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DEVELOPING A DEEP LEARNING MODEL WITH TRANSFER LEARNING FOR BREAST CANCER DETECTION AND CLASSIFICATION USING MAMMOGRAPHY IMAGES

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ABSTRACT

Breast cancer affects people all around the world and is a major cause of death for women. For the disease to be prevented and managed, early discovery is essential. Although there are other ways to identify breast cancer, mammography has shown to be a very successful strategy. The need to develop deep learning architectures and use transfer learning to increase detection performance has been brought to light by current research on the use of artificial intelligence (AI) and deep learning in breast cancer diagnosis. In this research, we offer a deep learning architecture that uses mammography imagery to autonomously diagnose breast cancer. Our framework utilizes a modified DenseNet-121 model and transfer learning, resulting in the Intelligent Learning Based Breast Cancer Detection (ILB-BCD) algorithm. An empirical study with a benchmark dataset, known as CBIS-DDSM, demonstrates that our proposed model surpasses numerous existing deep learning models with an impressive 99.16% accuracy. The success of our deep learning framework suggests its potential integration into existing healthcare systems to create an automated clinical decision support system (CDSS) for the detection of breast cancer.

Keywords – *Breast Cancer Screening, Artificial Intelligence, Deep Learning, Mammography Imaging, Cancer Detection*

1. INTRODUCTION

Globally, breast cancer is a common kind of cancer that varies in severity and occurrence among different geographic areas. Breast cancer is usually staged from 0 (non-invasive) to IV (metastatic), depending on the degree of the disease. Tumor size, lymph node involvement, and the existence of distant metastases are some of the variables that affect severity. Globally speaking, breast cancer is the most frequent cancer among women in terms of incidence, with varying rates in different countries. Factors such as genetics, lifestyle, reproductive patterns, and access to health care can influence the incidence rates of breast cancer. For example, high-income countries tend to have higher incidence rates compared to low-income countries, partly due to differences in screening practices and awareness.

Research on breast cancer detection using the DenseNet121 model and CBIS-DDSM mammography imagery involves utilizing a deep learning model called DenseNet121 to analyze to diagnose breast cancer early, mammography p ictures from the CBIS-DDSM dataset are used. A convolutional neural network design called DenseNet121 has demonstrated encouraging performance in image classification challenges. Images from mammograms with annotations pertaining to breast cancer may be found in the CBIS-DDSM collection. By training the DenseNet121 model on the CBIS-DDSM dataset, researchers aim to develop a system that can accurately classify mammography images as either indicative of breast cancer or not. This research can potentially contribute to increasing the efficacy and accuracy of breast cancer detection, which will result in earlier diagnoses and improved patient outcomes after treatment. From the existing research such as [1], [5], [7], [9], to mention a few, it was observed that there is a need for improving deep learning architectures and exploiting transfer learning towards leveraging performance in breast cancer detection from mammography images.

Despite the progress in AI-assisted mammography analysis, current systems often lack sufficient generalization, robustness, and clinical integration readiness. Objectives: (1) To develop an enhanced DenseNet121 architecture using transfer learning. (2) To evaluate the model against existing deep learning frameworks. (3) To demonstrate clinical applicability through empirical validation on the CBIS-DDSM dataset. Integrating transfer learning with a modified DenseNet121 model significantly improves the accuracy of breast cancer detection from mammography images compared to baseline CNN architectures.

The aim of the study is to develop a modified DenseNet121-based deep learning architecture that integrates transfer learning to enhance breast cancer detection from mammography images. The novelty lies in combining model-level architectural tuning with transfer learning and benchmarking its performance rigorously against existing deep learning models on a publicly available CBIS-DDSM dataset.

In this study, we provide an autonomous breast cancer detection system using deep learning through mammography imaging. Our framework uses a modified DenseNet-121 model and transfer learning, resulting in the Intelligent Learning Based [41]Breast Cancer Detection (ILB-BCD) algorithm. We conducted an empirical study using the CBIS-DDSM dataset, and our proposed model achieved an impressive 99.16% accuracy,[42] surpassing numerous existing deep learning models. The success of our framework suggests its potential integration into healthcare systems to develop a Clinical Decision Support System (CDSS) for automatic breast cancer screening. The scope of this study is confined to mammography-based breast cancer detection using the CBIS-DDSM dataset. While the proposed model demonstrates high accuracy, its generalization is limited by dataset-specific characteristics and does not yet include multi-modal inputs such as ultrasound or histopathological data.

The following is the format of the paper: In Section 2, the literature is reviewed with regard to current techniques for detecting breast cancer using various imaging modalities. The suggested technique is shown in Section 3, along with our framework and the updated DenseNet-121 model. Our work is concluded with the outcomes of our empirical investigation, which are presented in Section 4. In Section 5, the results of the research are presented together with recommendations for future paths for the field.

2. RELATED WORK

The following text contains an overview of various methods for breast cancer detection using medical imagery. Sereshkeh et al. [1] conducted a study using deep features from mammography to predict tumor stage regarding sentinel lymph nodes' participation in breast cancer patients. They achieved higher AUCs for training and for validation, indicating the model's ability to provide accurate diagnosis and treatment planning. Islam et al. [2] utilized ultrasound images and an Ensemble Deep Convolutional Neural Network (EDCNN) to identify breast cancer accurately. Singh and Alam [3] combined Faster R-CNN with pixel-based pre-processing to achieve great sensitivity and accuracy in detecting concerning masses in digital mammograms.[43,44,45] Karthiga et al. [4] used a modified convolutional neural network and preprocessing based on Haar wavelets for AI-driven digital mammography, surpassing conventional approaches with an accuracy of 84.6% and an AUC of 0.92.[46,47,48] Koshy and Anbarasi [5] introduced LMHistNet for accurate breast cancer histopathology image classification, achieving better binary and multiclass accuracy. Anas et al. [6] employed YOLOv5 and Mask R-CNN to improve detection accuracy, ,demonstrating significant improvements in early prognosis and treatment decisions for breast cancer. Wen et al. [7] considered preprocessing, segmentation, feature extraction, and classification while evaluating machine learning and deep learning techniques for breast cancer detection. Shah et al. [8] [49,50]found that radiologists overwhelmingly prefer genuine mammography pictures over synthetic ones. Tan et al. [9] enhanced feature expression and adaptive sample selection to improve tiny breast mass identification. Torabi et al. [10] utilized adversarial approaches and self-supervised understanding how to improve the diagnostic precision and adaptability of breast cancer in several data areas.

Sani et al. [11] presented a CNN framework achieving rotation equivariance by utilizing DCT, group theory, and the SE(2) motion group.

Loizidou et al. [12] focused on the challenges and potential advancements in mammography's usage in order to identify and categorize breast cancer. Asadi and Memon [13] combined ResNet50 for classification and UNet for segmentation to achieve high F1 scores and precision in the early detection of breast cancer. Atrey et al. [14] combined ultrasound and mammography data to improve accuracy in classifying breast cancer. Gami et al. [15] discussed the technological advancements in medical deep learning-based computer-assisted detection systems. Frank [16] used YOLOv5 in conjunction with an integrated deep learning system to discover sensitive masses. Saran et al. [17] used transfer learning for accurate breast density classification in screening operations. Mohapatra et al. [18] found that deep learning techniques, especially CNNs, show promise for enhancing breast cancer identification compared to traditional CAD systems.

Mechria et al. [19] evaluated how the quality of mammography images affects the performance of detection of breast cancer using deep convolutional neural networks. Petrini et al. [20] demonstrated the superiority of deep convolutional neural networks in mammography-based utilizing transfer learning for breast cancer screening. Aljuaid et al. [21] introduced a new deep neural network and transfer learning method for detecting breast cancer using the BreakHis dataset. Their approach showed strong detection results with high accuracies and has the potential to improve with more robust datasets. Balkenende et al. [22] enhanced detection and assessment in ultrasonography, mammography, and magnetic resonance imaging, with the potential to outperform doctors in performance. However, clinical integration still relies on extensive studies and ethical considerations. Dadsetan et al. [23] developed a unique deep-learning network called LRP-NET to predict cancer risk by measuring spatiotemporal changes in breast tissue from previous mammograms.

