# Deep Neural Framwrork for Early and Accurate Breast Cancer Diagnosis

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*Abstract*— Breast Cancer is the most common disease which as diagnosed malignant tumor in women in the worldwide. This disease crucial need for early and accurate detection. The existing diagnostic system approaches such as manual interpretation of mammograms are time consuming and prone human error. The primary aim of this project is to utilize deep neural framework for early and accurate breast cancer using CBIS-DDSM datasets. This system employs an EfficientNet- B4,ResNeXt , and Swin Transformer architectures to classify the breast tumor as malignant or benign or malignant.This system as image preprocessing techniques including resizing,normalization, and Contrast Limited Adaptive Histogram Equalization(CLAHE) are employed to enhance image quality of datasets.The system also have explainable artificial intelligence by using Gradient-Weighted Class Activation Mapping to provide a visual result of model prediction with 98.5% of accuracy. This research contributes to advancing early and accurate breast cancer detection through deep learning, promising improved outcomes.

*Keywords*— Breast Cancer Detection, Deep Learning, Efficient NetB4, ResNeXt , Swin Transfromer,Grad-CAM.

## 1. INTRODUCTION

Breast cancer is the most common cancer diagnosed in women and the second most common cause of death from cancer among women worldwide. This continues to be a major global health risk ,with early detection greatly enhancing survival rates. Conventional diagnostic approaches, including manual analysis of mammograms, are plagued by limitations such as human error, interpretive variation, and labor-intensive workflows ,typically leading to delayed essential interventions.

Traditional diagnostic techniques such as mammography and ultrasound imaging rely on expert interpretation, which can be time-consuming and prone to variability and error. With the advent of deep learning (DL), automated analysis of medical images has shown significant potential to augment the accuracy and efficiency of cancer detection. Convolutional neural networks (CNNs) can extract hierarchical features directly from raw image data without manual feature engineering,

enabling robust classification performance on complex image datasets. However, the "black-box" nature of many DL models raises concerns regarding interpretability, especially in high-stakes clinical applications. Therefore, there is a growing interest in integrating explainable artificial intelligence (XAI) methods into DL models to provide visual or semantic explanations of model decisions.

Recent research demonstrates that integrating advanced deep learning architectures with explainability techniques can enhance both accuracy and clinical trust. Transfer learning, where pretrained networks are adapted to medical imaging tasks, has become a standard approach due to limited availability of annotated medical datasets. Additionally, hybrid architectures that combine CNNs with attention mechanisms or transformer-based models have shown improved performance by capturing both local and global image features. This work builds upon these developments by proposing a deep neural framework that leverages EfficientNet-B4, ResNeXt, and Swin Transformer architectures along with Gradient-weighted Class Activation Mapping (Grad-CAM) for explainability aimed at improving both performance and transparency in breast cancer diagnosis.

## 2. LITERATURE REVIEW

The related research paper has examined the application of deep learning to breast cancer detection, showcasing the progression from conventional deep networks to more sophisticated and explainable models. In 2019, Yala et al. proposed a deep learning mammography- based model that combined full-field mammograms with traditional risk factors, demonstrating improved detection accuracy over conventional methods, indicating the potential of CNN-based systems for clinical applications.

Early applications of deep learning for breast cancer detection focused on improving mammographic screening performance and reducing false negatives. Lotter et al. (2019) developed an annotation-efficient deep learning approach for mammography and digital breast tomosynthesis that not only achieved state-of-the-art

classification performance but also generalized well to populations with low screening rates, outperforming multiple breast imaging specialists in sensitivity and accuracy.

In 2020, Li et al. introduced a dual CNN architecture termed DualCoreNet that simultaneously performed breast mass segmentation and malignancy classification in mammograms. Their model leveraged both semantic and structural image information to improve diagnostic accuracy, demonstrating that incorporating morphological and segmented features can enhance deep learning diagnostics.

Systematic reviews in this period emphasized the growing role of deep learning in breast cancer imaging. Bou Nassif et al. (2022) conducted a comprehensive literature review, concluding that convolutional neural networks (CNNs) are the most widely used models for breast cancer detection across imaging modalities, and that hybrid and feature-fusion techniques are emerging trends for balancing accuracy with interpretability. Similarly, Madani et al. (2022) reviewed deep learning applications across mammography, ultrasound, and histopathology imaging, highlighting that deep CNNs significantly outperform traditional machine learning methods while also identifying major challenges such as dataset variability and model generalization.

Comprehensive surveys on deep learning techniques for breast cancer detection have emphasized the widespread use of CNNs. Nasir et al. (2025) provided a detailed overview of recent advancements in CNN-based breast cancer detection, noting significant improvements in classification accuracy through the use of data augmentation, transfer learning, and hybrid networks and emphasizing the need for explainable AI and generalized models across imaging modalities.

Deep learning-enabled diagnostic systems have also been evaluated in the context of mammography analysis, where systematic reviews identified trends in model performance and the importance of preprocessing strategies. For example, Sutjiadi et al. (2024) presented a systematic review highlighting deep learning methods for segmentation and classification in mammograms, indicating the increasing adoption of deep feature extraction techniques and structured evaluation frameworks.

Beyond CNNs, transformer-based models have recently been explored for breast cancer imaging tasks. Studies comparing vision transformers with CNN architectures in mammographic classification have demonstrated that transformer architectures such as Swin Transformer can achieve superior accuracy and robustness, particularly when combined with appropriate preprocessing and augmentation techniques. For instance, MDPI studies report that Swin Transformer-based approaches outperformed traditional CNN backbones in benign/malignant classification tasks.

