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Early Detection of Breast Cancer Using Machine Learning and Deep Learning Techniques

Vanshika Gangwar, Nikita Kumari

Department of Computer Science and Engineering
Galgotias University, Greater Noida, Uttar Pradesh, India.
Corresponding Author: nikitakumari4443@gmail.com

ABSTRACT

Breast cancer is a major health concern in the world, and requiring early and accurate diagnosis in order to be treated. Due to the improved artificial intelligence, deep learning approaches have been used. Have demonstrated much potential in medical image analysis through giving automated and reliable diagnostic support. However, single-model processes can easily struggle to locate the complex. Patterns that are in medical data. This study proposes a hybrid deep learning model. for breast cancer detection through feature-level fusion of convolutional neural networks. The technique employs DenseNet and EfficientNet along with it to extract various features on input images. This allows the model to learn deep and efficiently scaled. Representations. We also created a model, which compares ResNet. and Inception architectures to find out how well various hybrid combinations work.

In order to make the system more stable and generalize, it takes advantage of. data augmentation and normalization preprocessing techniques. It is designed to classify pictures into three categories, normal, malignant, and benign. The findings indicate that feature-level fusion. is effective in enhancing model performance and might be used to assist with. early diagnosis. This work stresses how important hybrid architectures are for medical imaging and preconditions the further development of the smart breast cancer detecting systems.

Keywords: Breast Cancer, Deep Learning, Convolutional Neural Networks (CNN), Feature-Level Fusion, DenseNet, EfficientNet, Medical Image Analysis.

I. INTRODUCTION

Breast cancer is a very prevalent and life threatening disorder that is found in women all over the world. Early diagnosis is rather important to increase the chances of survival and effective treatment. The conventional diagnostic techniques are more dependent on expert analysis, which is time consuming and prone to error. As artificial intelligence develops, deep learning has become a potent automated medical image processing method, with increased efficiency and reliability.

DenseNet, ResNet, Inception, and EfficientNet are types of Convolutional Neural Networks that have shown good results in image classification, breast cancer included. Nevertheless, both models possess their advantages and disadvantages in their ability to extract complex features using medical images. Consequently, the use of one model might not be adequate in attaining optimum performance in various data types.

To overcome this problem, this paper suggests a hybrid deep learning system based on feature-level fusion to merge the advantages of various CNN systems. The individual models are initially tested, and the hybrid models are developed like DenseNetEfficientNet and ResNetInception The suggested system is expected to categorize breast cancer images as benign, cancerous or normal, and the fusion techniques prove to be more effective in enhancing the performance of this category.

II. LITERATURE REVIEW

The latest developments in deep learning have considerably enhanced the accuracy of automated systems of breast cancer detection. Convolutional Neural Networks (CNNs) have enjoyed popularity in medical image classification owing to their capacity to obtain hierarchical and complex features. Architectures like ResNet, DenseNet and Inception have demonstrated encouraging performance in medical image abnormality detection. ResNet solves the vanishing gradient issue with residual connections, whereas DenseNet enhances the propagation of features by linking every layer to all other layers. Inception networks have been created to learn multi-scale features, which is why they work with a wide range of image patterns.

The ability of EfficientNet to scale compound-based performance with a reduced number of parameters by compound scaling has also drawn attention. Although these individual models are successful, they are sensitive to the performance depending on the dataset and complexity of the task. Singlemodel methods usually have difficulty in representing all the important features, particularly in medical images where patterns may be very subtle and complicated.

Recent literature has investigated hybrid and ensemble methods that train several CNN models to overcome

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these limitations. The example of feature-level fusion in particular has shown to be effective in combining complementary features obtained using various models prior to classification. Such a solution facilitates better representation learning and boosts the capacity of this model to differentiate between benign, malignant, and normal cases. Nevertheless, issues with the imbalance in classes and the lack of available data also persist, and additional studies in the field are required.

III. METHODOLOGY

In this section, the dataset, preprocessing, each of the deep learning models, and the suggested hybrid method based on feature-level fusion in breast cancer classification are described.

A. Dataset

The BUSI with Ground Truth (BUSI _GT) dataset consists of publicly available on Kaggle which contains breast ultrasound images classified into three categories: Benign (437 images), Malignant (210), and Normal (133). Each image has an accompanying mask to denote where the tumor is located within the image. The dataset contains 780 images in total. For the purpose of evaluating the performance of our models, we randomly divided the images into training and validation datasets. Because the busi GT dataset contains a large variety of images and has ground truth annotations associated with each image, it is useful for training and testing deep learning algorithms for breast cancer classification The data to be analyzed in this work is the breast cancer images that are classified into three groups such as benign, malignant, and normal. These classes are non-cancerous, cancerous, and healthy tissue samples, Respectively. The data is split into training and validation sets so that there will be the right evaluation of the model performance. It is essential to balance the classes to eliminate prejudice in training.