Garrucho et al. [24] explored deep learning techniques for mammography mass identification and highlighted the challenges associated with domain generalization. Dey et al. [25] improved early breast cancer detection using DenseNet121 as a classifier, proposing a thermography-based system that achieved 98.80% accuracy on the DMR-IR dataset. Hassan et al. [26] emphasized the challenges and constraints of deep learning and traditional methods used in breast cancer CAD systems. Masud et al. [27] investigated the use of ultrasound images for diagnosing breast cancer using convolutional neural networks and achieved superior accuracy and AUC through transfer learning. They plan to validate the model using additional datasets. Abdelrahman et al. [28] discussed the limitations of mammography, such as limited sensitivity in breast density, and the potential for CNNs to enhance diagnosis effectiveness. Omonigho et al. [29] improved breast cancer detection accuracy with an enhanced AlexNet CNN reaching 95.70% classification accuracy.

Agnes et al. [30] emphasized the importance of early detection using digital mammography in increasing the proportion of breast cancer survivors. The Multiscale All Convolutional Neural Network (MA-CNN) was their suggested architecture with higher sensitivity and higher AUC to aid radiologists in categorizing mammography images correctly. Shakeel and Raja [31] introduced a revolutionary CAD system using a customized DCNN to identify breast cancer from mammograms with 88.7% accuracy and 0.885 AUC, enhancing early detection capabilities. Chouhan et al. [32] discussed the DFeBCD system, which performs better than ad hoc feature sets by using dynamic characteristics for categorizing mammograms as normal or abnormal using a highway-network-based CNN. Ekici and Jawzal et al. [33] provided non-invasive breast cancer detection, expanding the limits of mammography, particularly in cases with dense breast tissue. Hassan et al. [34] introduced a deep learning network (DCNN) based automated method for the identification and categorization of breast cancer masses.

Nagpure et al. [35] highlighted the seriousness of breast cancer for Indian women and proposed using data mining and neural networks to identify early. Kavitha et al. [36] introduced OMLTS-DLCN, which integrates various techniques for diagnosing breast cancer with excellent accuracy on the DDSM and Mini-MIAS datasets. Patil and Biradar [37] developed a hybrid classifier for identifying breast cancer in mammography images, integrating CNN, RNN, and FC-CSO for segmentation to achieve high accuracy.

Table 1: Summary Of Literature Findings

Reference No	Approach	Technique	Algorithm	Data set	Limitation
[5]	AI	ML and DL technique	ML-based algorithms	BreaKHis dataset	In the future, optimization of pre-processing is required.
[6]	AI	CNN	-	INbreast, CBIS-DDSM, and BNS dataset	3D layers are to be incorporated for better performance.
[7]	AI	ML and DL technique	Chaotic Krill Herd algorithm	INbreast dataset, DDSM, and MIAS dataset	Further investigation is desired to deal with problems like class imbalances.
[11]	Deep learning	G-CNN and CNN	DCT-GCNNs algorithm	ROTATED MNIST dataset and CBIS-DDSM dataset	DCT-GCNN to be applied to other datasets
[25]	Transfer learning approach	VGG16, VGG19, DenseNet169 and Xception	Bayes algorithm	DMR-IR dataset	Working on class imbalance is still desired.
[30]	Deep learning approach	MA-CNN and DCNN	DL algorithms	Mini-MIAS dataset	A patch-based approach is to be explored in the future.
[33]	AI	ML techniques	Bayes algorithm	DMI dataset	To be improved with hybridization with deep learning.
[36]	Deep learning approach	DL technique	Shell Game Optimization (SGO) algorithm	Mini-MIAS dataset and DDSM dataset	The segmentation procedure needs to be improved.
[38]	AI	CNN	DL algorithms	INbreast dataset and CBIS dataset	There is a need for automatically choosing the k value.
[40]	AI	DL technique	DL algorithms	CBIS-DDSM, MIAS, and INbreast databases	There is a need to investigate improving deep learning model architectures.

Shu et al. [38] outlined a comprehensive mammography categorization system technique using a deep neural network that incorporates unique pooling structures to enhance lesion identification without the need for manual segmentation. Salama and Aly [39] introduced a reliable structure about breast cancer detection from mammography images, leveraging various deep-learning models. Their approach, employing a modified version of U-Net for segmentation, demonstrated superior accuracy AUC compared to InceptionV3 on DDSM datasets. Isaza et al. [40] investigated the use of deep learning architectures to mammography picture recognition, segmentation, and classification of breast cancer. They found that VGG19 and ResNet50V2 achieved higher accuracy in lesion classification, while EfficientNet excelled in segmentation. While Anas et al. [6] improved detection using YOLOv5, their approach lacked

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fine-grained lesion classification, which our proposed model addresses. Similarly, Asadi and Memon [13] achieved good results using ResNet50 and UNet, yet their segmentation component increased computational complexity, unlike our streamlined DenseNet-based design. The literature suggests a need to enhance deep learning architectures and exploit transfer gaining expertise in identifying breast cancer from mammography pictures.

3. PROPOSED FRAMEWORK

We have developed an automated system utilizing deep learning to identify breast cancer from mammograms. This framework utilizes a modified DenseNet121 model with transfer learning to enhance performance and the detection process. Belonging to the DenseNet family, DenseNet121 is a convolutional neural network design. Through dense, feed-forward connections between each layer and all subsequent layers, it is intended to solve the vanishing gradient problem and enhance feature propagation. The network's total number of layers is indicated by the "121" in DenseNet121.

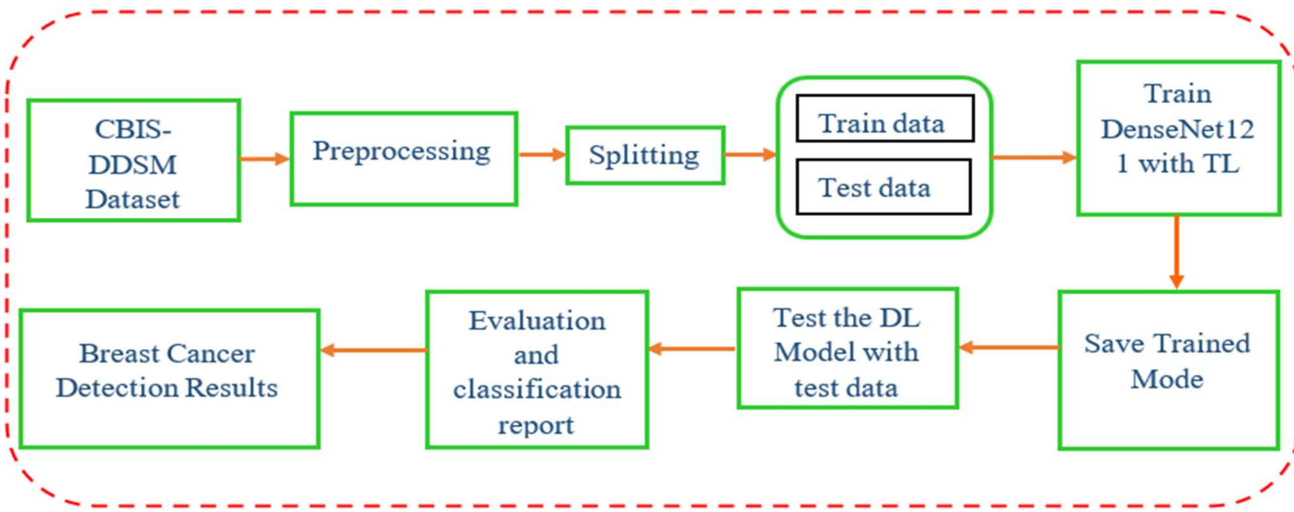

Figure 1: The Proposed Deep Learning-Based Framework For Breast Cancer Detection

The workflow structure for a system that uses the DenseNet architecture to identify breast cancer is shown in Figure 1. Utilizing the CBIS-DDSM (Curated Breast Imaging Subset of the Digital Database for Screening Mammography) dataset for training and testing, the procedure starts here. Preprocessing is applied to the dataset, which may involve operations like augmentation, resizing, and normalization in order to get the photos ready for model training. Afterwards, training and testing datasets are created from the pre-processed material. The DenseNet121 model, a specific version of DenseNet, is trained using the training data, with "TL" standing for Transfer Learning, indicating that pre-trained weights enhance training efficiency and performance. Once the model is trained, it is saved for future use. Following training, the model is evaluated for performance using the test data. Metrics like accuracy, precision, recall, and F1 score are included in the classification report that is produced once the model's performance is evaluated. Finally, the results of breast cancer detection are obtained, which can be used for further analysis or in clinical settings. This workflow highlights the importance of data preparation, model training, and comprehensive evaluation to ensure accurate and reliable breast cancer detection using deep learning models.

