details about the datasets and image types:

i) Datasets: make use of open-source datasets like DDSM, BreakHis, and MIAS dataset.
ii) Image types: include mammograms, ultrasound images, and histopathological slides to ensure a comprehensive analysis across different imaging modalities.

3.2. Data preprocessing

Data preprocessing includes image resizing, normalization, and augmentation techniques to improve model performance. Image resizing ensures uniform input dimensions suitable for CNN architectures, while normalization standardizes pixel intensity values to accelerate convergence during training [1], [15]. Data augmentation techniques such as flipping, rotation, and zooming are applied to increase dataset diversity and reduce overfitting, which has been shown to significantly enhance CNN performance in medical image analysis [13], [20].

i) Resizing: get all the images cropped to the same size with (200×600 pixels) so the neural network's input layer may use them.
ii) Normalization: improving convergence speed during training may be achieved by standardizing pixel values to a range, such as 0 to 1.
iii) Data augmentation: improve the model's resilience by using data augmentation methods like flipping, cropping, zooming, and rotating to artificially expand the training set.

3.3. Model architecture (convolutional neural network)

The proposed system employs a CNN architecture to automatically extract meaningful features from breast cancer medical images. CNNs are highly effective in medical imaging tasks due to their ability to learn spatial hierarchies of features [1], [3]. Convolutional layers capture low- and high-level features, while activation functions such as ReLU introduce non-linearity and improve learning capability [7]. Pooling layers reduce spatial dimensions and computational complexity, and fully connected layers perform classification based on extracted features [8].

i) Convolutional layers: use multiple convolutional layers with increasing filter sizes to learn hierarchical features.
ii) Activation functions: after every convolutional layer, add non-linearity by using rectified linear unit (ReLU) activation functions.
iii) Pooling layers: most critical characteristics while reducing spatial dimensions, use max pooling layers.
iv) Fully connected layers: for categorization, add fully linked layers to the network's end.
v) Output layer: use SoftMax layer for multi-class classification or sigmoid layer for binary classification.

ResDenseNets architecture:

i) Residual blocks: implement residual blocks with identity shortcut connections to enable the training of very deep networks.
ii) Deep architecture: use ResNet with DensNet201 models and fine-tune them on the breast cancer dataset.
iii) Transfer learning: adjust the last few layers of the pre-trained ResNet while maintaining the first layers unchanged in order to make use of the features that have been learnt.

3.4. Training

In this stage, data split into train and test. This helps to evaluate the performance using loss and accuracy metrics with appropriate functions. Perfect optimizers are used for efficient training and apply hyperparameters tuning with learning rate, batch size and epoch count for optimal configuration. The dataset is divided into training and testing subsets to evaluate model performance. Optimization techniques such as adaptive learning rates and batch-based training are used to improve convergence and stability. Hyperparameter tuning, including learning rate, batch size, and epochs, is essential for achieving optimal performance, as demonstrated in prior deep learning studies on breast cancer classification [3], [13].

3.5. Evaluation

Evaluation metric and confusion matrix are the two evaluation parameters considered for the proposed model. Evaluation metric helps to assess the major performance like accuracy and loss measures. Confusion matrix helps to understand the model’s performance for various classes. Data preprocessing, strong model architecture, and exhaustive assessment are the three pillars upon which this suggested technique rests, outlining a full-strength strategy for building and implementing CNN and ResNet models for breast cancer diagnosis. Model performance is evaluated using metrics such as accuracy, loss, and confusion matrix analysis. These evaluation metrics are widely used in medical image classification to assess diagnostic performance and reliability [2], [8].

4. IMPELEMENTATION

4.1. Working of convolutional neural network with 3 layered architectures

The CNN architecture consists of multiple convolutional layers that extract hierarchical features from input images. Convolution operations help detect patterns such as edges and textures, which are crucial for identifying abnormalities in medical images [1], [3]. Activation functions such as ReLU introduce non-linearity, enabling the network to learn complex representations [7]. Pooling layers reduce spatial dimensions and computational cost while preserving important features [8]. Fully connected layers integrate extracted features to perform final classification, typically using SoftMax for multi-class problems. Figure 2 illustrates a CNN with a 3-layered architecture. An CNN with three convolutional layers makes up the model's architecture. The kernel size for each convolutional layer is set to 3, with channel sizes of 7, 5, and 3, correspondingly.