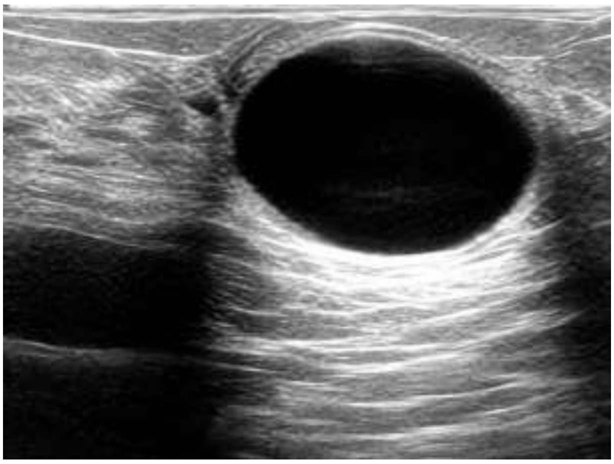

Fig. 1. Benign

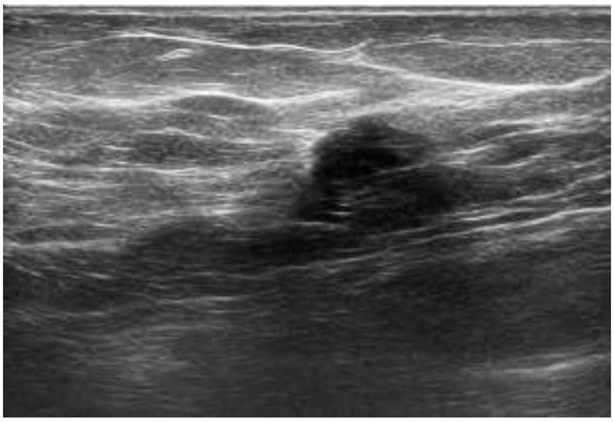

Fig 2. Malignant

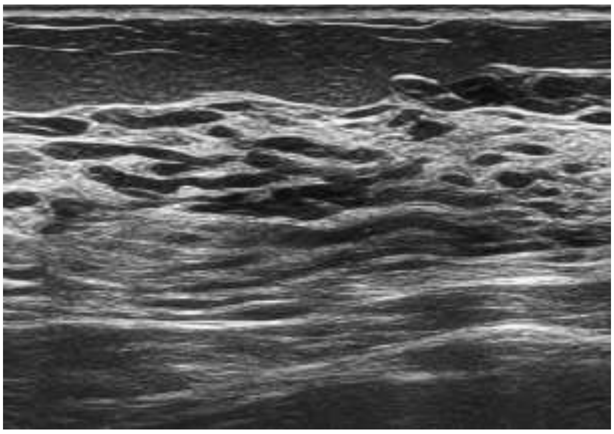

Fig 3. Normal

B. Data Preprocessing

In order to improve the performance of the models and generalization, there are a number of preprocessing methods that are used. All the images are rescaled to the input size needed by various CNN architectures (224x224 and 299x299). The value of pixels is scaled between 0 and 1 to normalize them.

The methods of data augmentation are used to artificially enhance the diversity of the dataset and minimize the tendency to overfitting. These are rotation, zoom, horizontal flipping and shearing. These changes assist the model to acquire the features of invariance and enhance resilience.

C. Individual CNN Models

Four pre-trained Convolutional Neural Network (CNN) models, namely DenseNet201, ResNet50, InceptionV3, and EfficientNetB0 are used to classify breast cancer in this study. The reason why these models are chosen is that they have been shown to perform successfully in image classification tasks and are capable of pulling out deep and meaningful features of medical images.

DenseNet201 uses dense connectivity among layers, which enables to reuse features efficiently and to enhance gradient flow. ResNet50 employs the residual linkage to make it possible to train deeper networks

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without the vanishing gradient problem. InceptionV3 uses parallel convolutional filters of varying sizes which capture multi-scale features and therefore it is efficient in detecting patterns at different resolutions. EfficientNetB0 uses a compound scaling scheme to balance the network depth, width and resolution to achieve computational efficiency and good performance.

The models are pre-trained with weights and fine-tuned on the breast cancer dataset. The models are trained separately to examine their aptitude in extracting pertinent features and conducting classification. This analysis serves as a reference point to be compared with and assists in the process of choosing appropriate architectures to the proposed hybrid model. Section 4 further discusses the performance of these models.

D. Proposed Hybrid Model

A hybrid deep learning model is suggested to enhance the performance of classification by feature-level fusion. The model is based on a combination of both the DenseNet201 and EfficientNetB0 to create complementary representations of the features on the input images.

The two networks are fed identical input image. The feature maps obtained are subjected to Global Average Pooling layers in order to decrease the dimensions. These feature vectors are subsequently combined to be a single representation.

The combination of the features is carried over by means of fully connected layers enhanced by batch normalization and dropout to avoid overfitting. Lastly, the images are classified into benign, malignant, and normal with the help of a softmax layer.

E. Comparative Hybrid Model

In addition to the proposed model, a comparative hybrid model is developed by combining ResNet50 and InceptionV3. This model follows a similar feature-level fusion approach, where features extracted from both networks are concatenated before classification.

This comparison helps evaluate the effectiveness of different combinations of CNN architectures and highlights the importance of selecting suitable models for fusion.

F. Feature-Level Fusion

Before the last classification, feature-level fusion is carried out through a combination of feature vectors obtained using multiple CNN models. In this method, all networks individually process the input image and learn different feature representations depending on their architecture. These feature vectors are then not only combined to result in a single and more informative representation. This combination approach allows the model to obtain complementary information of disparate architectures, including deep hierarchical features and multi-scale patterns.

Through the combination of these various features, the model will have a more detailed view of the input data, and this will enhance its capability to differentiate various classes. Moreover, feature-level fusion lessens the constraints of a single model using the strength of the models altogether. Due to this, the method improves feature representation, raises robustness, and results in superior aggregate classification performance in breast cancer detection.