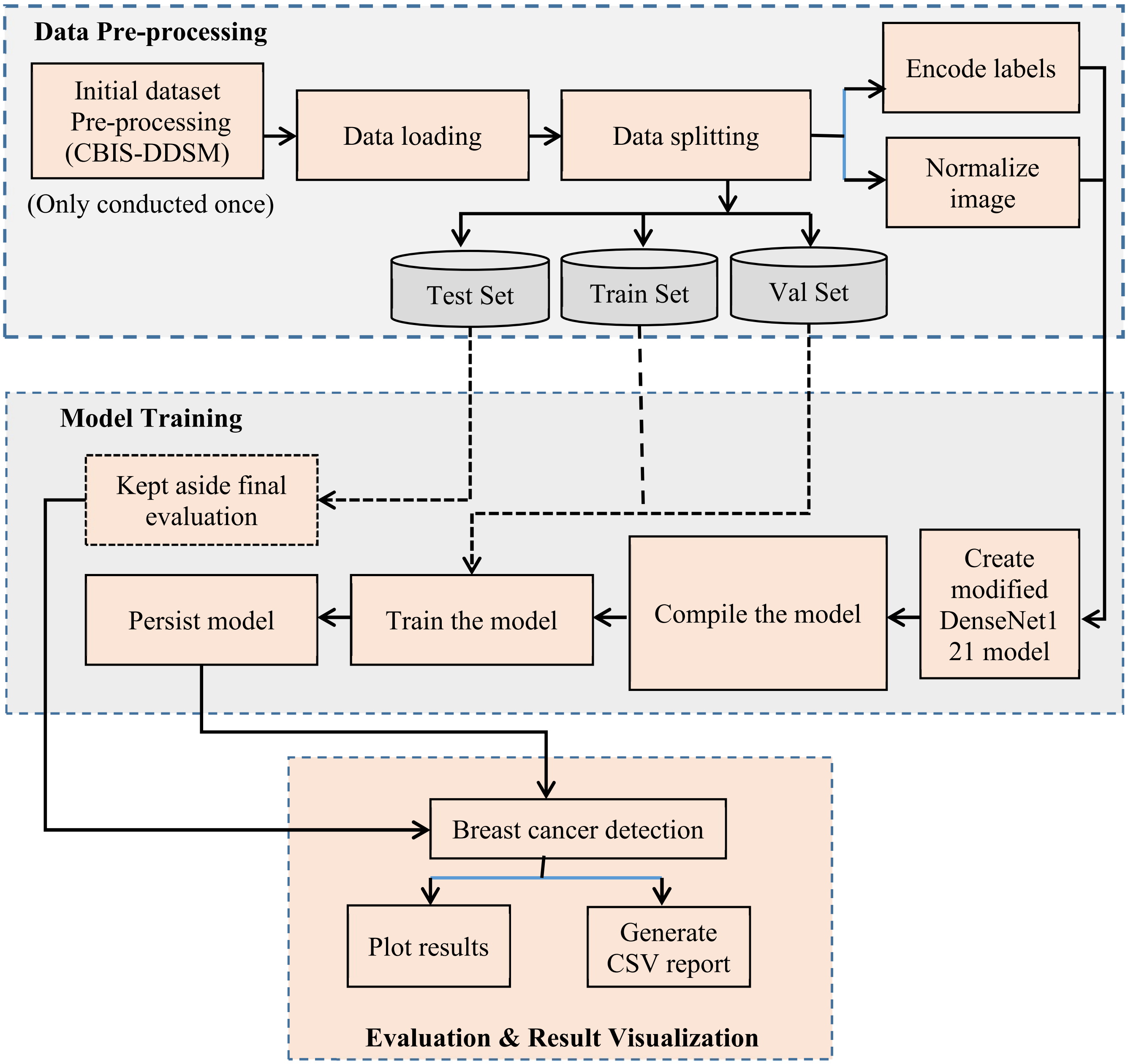

Figure 2: Technical Details Of The Proposed Framework

Figure 2 shows a pipeline for training a Convolutional Neural Network (CNN) model for image classification using a dataset such as CBIS-DDSM. The raw dataset, CBIS-DDSM, goes through initial pre-processing, which could include actions like resizing images, data augmentation, and noise removal. The data is loaded in parallel batches to enhance computational efficiency. Next, it is split up into three smaller groups: the test set, validation set, and training set. This separation ensures that Different types of data may be used to train, validate, and test the model, allowing for an accurate evaluation of its performance. The labels (categories of images) are encoded into a numerical format that is compatible with the model. Additionally, the images are adjusted to make sure the values of their pixels fall into a predetermined range, often 0 to 1 to enhance the model's performance.

A new CNN model, known as modified DenseNet121, is created based on the desired

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architecture and then compiled by specifying the optimizer, learning rate, loss function, and other parameters. After then, the model is trained using the training set. Early stopping may be utilized to end training when the validation loss no longer improves, hence avoiding overfitting. During training, the model's weights are saved for future use. A subset of the data is reserved for final evaluation to test the model's performance after training. On the test set, the trained model is used to generate predictions, and the outcomes are displayed to show how well the model performed. A CSV report is generated to document the evaluation metrics and results. This pipeline offers a systematic approach to training, validating, and testing a CNN model for image classification tasks, making sure the model performs properly when applied to fresh, untested data.

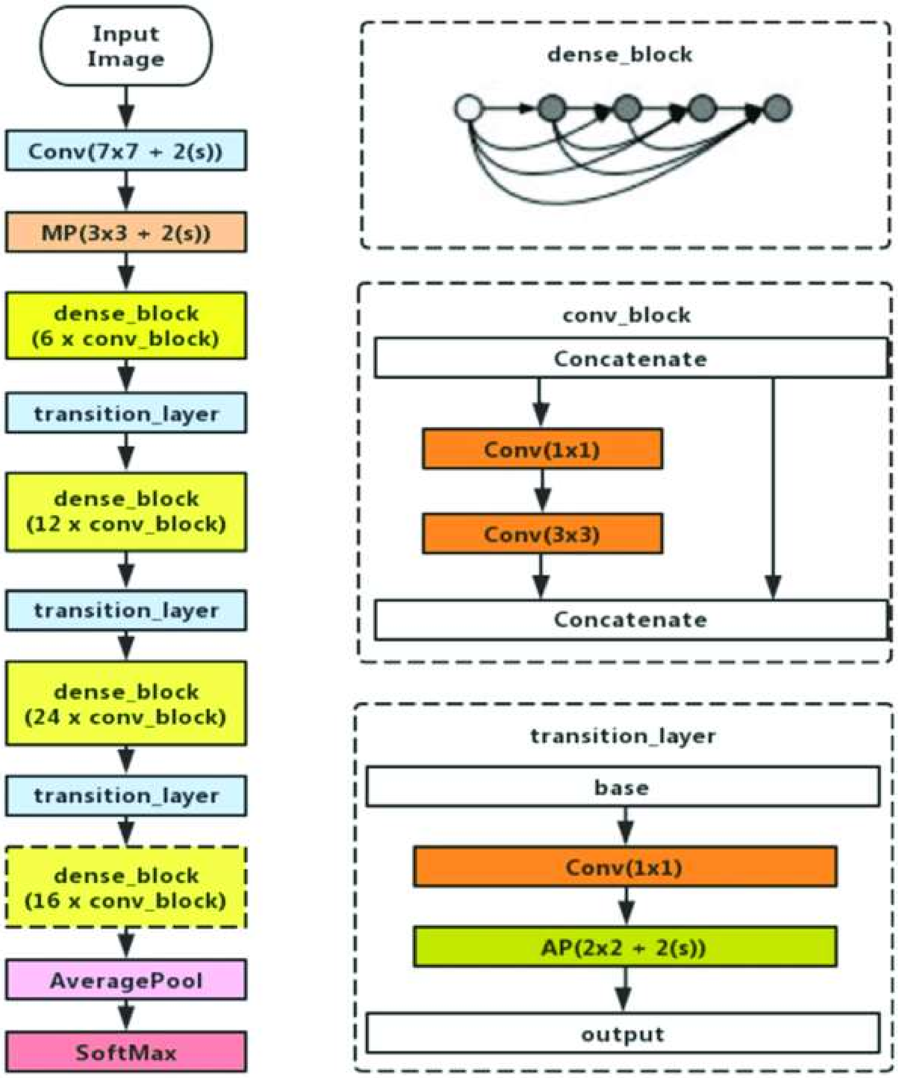

Figure 3: Illustrates The Architecture Of Modified Densenet121 (Left) And Its Dense Block (Right)