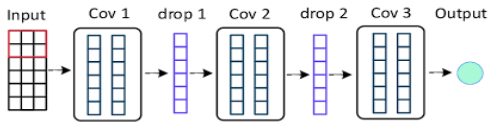

Figure 2. CNN with 3 layered architectures

The key concepts of CNNs are as follows:

i) Convolutional layers: convolutional layers use a collection of filters (also known as kernels) to process the input picture. The filter is applied to the images by sliding it spatially and at each location, finding the dot product of the input values and the filter elements. This procedure generates a feature map that accentuates certain characteristics of the input, such as edges, textures, or specific forms. The use of many filters enables the network to acquire diverse properties that are crucial for the given job.
ii) Activation functions: following the convolution procedure, the model introduces non-linearity by applying an activation function, usually the ReLU. The presence of non-linearity is essential for acquiring a deep understanding of intricate patterns within the data. To help the network understand the connections between different features, the ReLU activation function makes sure that any negative pixel values in the feature map are set to zero.
iii) Pooling layers: by progressively reducing the spatial dimensions of the feature maps, the computational cost and number of parameters in the network may be reduced via the use of pooling layers. Also, this makes it easier to guarantee that the representation won't change even if the input is slightly translated. One common method in neural networks for pooling data is max pooling, which involves selecting the highest value from each feature map region. Another common method is average pooling, which involves calculating the average value.
iv) Fully connected layers: the network typically includes one or more dense layers—fully coupled layers—following a sequence of convolutional and pooling layers. These layers function on input data that has been flattened, treating the input as a singular vector. Fully connected layers acquire comprehensive patterns in the data by integrating characteristics retrieved by the convolutional layers to provide final predictions.
v) Output layer: depending on the task at hand, the output layer is determined. It is common practice to utilize the SoftMax activation function to create a probability distribution across all of the classes in a classification issue.

4.2. Residual DenseNets

Deep neural networks often suffer from the vanishing gradient problem, which limits their ability to learn effectively as depth increases. Residual learning addresses this issue by introducing shortcut connections that allow gradients to flow directly through the network [5]. Dense connections further enhance learning by enabling each layer to receive inputs from all preceding layers, improving feature reuse and reducing redundancy [6]. The combination of these two mechanisms in ResDenseNet enables efficient training of very deep networks and has been shown to outperform traditional CNN architectures in medical image classification tasks [7], [21]. Figure 3 illustrates a ResDenseNets model architecture. Figure 3 illustrates a ResDenseNets model architecture. The key concepts of ResNets are as follows:

i) Vanishing-gradient-problem: in a deep neural network, known as a vanishing-gradient-problem, the propagation of gradients needed to update weights slows or stops the learning process. Deep neural networks take train difficulty to train, which leads in difficult for vanishing gradient problem, as gradients not propagate to earlier layers.

ii) Residual learning: ResDenseNets learning in short called as ResDenseNets. ResDenseNets focus on learning the residual function instead of learning a direct map from input to output and this tells the difference between input and desired output. The desired mapping in mathematically denote as $H(x)$ as shown in (1) and rewrite them as (2) for better understanding. In ResDenseNets, the stack layers fit a residual mapping as (1).

$$F(x) = H(x) - x \tag{1}$$

Which we can also rewrite as (2).

$$H(x) = F(x) + x \tag{2}$$

Where x is the inputs, $H(x)$ is desired output, $F(x)$ is fitting the stack layers.

iii) Residual blocks: the backbone of ResNet are a residual block. The convolutional layers in each block are activated using ReLU and batch normalization. After that, you'll see a similar shortcut connection that joins the block's input and output. Depending on whether the input and output dimensions are same or not, the shortcut connection may take the form of an identity mapping or a linear projection using 1×1 convolutions.

iv) Identity shortcut connections: the identity shortcut connections provide the direct passage of gradients across the network, skipping one or more levels. Because of this, the vanishing-gradient-problem is no longer a concern, and far deeper networks may be constructed. These connections guarantee that even if some levels deteriorate, the network may nevertheless function adequately by using identity mappings.

v) Residual connection: make steady gradient flow possible, allowing for the training of very deep networks; this will mitigate the vanishing gradient issue.

vi) Dense connection: make it easier to reuse features by enhancing information flow and gradient propagation via feed-forward connections between all of the layers.

vii) Hybrid architecture: combines the advantages of residual and dense connections to learn more comprehensive and discriminative features from breast cancer images.