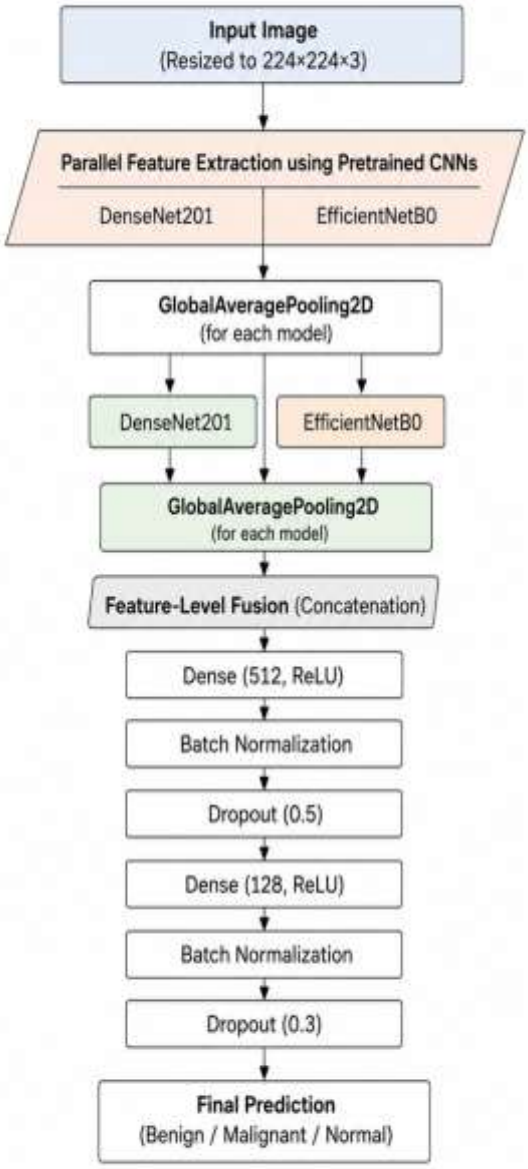

Fig. 4. Proposed feature-level fusion architecture using DenseNet and EfficientNet.

G. Training Strategy

The optimizer employed to train the models is the Stochastic Gradient Descent (SGD). Categorical cross-entropy is used as the loss function for multi-class classification. Early termination is implemented to avoid overfitting whereas learning rate reduction is implemented to enhance convergence. Class weights are

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added to control the imbalance in classes and enhance the performance of a model on minor classes.

IV. RESULTS AND DISCUSSION

Section includes the overall assessment of the This suggested deep learning models of breast cancer classification. Evaluation metrics used to test the performance of the individual CNN architectures and hybrid models include standard evaluation metrics, including accuracy, precision, recall, and F1score. Further, the graphical results, such as confusion matrix, ROC curves, and training performance plots, are also presented to give more in-depth understanding of the model behavior.

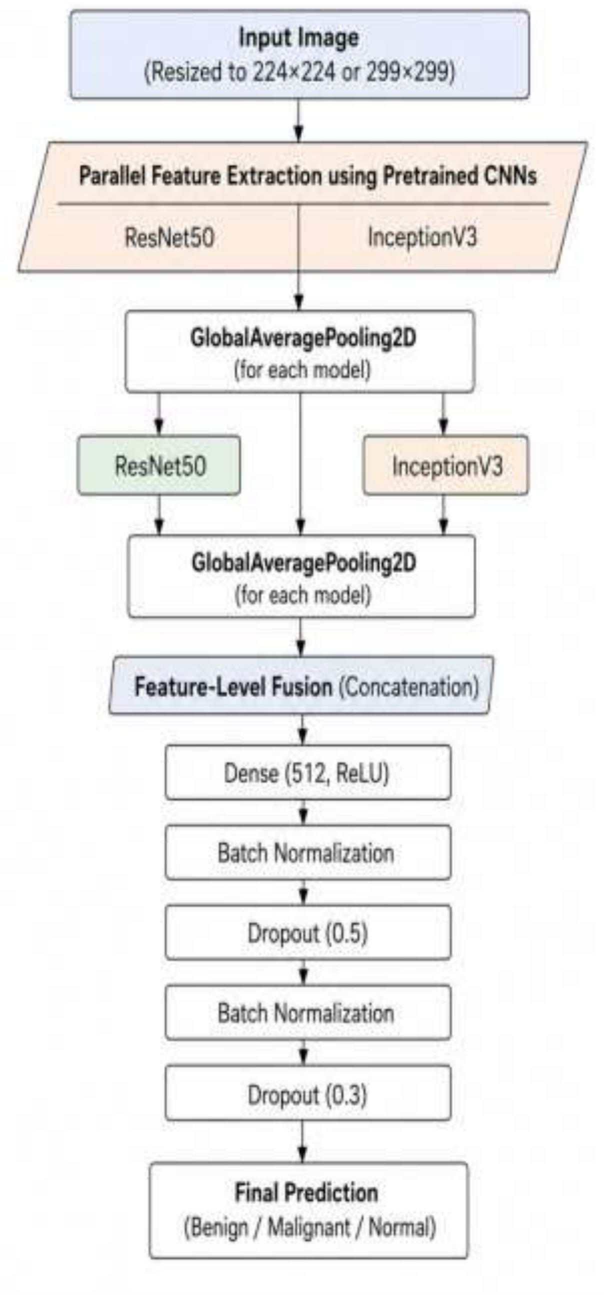

Fig. 5. Comparative architecture using ResNet and Inception.