DenseNet121 is a kind of neural network designed for computer vision applications. Figure 3 depicts its architecture. After applying a 7x7 filter convolutional layer with a stride of 2, the network first processes an input picture. Next, add a max pooling layer with a stride of 2 and a 3x3 filter. Several convolutional layers make up each dense block, and these layers are feed-forward coupled to one another.This connectivity is illustrated in the 'dense_block' diagram on the right side. The convolution block within a dense block includes a sequence of a 1x1 convolution followed by a 3x3 convolution, and their outputs are concatenated. Layers connecting dense blocks help reduce the feature map size through 1x1 convolutions followed by average pooling in a transition layer indicated by a 1x1 convolution followed by average pooling (AP).

The model incorporates multiple dense blocks with varying numbers of convolutional blocks: the first dense block contains six convolutional blocks, the second has 12, the third has 24, and the fourth has 16. Next, there's a layer of global average pooling. Convolutional neural networks frequently employ the global average pooling strategy, which computes the average of all the feature maps in the final convolutional layer, for image classification problems. For each feature map, this results in a reduction of the spatial dimensions to a single value, which can then be used as input to a fully connected layer for classification purposes. Global Average Pooling helps prevent overfitting by summarizing the entire feature map rather than focusing on specific details. Finally, the network employs a softmax layer for multi-class classification. With its dense connections, this architecture benefits from improved information and gradient flow throughout the network, leading to more efficient and potentially more accurate models. The research protocol includes data acquisition from the CBIS-DDSM dataset, preprocessing using image normalization and augmentation, model building with Keras and TensorFlow backend, training using Adam optimizer, batch size of 32, learning rate of 0.0001, 100 epochs, early stopping, and validation using a 70-15-15 train-test-validation split. All experiments were run on an NVIDIA RTX GPU-enabled system using Python 3.9.

3.1 Transfer Learning

To use transfer learning with DenseNet121, begin with a DenseNet121 model that has already been trained using a big dataset, such ImageNet. Next, modify the model to fit a fresh dataset or job that may contain fewer data. By utilizing the information from the first work, this method can greatly enhance the model's performance on the subsequent assignment with low data requirements. Begin with a DenseNet121 model that has already been trained on a sizable dataset to find features relevant to a range of jobs. Prepare the custom dataset for the new task, ensuring it is relevant and contains enough samples for training. Adjust the pre-trained DenseNet121 model by "fine-tuning" its parameters on your custom dataset. This can involve freezing some layers or allowing all layers to be trainable, based on the size and similarity of the new dataset. Train the adapted DenseNet121 model on your custom dataset, monitor its performance on validation data, and adjust hyperparameters if necessary. When evaluating the transfer learning model's efficacy in the new task, compare its results on a different test set.

When subjecting the DenseNet121 model to transfer learning with additional layers, consider adding a normalization layer to make the prior layer's activations more natural. This may enhance the neural network's stability and training speed. Add a completely linked layer with 2048 units and the ReLU activation function after that. Use L1 and L2 regularization with a penalty of 0.01 to prevent overfitting. Add another batch normalization layer for normalization after the dense layer. Incorporating an 8-unit output layer with a softmax activation function appropriate for multi-class classification tasks is the final step. The output of the softmax function is transformed into a probability distribution over the various classes. This neural network model architecture consists of a convolutional base (pre-trained DenseNet121), batch normalization layers, dense layers with ReLU activation, and an output layer with softmax activation for classification tasks.

3.2 Proposed Algorithm

In order to precisely identify breast cancer using mammography pictures from the CBIS-DDSM dataset, we developed the Intelligent Learning Based Breast Cancer Detection (ILB-BCD) method. This method analyzes photos and provides performance statistics and identification results using a modified DenseNet121 model with transfer learning. Assisting in the early diagnosis of breast cancer is the main objective as it improves patient outcomes and survival rates.

Algorithm: Intelligent Learning Based Breast Cancer Detection (ILB-BCD)
Input: CBIS-DDSM (mammography images) dataset D
Output: Breast cancer detection results R, performance statistics P

1. Begin
2. D'←PerformPreprocessing(D)
3. (T1, T2, T3)←DataPreparation(D') //split into train, test, validation data
4. Configure modified DenseNet121 model m (as in Figure 3)

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5. Enhance model m with transfer learning
6. Compile model m
7. m'←TrainModifiedDenseNet121(T1, m)
8. Persist model m'
9. Load model m'
10. R←DetectBreastCancer(m', T2)
11. P←EvaluateDenseNet121(T3, R)
12. Print R
13. Print P
14. End

Algorithm 1: Intelligent Learning Based Breast Cancer Detection (Ilb-Bcd)

The Intelligent Learning Based Breast Cancer Detection (ILB-BCD) algorithm utilizes the CBIS-DDSM dataset of mammography images as input and provides breast cancer detection results as well as performance statistics. The algorithm involves preprocessing the dataset and dividing it into training, testing, and validation sets. It employs a modified DenseNet121 model, which is further improved through transfer learning techniques. The model is then compiled and trained using the training set, and the trained model is saved for future use. Subsequently, the trained model is loaded to detect breast cancer in the test set. The algorithm concludes by evaluating the performance of the DenseNet121 model using the validation set and presenting both the detection results and performance statistics. The algorithm is designed with clear steps, from data preparation to model training and evaluation, aiming to deliver accurate breast cancer detection results. The use of a modified DenseNet121 model and transfer learning reflects a sophisticated approach to the challenge of detecting breast cancer in mammography images.

4. EXPERIMENTAL RESULTS

The outcomes of our empirical investigation utilizing the benchmark dataset CBIS-DDSM [41] will be presented in this part. Mammography pictures and annotations for tasks including calcification detection, anomalies, and breast mass detection are included in the CBIS-DDSM dataset, which is extensively utilized in studies on breast cancer diagnosis. This dataset serves a critical role in enhancing the accuracy of breast cancer detection techniques and in the advancement of medical imaging. It is essential for the creation and assessment of algorithms for automated breast cancer detection and diagnosis. We evaluated the suggested updated DenseNet121 model's experimental outcomes against a variety of deep learning models.

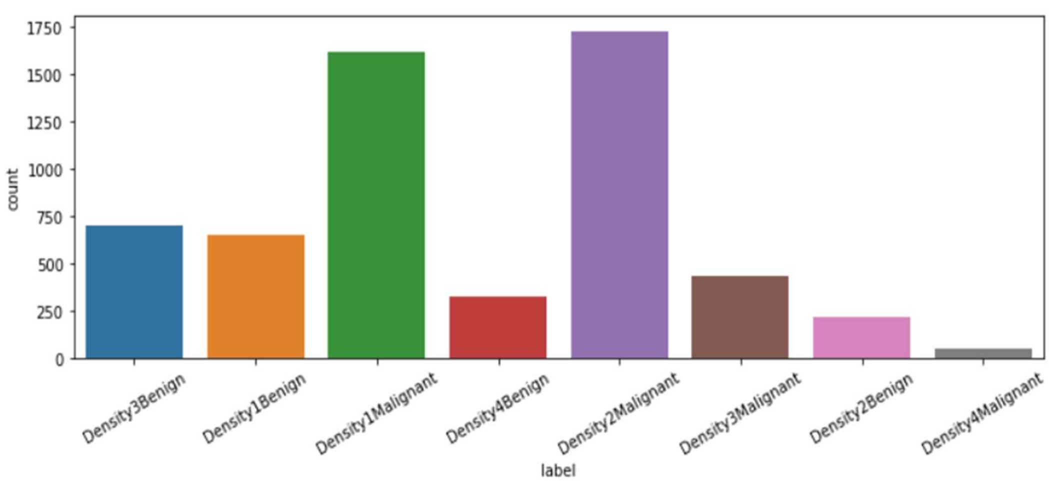

Figure 4: Data Distribution Dynamics In The Mammography Dataset

The distribution of benign and malignant patients is depicted in Figure 4 across different density categories. On the x-axis, you'll find the combined labels of density and case type, while the y-axis shows the count of cases, ranging up to 1750. The categories "Density1Malignant" and

"Density2Malignant" have the highest counts, with approximately 1650 and 1750 cases, respectively. On the other hand, "Density4Benign" and "Density4Malignant" have the lowest counts, just above zero. Among benign cases, "Density3Benign" and "Density1Benign" have around 750 cases each, making them the highest among benign cases. The graph effectively shows that malignant cases are more predominant in certain density categories, particularly Density1 and Density2, while benign cases are more evenly distributed but with lower counts overall.