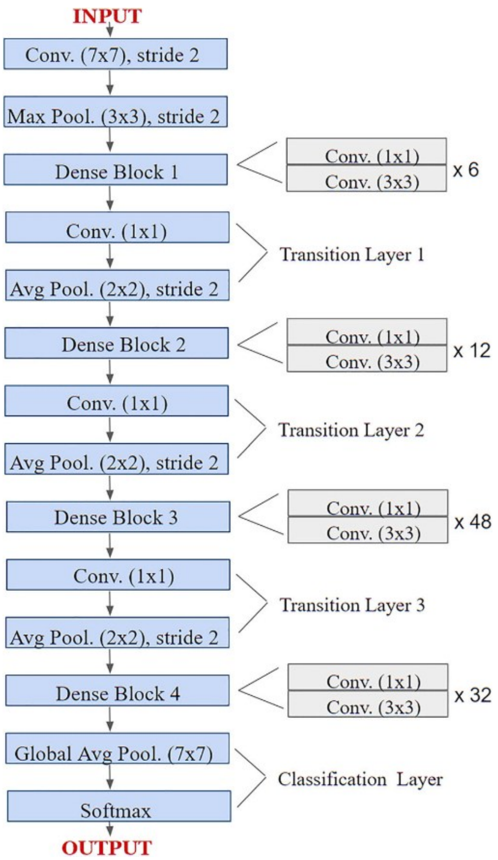

Figure 3. ResDenseNets model architecture

4.3. Algorithm: ResDenseNet algorithm

The proposed ResDenseNet algorithm integrates the advantages of residual learning and dense connectivity to improve feature propagation and classification performance in breast cancer detection. Residual connections help overcome the vanishing gradient problem in deep networks, while dense connections enhance feature reuse by allowing each layer to receive inputs from all preceding layers. This hybrid architecture enables the network to learn complex patterns from medical images such as mammograms, ultrasound scans, and histopathological images more effectively. The step-by-step workflow of the proposed model is summarized in Algorithm 1, which describes the major stages involved in feature extraction, dense block processing, residual connections, and final classification. Algorithm 1 presents the detailed procedure followed by the proposed ResDenseNet model for breast cancer image classification. The integration of residual and dense connections in this algorithm improves feature propagation and classification performance, as supported by recent studies on hybrid deep learning architectures for breast cancer detection [7], [23].

Algorithm 1. Residual DenseNet

Step 1: Input layer:
- Input: X (a batch of images, e.g., size 200×600×3 for RGB images)

Step 2: Initial convolution:
- Apply a convolution with a filter size of 7×7, stride 2, and padding, followed by batch normalization and ReLU activation.
- Apply a max pooling operation with a filter size of 3×3 and stride 2.

Step 3: Dense block 1:
- Number of layers: 6
- For each layer 1 in the dense block:
- Applying the batch normalization, ReLU activation, and conv layer with 1×1 convolution which is a bottleneck layer.
- Apply batch normalization, ReLU activation, and a 3×3 convolution.
- Concatenate output of this layer with the input to the dense block to form the input to the next layer.

Step 4: Transition layer 1:
- Applying the batch normalization, ReLU activation, and conv layer with 1×1 convolution.
- Applying the average pooling with 2×2 layer with 2 strides.

Step 5: Dense block 2:
- Number of layers: 12
- Repeat the process described in dense block 1.

Step 6: Transition layer 2:
- Applying the batch normalization, ReLU activation, and conv layer with 1×1 convolution.
- Applying the average pooling with 2×2 layer with 2 strides.

Step 7: Dense block 3:
- Number of layers: 48
- Repeat the process described in dense block 1.