A. *Performance of Individual Models*

In order to assess the performance of various convolutional neural network architectures, four pre-trained models DenseNet201, ResNet50, InceptionV3, and EfficientNetB0 were trained and tested separately on the dataset. All models were adjusted to the classification task and their performance was measured.

Based on the findings, it is possible to note that InceptionV3 demonstrated the highest accuracy of the individual models, which implies that it is highly efficient in terms of multiscale features. DenseNet201 also did well because it is dense connected and effective in feature reuse. Conversely, EfficientNetB0 demonstrated relatively low results, which could be

TABLE I
PERFORMANCE OF INDIVIDUAL CNN MODELS

Model	Accuracy
DenseNet201	75.21%
ResNet50	66.67%
InceptionV3	78.63%
EfficientNetB0	56.41%

Explained by the nature of the datasets or lack of fine-tuning. These observations underscore the fact that there is no single model that works well in every instance, which justifies the use of hybrid methods.

B. *Performance of Hybrid Models*

In order to counter the shortfalls of the individual models, feature-level fusion was used to formulate hybrid architectures. The major hybrid approach is one that mixes DenseNet201 and EfficientNetB0, whereas a comparative model is one that mixes ResNet50 and InceptionV3. These models seek to exploit complementary characteristics which are obtained out of various architectures.

TABLE II
PERFORMANCE COMPARISON OF HYBRID MODELS

Model	Accuracy
DenseNet + EfficientNet	87.91%
ResNet + Inception	83.22%

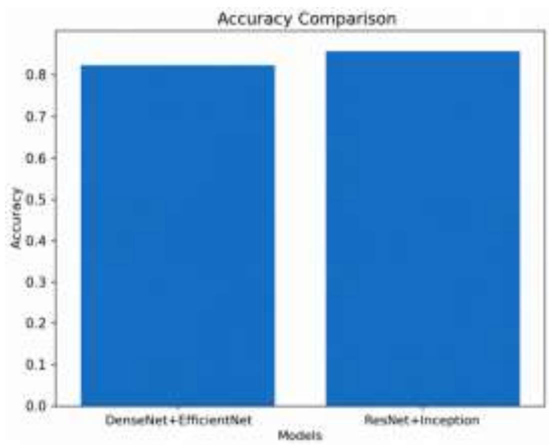

Fig 6. Accuracy Comparisons

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The findings prove that the hybrid model outperforms in classification by uniting the positive features of several models, DenseNetEfficientNet model performs better than the ResNetInception model, which means that the architecture selection is an important factor in fusion based systems. This can be attributed to the increased feature representation that is brought about by fusion.

C. Confusion Matrix Analysis

The confusion matrix gives a breakdown of the results of classification in various classes in a detailed manner.