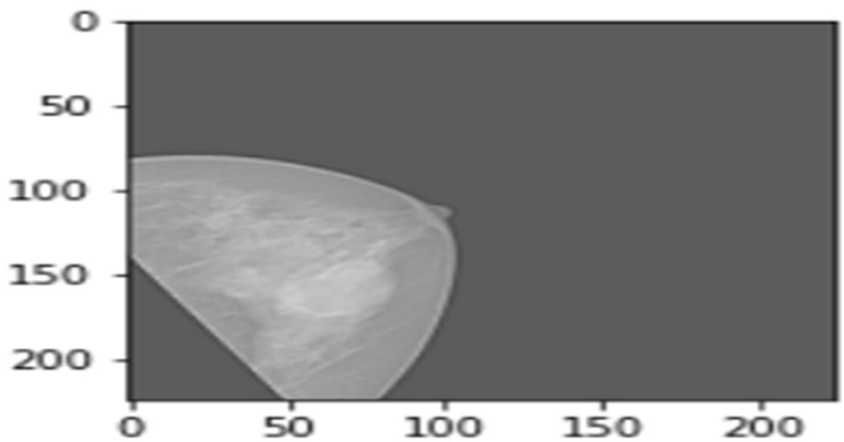

Figure 5: A Sample Image For Training

Figure 5 depicts a grayscale section of breast tissue outlined against a darker background, which makes internal structures more visible. The mammogram highlights various densities within the tissue, which may indicate different tissue types or potential abnormalities. The image is clear enough to discern the general shape and some internal features, which are crucial for medical professionals to analyze further for diagnostic purposes.

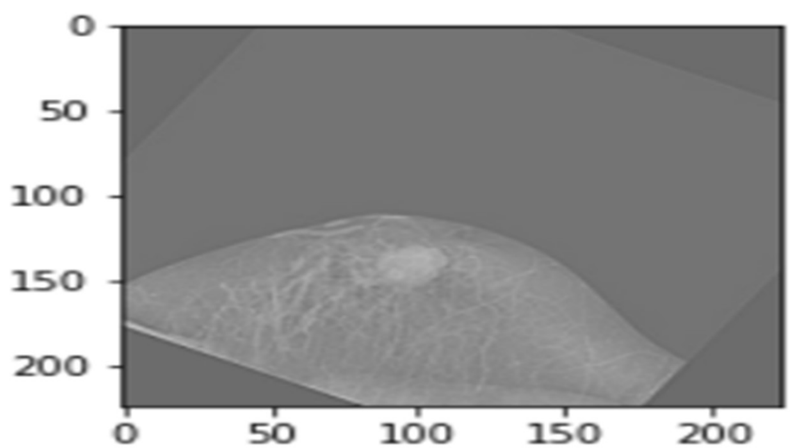

Figure 6: Another Sample Image For Training

Figure 6 shows a different section or angle of breast tissue. The grayscale format highlights various densities within the tissue, and a noticeable area of higher density may indicate a mass or other abnormality. The internal structure of the breast tissue is more visible, revealing the intricate network of ducts and fibrous tissue. This type of imaging is crucial for medical professionals to examine for any signs of breast cancer or other conditions. The clear contrast against the dark background helps to see these features, enabling detailed examination and potential diagnosis.

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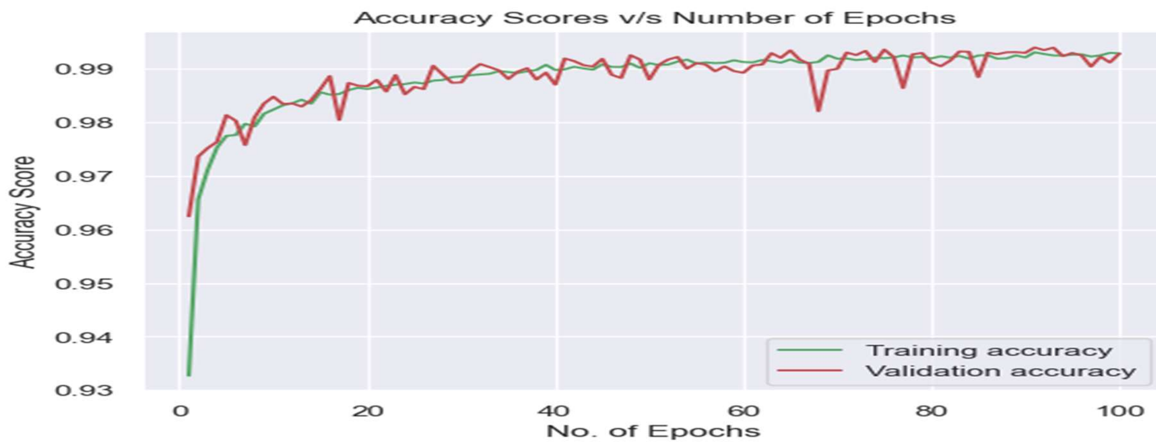

Figure 7: Training And Validation Accuracy Against The Number Of Epochs

A suggested model's accuracy ratings throughout several epochs are displayed in Figure 7. The X-axis, which runs from 0 to 100, shows how many epochs there are. The term "epoch" designates a single trip through the training set. The accuracy score, which ranges from 0.93 to 1.00, is shown on the Y-axis. The ratio of the model's accurate predictions to its total number of predictions is used to calculate accuracy. The model's accuracy over the epochs on the training dataset is shown by the green line. Typically, it shows a rising tendency before leveling off as the number of epochs rises. The red line represents the model's accuracy on the validation dataset over the epochs. It closely follows the training accuracy but exhibits more fluctuations, indicating some variability in performance. Both training and validation accuracy sharply increase at the start and then level off. Compared to training accuracy, validation accuracy varies considerably, which is common when the model might be slightly overfitting. The overall performance stabilizes after around 20 epochs.

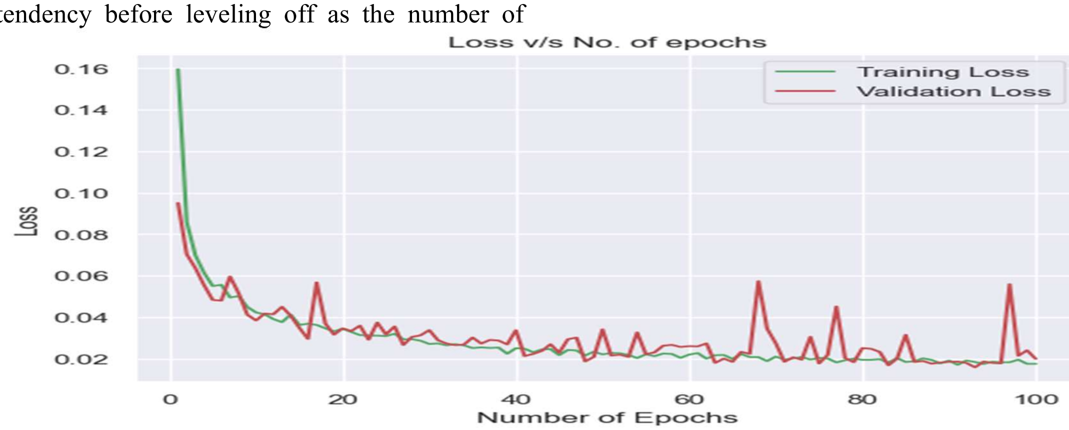

Figure 8: Training And Validation Loss Against The Number Of Epochs

The suggested deep learning model's variation in loss throughout several training epochs is shown in Figure 8. The training epoch count, shown by the X-axis, ranges from 0 to 100, while the loss value, represented by the Y-axis, ranges from 0.02 to 0.16. The loss value signifies the disparity between the model's prediction and the actual result, with lower values indicating a closer prediction to the actual result. On the training dataset, the model's lost value is shown by the green line. Training loss often falls down gradually and finally stabilizes as the number of training epochs rises. Conversely, the validation dataset's loss value for the model is shown by the red line. Validation loss is more erratic than training loss, indicating the model's performance on untested data. Validation and training losses both drop very quickly in the first stage. As more training epochs are added, the training loss stabilizes at a lower value; nonetheless, the validation loss trend shows significant fluctuations, indicating potential overfitting in some training epochs.