Step 8: Transition layer 3:
- Applying the batch normalization, ReLU activation, and conv layer with 1×1 convolution.
- Applying the average pooling with 2×2 layer with 2 strides.

Step 9: Dense block 4:
- Number of layers: 32
- Repeat the process described in dense block 1.

Step 10: Residual connection:
- Link the dense blocks' inputs to the transition layer's outputs via a shortcut link.

Step 11: Final layers:
- Apply a batch normalization layer.
- Apply a global average pooling layer to reduce the spatial dimensions to 1×1.
- Fully connected layer with SoftMax activation for classification with number of classes 3.

5. RESULTS AND DISCUSSION

The efficacy of the proposed ResDenseNet network for breast cancer detection was evaluated using widely accepted performance metrics such as accuracy and loss. These metrics provide insight into the model's ability to correctly classify breast cancer images while minimizing prediction errors during training and validation. To demonstrate the effectiveness of the proposed architecture, the performance of the ResDenseNet model was systematically compared with that of a conventional CNN model under the same experimental conditions. The comparative evaluation highlights the advantages of the hybrid architecture in improving classification accuracy and reducing loss values when applied to breast cancer image datasets.

5.1. Accuracy for training and validation

The accuracy of the models during both the training and validation stages provides important insights into the learning capability and generalization performance of the trained models. Monitoring accuracy across epochs helps determine how effectively the models learn patterns from the training dataset and how well they perform when exposed to unseen validation data. In this study, the training and validation accuracy curves for both the proposed ResDenseNet model and the conventional CNN architecture are illustrated in Figure 4, which enables a visual comparison of their performance across the training process. The trends observed in the accuracy graphs help evaluate whether the models converge properly and whether the proposed architecture offers improvements over the baseline CNN model. The ResDenseNet network demonstrated superior accuracy compared to the conventional CNN model. This observation is consistent with previous studies where hybrid architectures combining residual and dense connections significantly improved classification performance in breast cancer detection tasks [7], [11], [23].

5.2. Accuracy graph

Throughout the training epochs, the ResDenseNet network demonstrated superior accuracy in comparison to the classic CNN. The training accuracy of Res-DenseNet201 consistently and gradually improved, ultimately reaching a higher value. This suggests effective learning and improved ability to generalize. The validation accuracy for Res-DenseNet201 shown exceptional performance, showcasing the model's resilience and proficiency in efficiently handling unfamiliar data. The validation accuracy of ResDenseNet showed improved generalization capability, which aligns with findings reported in prior research that residual connections enhance gradient flow while dense connections improve feature reuse [5], [6], [1].

5.3. Training and validation loss

The loss values observed during the training and validation stages indicate how effectively the model minimizes the difference between the predicted outputs and the actual target values. Monitoring the loss across training epochs helps evaluate the convergence behavior of the model and determines whether the learning process is stable and improving over time. In this study, the loss curves for both the proposed ResDenseNet model and the conventional CNN architecture are illustrated in Figure 5, providing a visual comparison of their training and validation loss trends.

The analysis of these loss graphs helps identify improvements in model optimization and highlights the effectiveness of the proposed architecture in reducing prediction errors. The loss values indicate improved convergence behavior for the ResDenseNet model. Similar trends have been observed in studies where DenseNet-based architectures achieved lower loss due to efficient feature propagation and reduced redundancy [8], [21].