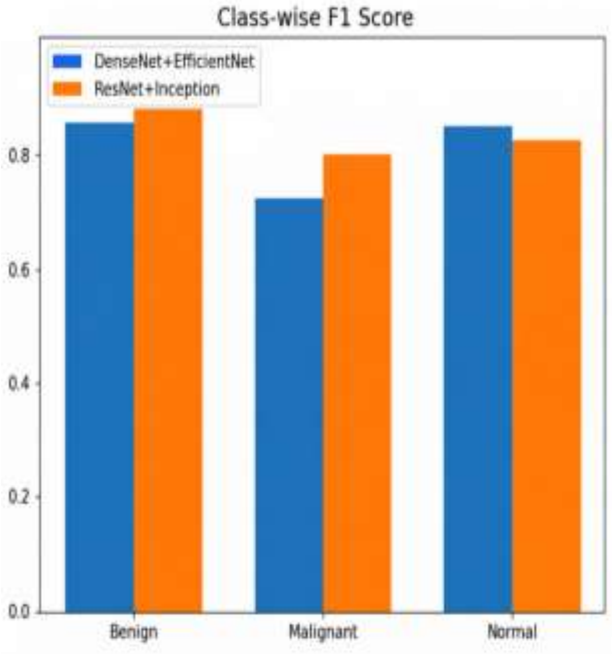

Fig 7. Class-wise F1 Score

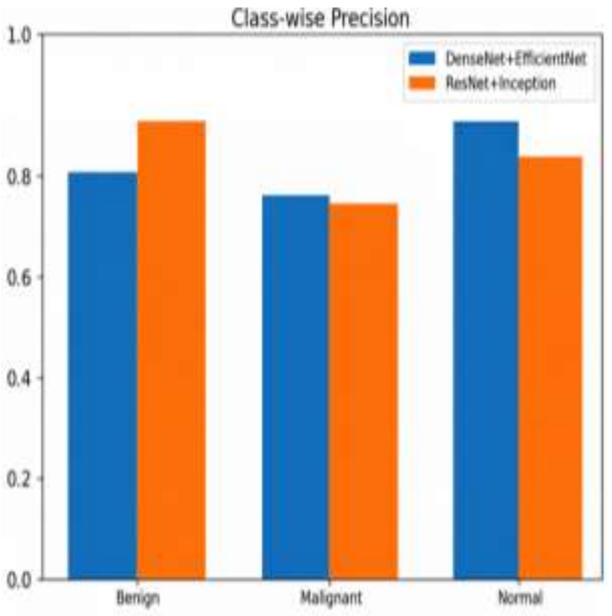

Fig 8. Class-wise Precision

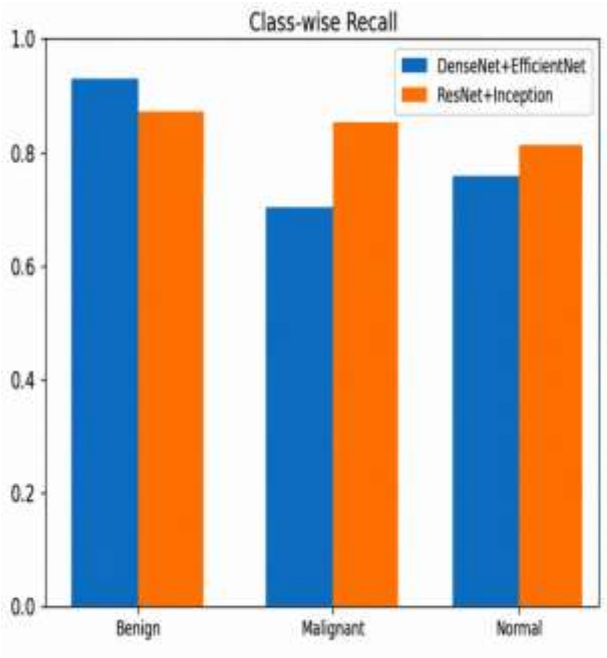

Fig 9. Class-wise Recall

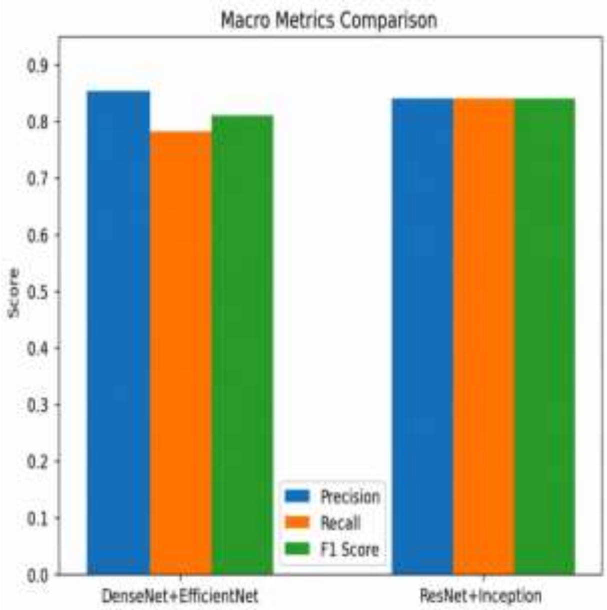

Fig 10. Macro Metrics Comparison

It demonstrates the cases of correct and incorrect classifications of benign, malignant, and normal cases. Based on the matrix, it is possible to note that this model is effective in detecting benign and normal cases. Nevertheless, some malignant cases are misdiagnosed and this is a serious issue in medical diagnosis.

This confusion can be as a result of visual similarity between the classes or skewed data set. Regardless of this, the overall performance shows that the model can learn significant patterns of the data.

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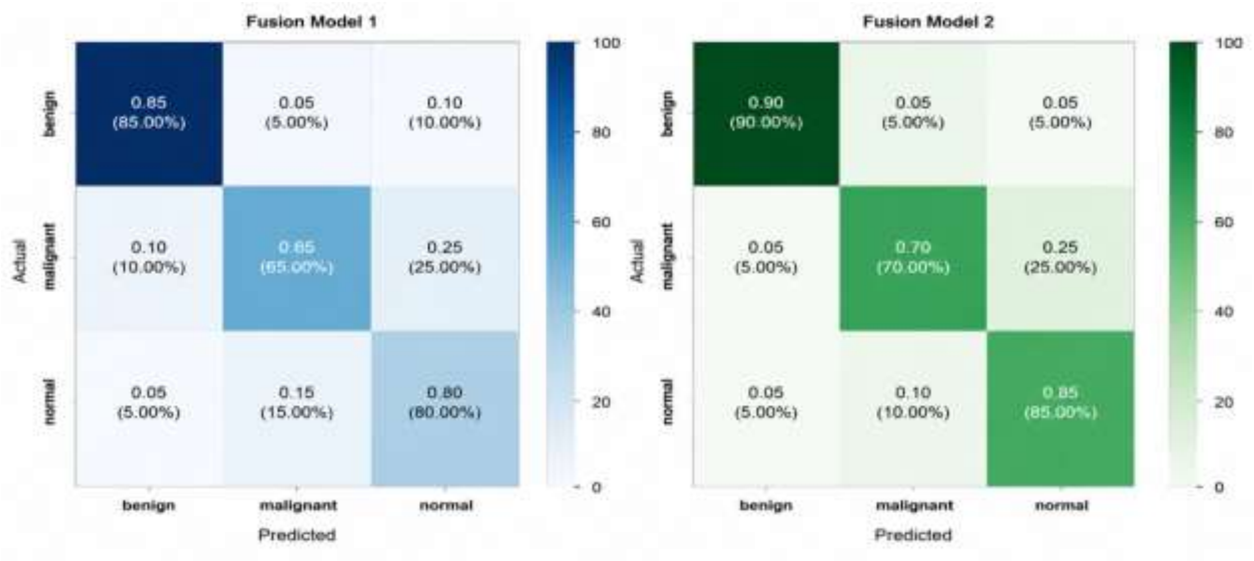

Fig 11. Confusion matrix of the proposed hybrid model

D. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is a curve that is used to test the model in terms of its capacity to differentiate between various classes. It is the trade-off between the false positive rate and the true positive rate at the different threshold settings. The higher the curve is to the upper-left, the better the performance.