Model	Precision	Recall	F1-Score	Accuracy
Baseline CNN	94.56	89.56	91.99	94.07
MobileNetV2	94.59	94.39	94.49	96.52
VGG19	96.07	95.59	95.83	98.01
DenseNet121	97.98	94.86	96.39	98.74
DenseNet121 with Transfer Learning	99.07	96.58	97.81	99.16

Table 1: Performance Comparison

Table 1 compares many deep learning models, including the one that is suggested, based on accuracy, precision recall, and F1 score.

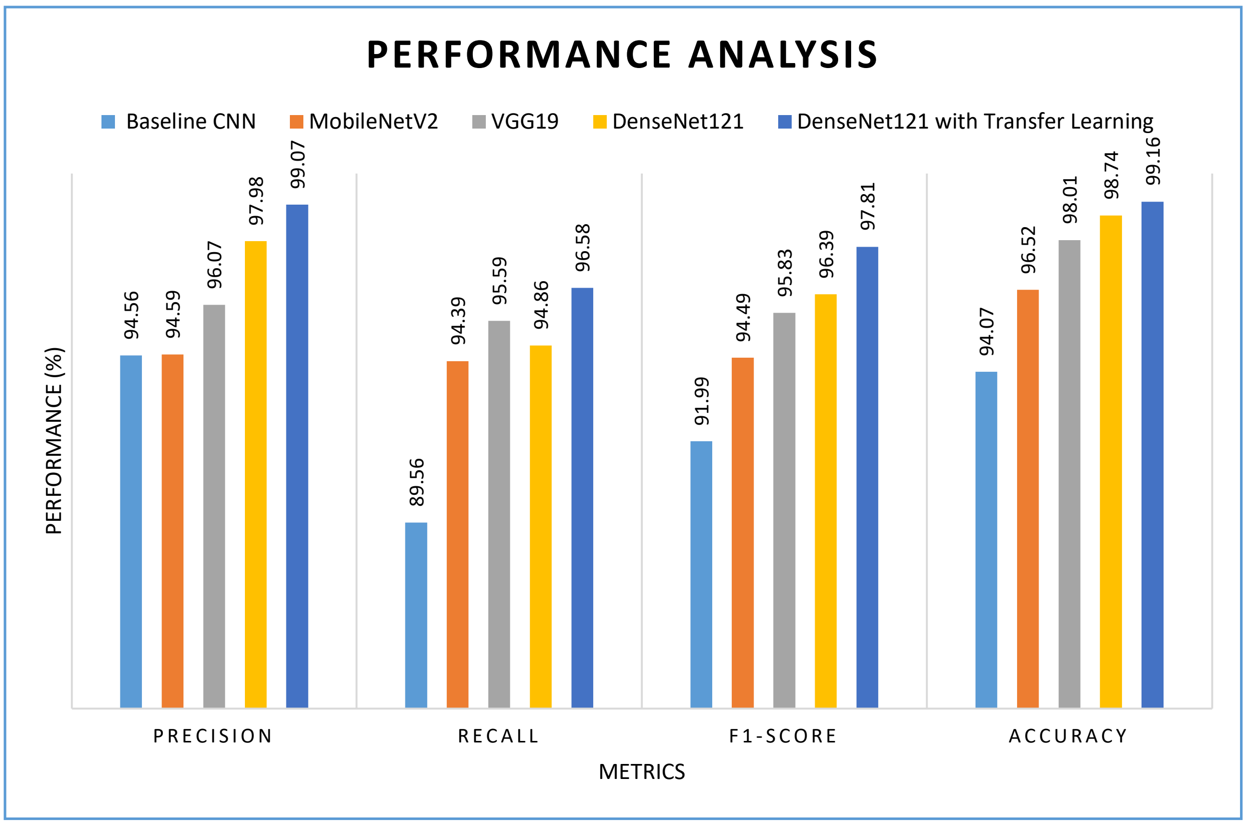

Figure 9: Performance Analysis Of Breast Cancer Detection Models

Figure 9 illustrates the evaluation of many machine learning models' performance using four metrics: accuracy, precision, recall, and F1-score. The compared models include Baseline CNN, MobileNetV2, VGG19, DenseNet121, and DenseNet121 with Transfer Learning. In terms of precision, Baseline CNN achieved 94.56%, MobileNetV2 94.59%, VGG19 96.07%, and DenseNet121 exhibited 97.98%, while DenseNet121 with Transfer Learning achieved 99.07% precision. Baseline CNN achieved 94.39% for the recall measure, MobileNetV2 89.56%, VGG19 94.59%, and DenseNet121 95.86%, while DenseNet121 with Transfer

Learning exhibited 96.58% recall. Regarding the F1 score, Baseline CNN scored 91.99%, MobileNetV2 94.49%, VGG19 95.83%, DenseNet121 96.39%, and DenseNet121 with Transfer Learning achieved 97.81%. Regarding accuracy, Baseline CNN achieved 94.07%, MobileNetV2 96.52%, VGG19 98.01%, and DenseNet121 97.74%, while DenseNet121 with Transfer Learning achieved 99.16%. It is worth noting that DenseNet121 with Transfer Learning consistently outperformed other models across all metrics, showing the highest Precision (99.07%), Recall (96.58%), F1-Score (97.81%), and Accuracy (99.16%). This signifies the efficiency of transfer learning in enhancing model functionality. The Baseline CNN and MobileNetV2 generally performed less effectively than VGG19 and DenseNet121.

5. DISCUSSION

The use of AI in breast cancer detection has become increasingly important due to its ability to learn from training samples and accurately detect breast cancer. Among different imaging modalities, mammography images are considered the most effective for breast cancer detection. Deep learning models, particularly CNN-based approaches, have proven efficient in medical image processing. This work addresses improving a CNN model to enhance its detection performance for automatic breast cancer diagnosis. We have proposed a deep learning framework that leverages our modified DenseNet 121 model, capable of learning thoroughly from training samples and accurately detecting breast cancer in test samples. The model is supported by an algorithm designed specifically for breast cancer detection from mammography images. The excellent accuracy demonstrated by our suggested deep learning model suggests its potential use in real-world clinical decision support systems for breast cancer screening. Compared to baseline CNN and MobileNetV2, the proposed DenseNet121 with transfer learning demonstrates superior precision and recall. However, it relies heavily on high-resolution mammograms and may be less effective for low-quality or noisy images. A fascinating insight is that while VGG19 performed well, it lacked the parameter efficiency seen in DenseNet-based architectures. Nonetheless, it's critical to recognize the constraints of our proposed deep learning framework, which are discussed in section 5.1.

5.1 Limitations

Certain restrictions apply to the suggested deep learning framework. It has been evaluated using a mammography image dataset. However, there is a need to diversify the training samples to generalize the findings of the proposed deep learning framework. It is also essential to hybridize the models with optimizations to improve performance and the detection process. Another direction for future research is to incorporate generative adversarial network models to enhance the breast cancer detection process.