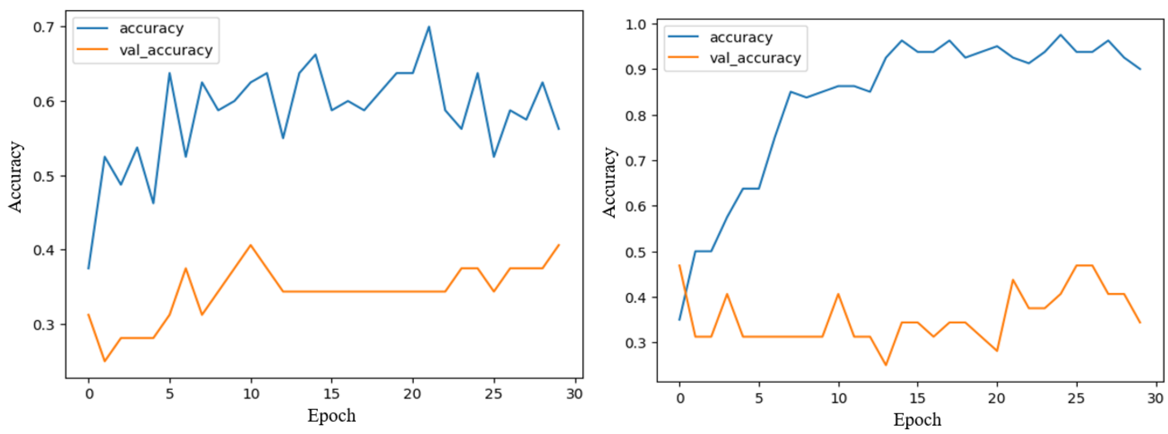

Figure 4. Accuracy graph for CNN with 3 layered architecture and ResDenseNet model

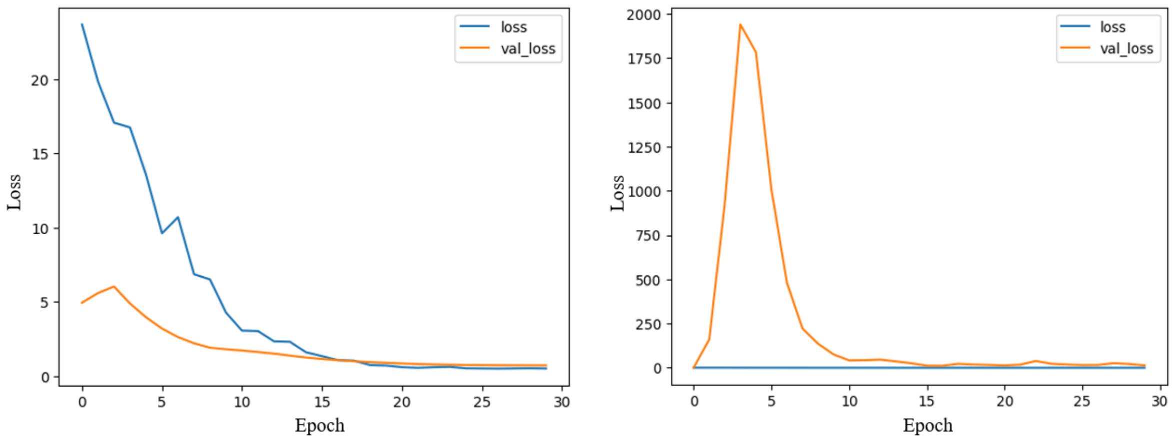

Figure 5. Loss graph for CNN 3 layered architecture

5.4. Loss graph

The ResDenseNet network exhibited a steady reduction in training loss, ultimately converging to a lower value in comparison to the conventional CNN. The validation loss of ResDenseNet was smaller than that of the standard CNN, suggesting superior generalization and less overfitting. The loss graphs indicate that the ResDenseNet network is superior in reducing mistakes during both training and validation.

Figure 4 explains the accuracy graph of CNN algorithm with train and validation data for 30 epochs and the accuracy graph of ResDenseNet algorithm with train and validation data for 30 epochs. Figure 5 explains the loss graph of CNN algorithm with train and validation data for 30 epochs. Also explains the loss graph of ResDenseNet algorithm with train and validation data for 30 epochs. The ResDenseNet network is superior in reducing prediction errors during both training and validation phases. This finding is consistent with recent hybrid models such as residual model (RM)-DenseNet, which demonstrated enhanced performance over traditional CNNs in mammographic image classification [7], [12].

Figure 6 displays the confusion matrix of the proposed ResDenseNet Model. The findings indicate that the ResDenseNet performs better than the classic CNN architecture in all assessment measures. The exceptional precision and low loss values of ResDenseNet underscore its efficacy in detecting breast cancer. The training and validation accuracy and loss graphs provide further evidence of the model's effectiveness in acquiring knowledge and applying it to new data. The findings indicate that the ResDenseNet model achieves better classification performance across all classes, which agrees with prior computer-aided diagnosis systems that integrate deep CNN architectures for improved diagnostic accuracy [2], [8], [18].