The ROC curves for the different classes demonstrate that the model has a strong discriminative ability. The distance between the curves shows that the model is effective in distinguishing between benign, malignant, and normal cases and is applicable in medical classification problems.

E. Sample Prediction Results

This figure presents sample outputs generated by the proposed model for different input images. Each image is classified into one of the three categories: benign, malignant, or normal.

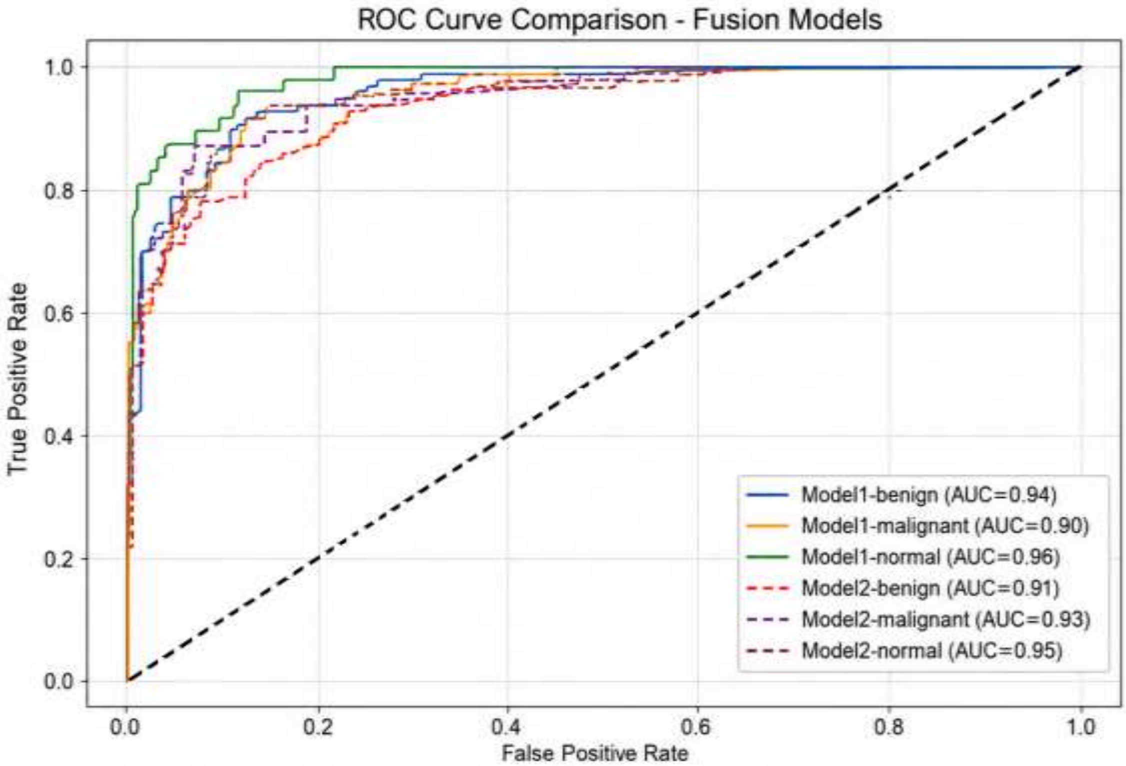

Fig 12. ROC curve for multi-class breast cancer classification

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The results demonstrate that the model is capable of accurately identifying patterns in breast cancer images. Most predictions align with the actual class labels, indicating the effectiveness of the feature extraction and classification process. These visual results further validate the performance of the proposed hybrid model.