6. CONCLUSION AND FUTURE WORK

Our research this study presents a deep-learning framework designed to detect breast cancer automatically using mammography imaging. Our framework makes use of a modified DenseNet-121 model and transfer learning. The modified model leverages transfer learning to enhance performance and the detection process. DenseNet-121 is a convolutional neural network architecture part of the DenseNet family. It is constructed to address the vanishing gradient problem and improve feature propagation by allowing information to flow more freely throughout the network. We have developed an algorithm called Intelligent Learning Based Breast Cancer Detection (ILB-BCD) founded on the DenseNet-121 model that has been changed, and in an empirical study using a benchmark dataset, CBIS-DDSM, our proposed model achieved an impressive 99.16% accuracy, surpassing many existing deep learning models. The success of our deep learning framework suggests its potential integration into current healthcare systems to create a Clinical Decision Support System (CDSS) for automatic breast cancer screening. This study contributes a novel automated framework utilizing a modified DenseNet121 model with transfer learning, achieving a benchmark accuracy of 99.16%. The impact of our work lies in its potential clinical applicability through integration into decision support systems, improving early detection and survival outcomes in real-world scenarios. In the future, we plan to enhance our framework with hybrid deep learning models and explore the use of Generative Adversarial Network (GAN) architectures.

REFERENCES

[1] Elaheh Tarighati Sereshkeh, Hadi Keivan, Kiarash Shirbandi, Fatemeh Khaleghi and Mohammad Mahdi Bagheri Asl. (2024). A convolution neural network for rapid and accurate staging of breast cancer based on mammography. *Elsevier*. 47, pp.1-6. https://doi.org/10.1016/j.imu.2024.101497

[2] Md Rakibul Islam, Md Mahbubur Rahman, Md Shahin Ali, Abdullah Al Nomaan Nafi, Md Shahariar Alam, Tapan Kumar Godder, Md Sipon Miah and Md Khairul Islam. (2024). Enhancing breast cancer segmentation and classification: An Ensemble Deep Convolutional Neural Network and U-net approach on ultrasound images. *Elsevier*. 16, pp.1-12. https://doi.org/10.1016/j.mlwa.2024.100555

[3] Laxman Singh and Altaf Alam. (2022). An efficient hybrid methodology for an early detection of breast cancer in digital mammograms. *Springer*. 15, pp.337-360. https://doi.org/10.1007/s12652-022-03895-w

[4] Rengarajan Karthiga, Kumaravelu Narasimhan, Ravikumar Chinthaginjala, Rajesh Anbazhagan, Manikandan Chinnusamy, Giovanni Pau, Kumar Satish, Rengarajan Amirtharajan, and Mohamed Abbas. (2024). A novel exploratory hybrid deep neural network to predict breast cancer for mammography based on wavelet features. *Springer*, pp.1-27. https://doi.org/10.1007/s11042-023-18012-y

[5] SOUMYA SARA KOSHY AND L. JANI ANBARASI. (2024). LMHistNet: Levenberg–Marquardt Based Deep Neural Network for Classification of Breast Cancer Histopathological Images. *IEEE*. 12, pp.52051 - 52066. http://DOI:10.1109/ACCESS.2024.3385011

[6] MUHAMMAD ANAS, IHTISHAM UL HAQ, GHASSAN HUSNAIN, AND SYED ALI FARAZ JAFFERY. (2024). Advancing Breast Cancer Detection: Enhancing YOLOv5 Network for Accurate Classification in Mammogram Images. *IEEE*. 12, pp.16474 - 16488. http://DOI:10.1109/ACCESS.2024.3358686

[7] Xin Wen, Xing Guo, Shuihua Wang, Zhihai Lu and Yudong Zhang. (2024). Breast cancer diagnosis: A systematic review. *Elsevier*. 44(1), pp.119-148. https://doi.org/10.1016/j.bbe.2024.01.002

[8] DILAWAR SHAH, MOHAMMAD ASMAT ULLAH KHAN, MOHAMMAD ABRAR, FARHAN AMIN, BADER FAHAD ALKHAMEES, AND HUSSAIN ALSALMAN. (2024). Enhancing the Quality and Authenticity of Synthetic Mammogram Images for Improved Breast Cancer Detection. *IEEE*. 12, pp.12189 - 12198. http://DOI:10.1109/ACCESS.2024.3354826

[9] Ling Tan, Ying Liang, Jingming Xia*, Hui Wu, and Jining Zhu. (2024). Detection and Diagnosis of Small Target Breast Masses Based on Convolutional Neural Networks. *IEEE*. 29(5), pp.1524 - 1539. http://DOI:10.26599/TST.2023.9010126

[10] Mahnoosh Torabi, Amir Hosein Rasouli, Q.M. Jonathan Wu, Weipeng Cao and Farhad Pourpanah. (2024). Self-supervised adversarial adaptation network for breast cancer detection. *Elsevier*. 133, pp.1-9. https://doi.org/10.1016/j.engappai.2024.108489

[11] ZAHARADDEEN SANI, RAJESH PRASAD, AND EZZEDDIN KAMIL MOHAMED HASHIM. (2023). Breast Cancer Classification Using Equivariance Transition in Group Convolutional Neural Networks. *IEEE*. 11, pp.28454 - 28465. http://DOI:10.1109/ACCESS.2023.3253640

[12] Kosmia Loizidou, Rafaella Elia and Costas Pitris. (2023). Computer-aided breast cancer detection and classification in mammography: A comprehensive review. *Elsevier*. 153, pp.1-24. https://doi.org/10.1016/j.compbiomed.2023.106554

[13] Bita Asadi and Qurban Memon. (2023). Efficient breast cancer detection via cascade deep learning network. *Elsevier*. 4, pp.46-52. https://doi.org/10.1016/j.ijin.2023.02.001

[14] Kushangi Atrey Bikesh Kumar Singh, Narendra K. Bodhey and Ram Bilas Pachori. (2023). Mammography and ultrasound based dual modality classification of breast cancer using a hybrid deep learning approach. *Elsevier*. 86(A), pp.1-27. https://doi.org/10.1016/j.bspc.2023.104919

[15] Bhavin Gami, Khushi Chauhan, and Brijeshkumar Y. Panchal. (2023). Breast Cancer Detection Using Deep Learning. *Springer*, pp.85-95. https://doi.org/10.1007/978-981-19-7982-8_8
[16] Steven J. Frank. (2023). A deep learning architecture with an object-detection algorithm and a convolutional neural network for breast mass detection and visualization. *Elsevier*. 3, pp.1-7. https://doi.org/10.1016/j.health.2023.100186
[17] K B Saran, G Sreelekha and V C Sunitha. (2023). Breast Density Classification to Aid Clinical Workflow in Breast Cancer Detection Using Deep Learning Network. *IEEE*, pp.1-6. http://DOI:10.1109/TENCON58879.2023.10322346
[18] Subasish Mohapatra, Sarmistha Muduly, Subhadarshini Mohanty, J V R Ravindra and Sachi Nandan Mohanty. (2022). Evaluation of deep learning models for detecting breast cancer using histopathological mammograms Images. *Elsevier*. 3, pp.296-302. https://doi.org/10.1016/j.susoc.2022.06.001
[19] Hana Mechria, Khaled Hassine and Mohamed Salah Gouider. (2022). Breast cancer detection in mammograms using deep learning. *Elsevier*. 207, pp.2345-2352. https://doi.org/10.1016/j.procs.2022.09.293
[20] DANIEL G. P. PETRINI, CARLOS SHIMIZU, ROSIMEIRE A. ROELA, GABRIEL VANSUITA VALENTE, MARIA APARECIDA AZEVEDO KOIKE FOLGUEIRA AND HAE YONG KIM. (2022). Breast Cancer Diagnosis in Two-View Mammography Using End-to-End Trained EfficientNet-Based Convolutional Network. *IEEE*. 10, pp.77723 - 77731. http://DOI:10.1109/ACCESS.2022.3193250
[21] Hanan Aljuaid, Nazik Alturki, Najah Alsubaie, Lucia Cavallaro and Antonio Liotta. (2022). Computer-aided diagnosis for breast cancer classification using deep neural networks and transfer learning. *Elsevier*. 223, pp.1-10. https://doi.org/10.1016/j.cmpb.2022.106951
[22] Luuk Balkenende, Jonas Teuwen, and Ritse M. Mann. (2022). Application of Deep Learning in Breast Cancer Imaging. *Elsevier*. 52(5), pp.584-596. https://doi.org/10.1053/j.semnuclmed.2022.02.003
[23] Saba Dadsetan, Dooman Arefan, Wendie A. Berg, Margarita L. Zuley, Jules H. Sumkin,and Shandong Wu. (2022). Deep learning of longitudinal mammogram examinations for breast cancer risk prediction. *Elsevier*. 132, pp.1-48. https://doi.org/10.1016/j.patcog.2022.108919
[24] Lidia Garrucho, Kaisar Kushibar, Socayna Jouide, Oliver Diaz, Laura Igual, Karim Lekadir. (2022). Domain generalization in deep learning based mass detection in mammography: A large-scale multi-center study. *Elsevier*. 132, pp.1-14. https://doi.org/10.1016/j.artmed.2022.102386
[25] Subhrajit Dey, Rajarshi Roychoudhury, Samir Malakar, and Ram Sarkar. (2022). Screening of breast cancer from thermogram images by edge detection aided deep transfer learning model. *Springer*. 81, p.9331–9349. https://doi.org/10.1007/s11042-021-11477-9
[26] Nada M. Hassan, Safwat Hamad and Khaled Mahar. (2022). Mammogram breast cancer CAD systems for mass detection and classification: a review. *Springer*. 81, p.20043–20075. https://doi.org/10.1007/s11042-022-12332-1
[27] Mehedi Masud, Amr E. Eldin Rashed, and M. Shamim Hossain. (2022). Convolutional neural network-based models for diagnosis of breast cancer. *Springer*. 34, p.11383–11394. https://doi.org/10.1007/s00521-020-05394-5
[28] Leila Abdelrahman; Manal Al Ghamdi; Fernando Collado-Mesa and Mohamed Abdel-Mottaleb;. (2021). Convolutional neural networks for breast cancer detection in mammography: A survey . Computers in Biology and Medicine. http://doi:10.1016/j.compbiomed.2021.104248
[29] Omonigho, Emmanuel Lawrence; David, Micheal; Adejo, Achonu and Aliyu, Saliyu (2020). International Conference in Mathematics, Computer Engineering and Computer Science (ICMCECS) - Breast Cancer:Tumor Detection in Mammogram Images Using Modified AlexNet Deep