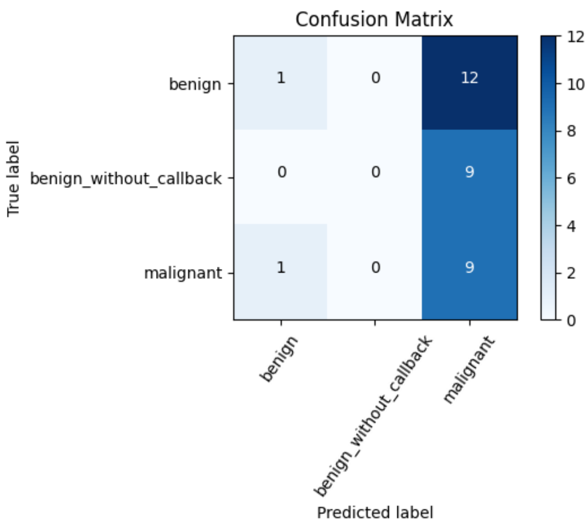

Figure 6. Confusion matrix for proposed ResDenseNet model

6. CONCLUSION

The global prevalence of breast cancer continues to be a major health issue, highlighting the need for the creation of sophisticated diagnostic instruments that may enable prompt and precise identification. The use of ResNets and CNNs is the focus of this study for the automated identification of breast cancer from medical photographs. The ability of CNNs to learn hierarchical characteristics and apply them to image analysis is remarkable. ResNets have tackled the difficulties of training deeper networks by integrating residual connections, which allows for the creation of more precise and resilient models. The proposed model ResDenseNet network used to enhance the accuracy and longevity of breast cancer diagnosis. To maximize performance, ResDenseNet combines the best features of DenseNets with ResNets. When tested against traditional CNN architectures, the ResDenseNet201 network outperformed them in both accuracy and loss. The use of a hybrid architecture facilitated the extraction of intricate and significant elements, resulting in enhanced classification outcomes. Traditional CNNs, while useful, have shown limits in dealing with very complex networks. They commonly encounter the issue of vanishing gradients and experience decreased performance as the depth of the network increases. Additionally devise methodologies to enhance the interpretability and transparency of the ResDenseNet201 model and to graphically depict the parts of input images that significantly influence the model's predictions, techniques such as Grad-CAM and saliency maps will be used further.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Naganandini Gururajarao	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Vishwanath R. Hulipalled		✓				✓	✓	✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are publicly available in open-source breast cancer imaging repositories. The mammography and histopathology datasets used in this research include the DDSM, the BreakHis histopathological image dataset, and the MIA dataset. These datasets are widely used in breast cancer research and can be accessed through their respective public repositories and research portals. The processed data and derived results generated during this study are available from the corresponding author upon reasonable request for research purposes. The authors confirm that all experimental results presented in this study were obtained using publicly accessible datasets and standard preprocessing procedures.

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BIOGRAPHIES OF AUTHORS

Naganandini Gururajarao is a dedicated academic professional pursuing a Ph.D. in Data Mining and Bioinformatics at REVA University, Bengaluru. With a strong educational background and research interests in information science, computer science, machine learning, and bioinformatics. She has extensive teaching experience as an assistant professor at various institutions, including M.S. Ramaiah University. Her expertise spans curriculum development, research coordination, and mentoring. She has been recognized with awards for her contributions to education and has published several research papers in reputed journals. She can be contacted at email: raonaganandini@gmail.com or R17pcs10@reva.edu.in.

Dr. Vishwanath R. Hulipalled is a professor in the School of Computing and Information Technology, REVA University, Bangalore, Karnataka, India. He completed B.E., M.E., and Ph.D. in Computer Science and Engineering. His area of interests includes machine learning, natural language processing, data analytics, and time series mining. He has more than 25 years of academic experience and research. He authored more than 50 research articles in reputed journals and conference proceedings. He can be contacted at email: vishwanath.rh@reva.edu.in.