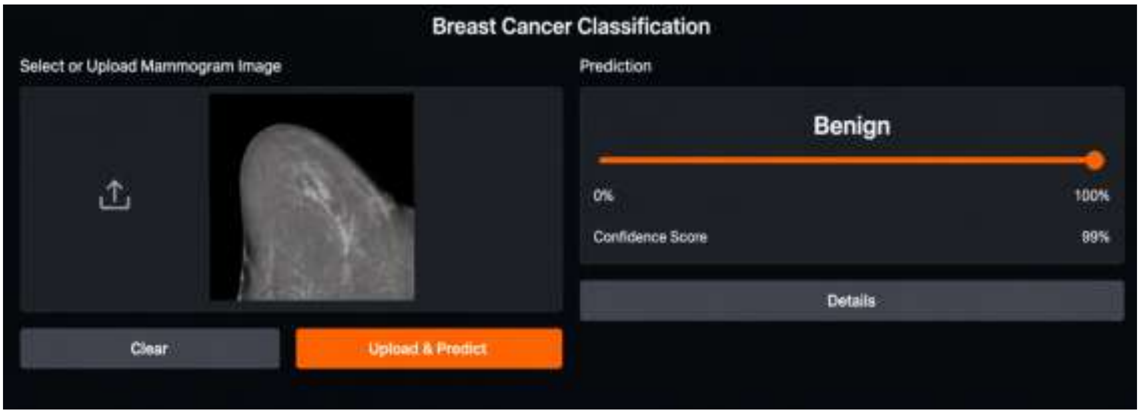

Fig 13. Sample prediction results of the proposed model for malignant class

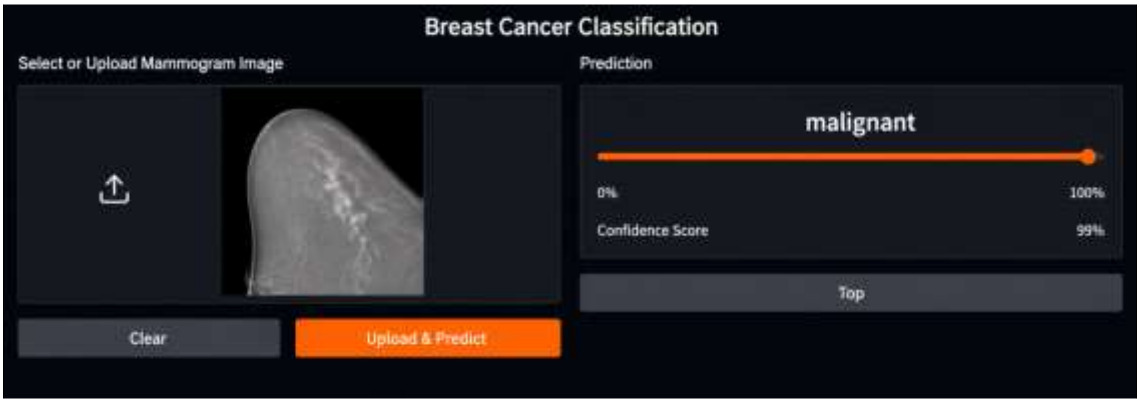

Fig 14. Sample prediction results of the proposed model for benign class

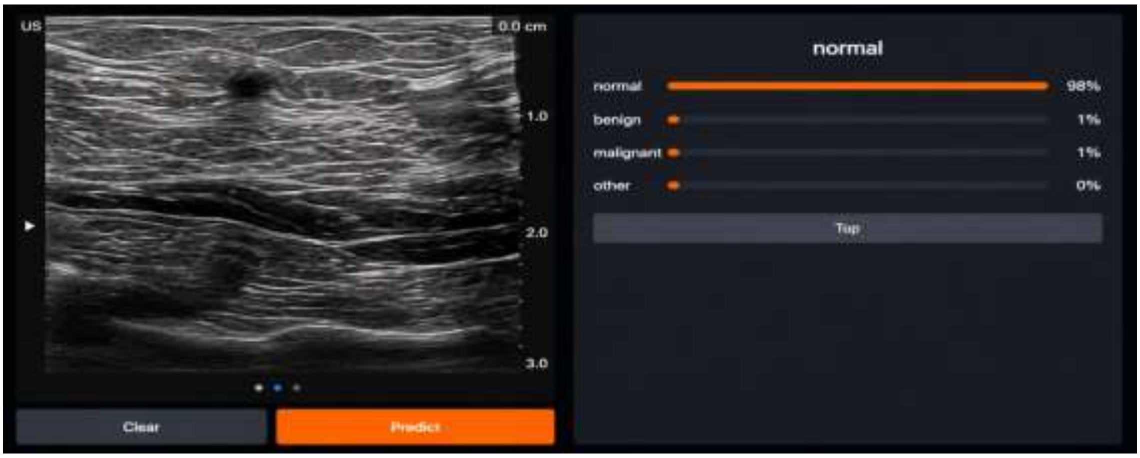

Fig 15. Sample prediction results of the proposed model for normal class

F. Discussion

The general findings indicate that the hybrid deep learning models perform better than the single CNN architectures because they are able to extract a variety of features and they are complementary. The DenseNetEfficientNet model is more effective than the ResNetInception model, which supports the role of appropriate architectures in fusion.

Nevertheless, some difficulties still persist especially in the proper classification of malignant cases. This weakness can be overcome in future research with more sophisticated methods like focal loss, attention, or bigger and more balanced datasets. Nevertheless, the suggested solution demonstrates a high potential of enhancing the detection of breast cancer through a deep learning method.

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V. CONCLUSION

This paper demonstrated a hybrid deep learning-based breast cancer classifier that fuses features in many convolutional neural network designs. At first, the performance of separate models, namely DenseNet201, ResNet50, InceptionV3, and EfficientNetB0, was tested to examine their work on the dataset. The findings showed that certain models had better results compared to others but none of the architectures was competent enough to represent all the relevant features.

In order to overcome this, hybrid models were created by integrating various CNN architectures. The DenseNetEfficientNet model was found to be better in performance among the suggested methods, as it is capable of using the complementary features through fusion at the level of features. Fusion allowed improved discrimination between benign, malignant and normal classes. Further analysis of the proposed method by the confusion matrix and ROC curve analysis also achieved the effectiveness and robustness of the proposed method.

All in all, the paper demonstrates that hybrid deep learning methods have the ability to enhance the detection of breast cancer. The findings indicate that using a combination of several models may positively affect the classification performance and offer more credible results than single models.