Convolution Neural Network. 1–6. http://doi:10.1109/ICMCECS47690.2020.240870

[30] Agnes, S. Akila; Anitha, J.; Pandian, S. Immanuel Alex and Peter, J. Dinesh (2020). Classification of Mammogram Images Using Multiscale all Convolutional Neural Network (MA-CNN). Journal of Medical Systems, 44(1), 30–. http://doi:10.1007/s10916-019-1494-z

[31] Sobia Shakeel and Gulistan Raja; (2021). Classification of Breast Cancer from Mammogram images using Deep Convolution Neural Networks . 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST). http://doi:10.1109/ibcast51254.2021.9393191

[32] Naveed Chouhan; Asifullah Khan; Jehan Zeb Shah; Mazhar Hussnain and Muhammad Waleed Khan; (2021). Deep convolutional neural network and emotional learning based breast cancer detection using digital mammography . Computers in Biology and Medicine. http://doi:10.1016/j.compbiomed.2021.104318

[33] Ekici, Sami and Jawzal, Hushang (2020). Breast cancer diagnosis using thermography and convolutional neural networks. Medical Hypotheses, 137, 109542–. http://doi:10.1016/j.mehy.2019.109542

[34] Hassan, Shaymaâ a A.; Sayed, Mohammed S.; Abdalla, Mahmoud I and Rashwan, Mohsen A. (2020). Breast cancer masses classification using deep convolutional neural networks and transfer learning. Multimedia Tools and Applications. http://doi:10.1007/s11042-020-09518-w

[35] Renuka Nagpure; Sumita Chandak and Nileema Pathak; (2020). Breast Cancer Detection using Neural Network Mammogram . 2020 International Conference on Convergence to Digital World - Quo Vadis (ICCDW). http://doi:10.1109/iccdw45521.2020.9318635

[36] T. Kavitha; Paul P. Mathai; C. Karthikeyan; M. Ashok; Rachna Kohar; J. Avanija and S. Neelakandan; (2021). Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images. Interdisciplinary Sciences: Computational Life Sciences. http://doi:10.1007/s12539-021-00467-y

[37] Patil, Rajeshwari S. and Biradar, Nagashettappa (2020). Automated mammogram breast cancer detection using the optimized combination of convolutional and recurrent neural network. Evolutionary Intelligence. http://doi:10.1007/s12065-020-00403-x

[38] Shu, Xin; Zhang, Lei; Wang, Zizhou; Lv, Qing and Yi, Zhang (2020). Deep Neural Networks with Region-based Pooling Structures for Mammographic Image Classification. IEEE Transactions on Medical Imaging, 1–1. http://doi:10.1109/TMI.2020.2968397

[39] Wessam M. Salama and Moustafa H. Aly; (2021). Deep learning in mammography images segmentation and classification: Automated CNN approach. Alexandria Engineering Journal. http://doi:10.1016/j.aej.2021.03.048

[40] ANDRÉS ANAYA-ISAZA, LEONEL MERA-JIMÉNEZ, JOHAN MANUEL CABRERA-CHAVARRO, LORENA GUACHI-GUACHI, DIEGO PELUFFO-ORDÓÑEZ, AND JORGE IVAN RIOS-PATIÑO. (2021). Comparison of Current Deep Convolutional Neural Networks for the Segmentation of Breast Masses in Mammograms. *IEEE*. 9, pp.152206 - 152225. http://DOI:10.1109/ACCESS.2021.3127862

[41] Srikanth, G., Raghavendran, C.V., Prabhu, M.R., Radha, M., Kumari, N.V.S. & Francis, S.K., 2025. Climate Change Impact on Geographical Region and Healthcare Analysis Using Deep Learning Algorithms. Remote Sensing in Earth Systems Sciences, 130359.

[42] Ravikumar Ch1, Marepalli Radha2, Maragoni Mahendar3, Pinnapureddy Manasa"A comparative analysis for deep-learning-based approaches for image forgery detection International journalof Systematic Innovation https://doi.org/10.6977/IJoSI.202403_8(1).0001

[43] Anitha Patil. (2019). Distributed Programming Frameworks in Cloud Platforms. International Journal of Recent Technology and Engineering (IJRTE). 7(6), pp.611-619.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[44] A. Patil and S. Govindaraj, "An AI-Enabled Framework for MRI-based Data Analytics for Efficient Brain Stroke Detection," 2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2023, pp. 1-7, doi: 10.1109/ACCAI58221.2023.10201136.

[45] Sreedhar Bhukya, A Novel Methodology for Secure De duplication of Imagedata in Cloud Computing using Compressive Sensing and Random Pixel Exchanging, Journal of Theoretical and Applied Information Technology (JATIT), Vol.102. No 4, ISSN: 1992-8645 (2024), SCOPUS.

[46] Sreedhar Bhukya, Multiclass Supervised Learning Approach for SAR-COV2 Severity and Scope Prediction: SC2SSP Framework, Volume (12) issue (1), 2025-01-31, SCOPUS.

[47] Ugendhar A.; Illuri B.; Vulapula S.R.; Radha M.; Sukanya K.; Alenezi F.; Althubiti S.A.; Polat K.A Novel Intelligent-Based Intrusion Detection System Approach Using Deep Multilayer Classification Mathematical Problems in Engineering,2022.https://www.scopus.com/sourceid/13082.

[48] Anitha Patil, Dr. Suresh Kumar Govindaraj. (2023). ADL-BSDF: A Deep Learning Framework for Brain Stroke Detection from MRI Scans towards an Automated Clinical Decision Sup. International Journal on Recent and Innovation Trends in Computing and Communication. 11(3), pp.11-23. DOI: https://doi.org/10.17762/ijritcc.v11i3.6195.

[49] P. Sudhakar, D. Prasanna N, S. Bhukya, M. Azhar, G. R Suresh and M. Ajmeera, "Wrapper-based Feature Selection for Enhanced Intrusion Detection Using Random Forest Classification," 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Bengaluru, India, 2024, pp. 1330-1335, doi: 10.1109/ICICNIS64247.2024.10823207.