VI. LIMITATIONS

Although the selected hybrid deep learning model has shown promising results, there are a number of limitations. The first problem is a relatively small size of the dataset which can influence the capacity of the model to be effective in its generalization to unseen data. The existence of a small or unbalanced set of data may result in biased learning and poor performance especially in the accurate detection of malignant cases.

The other limitation is misclassification that is found between some classes particularly the malignant samples. This could be attributed to the fact that the visual appearances of the various categories are similar and the model is not able to pick out subtle patterns. These are serious mistakes that should be improved in medical practice.

As well, the suggested model is based on feature-level fusion of pre-trained CNN designs, which adds complexity to computational and training time. This can restrict its use in real time or resource constrained settings. Moreover, hyper parameter tuning and model selection was done experimentally and the best settings can be different across datasets.

The drawbacks indicate that there should be additional improvements, such as using larger datasets, better training methods, and more effective model structures to obtain higher performance and reliability.

VII. FUTURE WORK

Even though the suggested method demonstrates promising outcomes, a number of enhancements can be pursued in the future. A significant weakness that has been witnessed is misclassification of some malignant cases, which are paramount in medical diagnosis. This can be resolved by employing sophisticated loss functions like focal loss to deal better with the problem of class imbalance.

The next step in research can be to add attention mechanisms to enhance feature extraction and saliency regions in medical images. Also, one can use larger and more diverse data to further improve the generalization ability of the model. The methods of ensemble and optimization may be also investigated to enhance the overall performance.

Moreover, it is possible to consider the integration of the proposed model into real-time clinical decision support systems, which will allow real practice in the field of healthcare. These developments would help in the early and more precise detection of breast cancer and eventually patient outcomes would improve..

REFERENCES

[1] A. Ben Miled and A. Cherif, "Early Breast Cancer Detection Using Deep Learning Classification," *Engineering, Technology & Applied Science Research*, vol. 15, no. 4, pp. 24885–24890, Aug. 2025, doi:10.48084/etasr.11030.

[2] "Deep Learning-Based Analysis of Mammographic Images for Breast Cancer Detection Using Transfer Learning," *PubMed*, 2025.

[3] S. C. and A. B. K., "Breast Cancer Detection Using CNNs on Mammogram Images: A Dataset-Level Comparison of CBIS-DDSM, INbreast, and MIAS," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 22s, pp. 2153–2161, Jul. 2024.

[4] M. U. et al., "Deep Learning Techniques for Mammogram Breast Cancer Detection," *Journal of Innovative Computing and Emerging Technologies*, vol. 5, no. 1, pp. 1–14, Aug. 2025, doi:10.56536/jicet.v5i1.212.

[5] "Deep ensemble transfer learning-based framework for mammographic image classification," *The Journal of Supercomputing*, vol. 79, pp. 8048– 8069, Dec. 2022.

[6] H. P. et al., "Breast Cancer Detection in Mammography Images: A CNNBased Approach with Feature Selection," *Information*, vol. 14, no. 7, p. 410, Jul. 2023, doi:10.3390/info14070410.

[7] S. Han, "Prediction and analysis of breast cancer based on transfer learning from DDSM mammography images," *Applied and Computational Engineering*, vol. 38, pp. 231–236, 2024.

[8] "Deep learning applications to breast cancer detection by magnetic resonance imaging: a literature review," *Breast Cancer Research*, vol.25, art. no. 87, Jul. 2023.

ISBN: 978-81-689089-0-1

[9] B. Jiang, L. Bao, S. He, X. Chen, Z. Jin, et al., "Deep learning applications in breast cancer histopathological imaging: diagnosis, treatment, and prognosis," *Breast Cancer Research*, vol. 26, art. no. 137, 2024, doi:10.1186/s13058-024-01895-6.

[10] A. Carriero, L. Groenhoff, E. Vologina, P. Basile, and M. Albera, "Deep learning in breast cancer imaging: State of the art and recent advancements in early 2024," *Diagnostics*, vol. 14, art. no. 848, 2024, doi:10.3390/diagnostics14080848.

[11] A. Amin, D. Acharya, P. Koteshwara, S. P. C. Siddalingaswamy, et al., "A systematic literature review on mammography: deep learning techniques for breast cancer detection with global and Asian perspectives," *BMC Cancer*, vol. 25, art. no. 1627, 2025, doi:10.1186/s12885-02514876-5.

[12] S. Vijayalakshmi, B. K. Pandey, D. Pandey, and M. E. Lelisho, "Innovative deep learning classifiers for breast cancer detection through hybrid feature extraction techniques," *Scientific Reports*, vol. 15, art. no. 22212, 2025, doi:10.1038/s41598-025-06669-4.

[13] M. R. Alom, F. A. Farid, M. A. Rahaman, A. Rahman, T. Debnath, et al., "An explainable AI-driven deep neural network for accurate breast cancer detection from histopathological and ultrasound images," *Scientific Reports*, vol. 15, art. no. 17531, 2025, doi:10.1038/s41598025-97718-5.

[14] U. Ergun, T. C¸oban, and¨ ˙I. Kayadibi, "BCECNN: an explainable deep ensemble architecture for accurate diagnosis of breast cancer," *BMC Medical Informatics and Decision Making*, 2025, doi:10.1186/s12911025-03186-2.

[15] T. A. Smrity, M. Z. Muntaqim, and H. M. Kaf, "Recent advancements in machine learning and deep learning for early detection of breast cancer: a comprehensive review," *International Journal of Breast Health*, 2026.

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