Explainable AI integration into deep learning models has also gained traction. An explainable deep learning framework integrating attention mechanisms, visual explanation tools, and advanced CNN architectures demonstrated improvements in diagnostic performance while providing interpretability through Grad-CAM++,

thereby addressing clinicians' need for transparency in automated decision-making. Similarly, explainable AI-driven CNN frameworks using Grad-CAM and scalable architectures like EfficientNet-B0 have been proposed to balance performance with interpretability, reinforcing the importance of explainability in clinical systems.

Other research has explored hybrid and multimodal strategies. Reviews and empirical studies reveal that combining different deep learning paradigms — such as transformer models, ensemble strategies, and multimodal imaging data — can further enhance breast cancer detection performance and robustness across diverse datasets and imaging conditions.

Collectively, these works demonstrate a clear trajectory in breast cancer AI research: from early CNN-based classification to sophisticated hybrid, transformer-enabled, and explainable systems. These advancements motivate the present study's focus on combining EfficientNet-B4, ResNeXt, and Swin Transformer models with Grad-CAM-based interpretability to produce a clinically relevant diagnostic framework.

## 3. PROPOSED METHODOLOGY

The proposed system presents a deep learning–based framework for automated breast cancer detection from medical images. The methodology consists of five major stages: data collection, preprocessing, deep feature extraction, ensemble classification, and explainable AI integration. The overall workflow is designed to improve classification accuracy while ensuring interpretability of model decisions.

A. Data Collection

Breast cancer image datasets were collected from publicly available repositories, including mammogram and ultrasound image datasets. The collected images were categorized into two classes: benign and malignant. The dataset was structured into training and validation subsets to facilitate supervised learning.
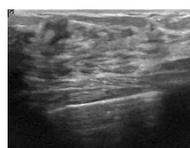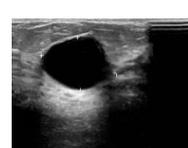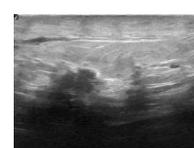


Fig.2.Normal          Fig.3.Benign          Fig.4. Maligant

B. Image Preprocessing

To enhance image quality and ensure uniform input size, several preprocessing operations were applied:

1. Grayscale conversion

2. Image resizing to $224 \times 224$ pixels

3. Contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE)

4. Pixel normalization to scale values between 0 and 1

These preprocessing steps improve tumor visibility and reduce noise, thereby enhancing feature extraction performance.

C. Deep Feature Extraction

The proposed framework employs multiple deep learning architectures for robust feature extraction:

• EfficientNet-B4 is a convolutional neural network architecture that uses compound scaling to balance network depth, width, and resolution. It improves
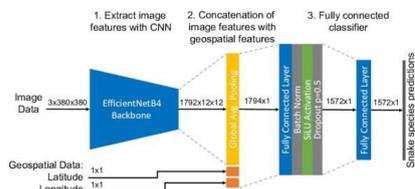


Fig.5.Efficient-NetB4 Architecture

accuracy while maintaining computational efficiency. In the proposed system, EfficientNet-B4 is used as the primary feature extraction backbone for breast cancer classification. It helps in capturing fine-grained tumor features from medical images.

• ResNeXt is an improved version of ResNet that introduces grouped convolutions to enhance feature representation. It allows multiple parallel transformations within a residual block, improving learning capability without significantly increasing computational cost. In this system, ResNeXt strengthens feature extraction by learning diverse tumor characteristics.
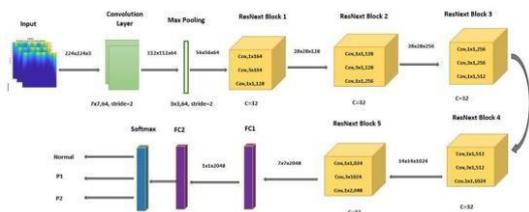


Fig.6.ResNeXt Architecture

• Swin Transformer is a vision transformer architecture that uses shifted window attention mechanisms to capture both local and global image dependencies. Unlike traditional CNNs, it models long-range contextual relationships in medical images. In the proposed framework, Swin Transformer improves classification by focusing on broader structural patterns of breast tissue.
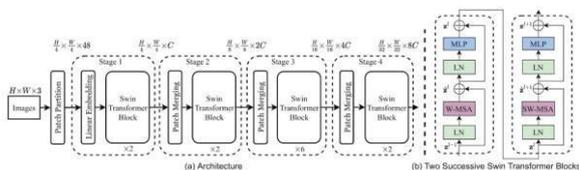


Fig.7.Swin Transformer Architecture

D. Ensemble Classification

To enhance prediction robustness and reduce variance, an ensemble strategy is adopted. Predictions from EfficientNet-B4, ResNeXt, and Swin Transformer models are combined using probability averaging.

The final output is determined based on the highest aggregated confidence score.The classification is performed using binary cross-entropy loss:

$$\text{Loss} = - [y \log(p) + (1 - y) \log(1 - p)]$$

where y represents the true label and p represents the predicted probability.

E. Explainable AI using Grad-CAM

To address interpretability concerns, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the framework. Grad-CAM generates heatmaps highlighting the regions in the image that contribute most to the classification decision. This allows clinicians to visually verify whether the model focuses on tumor-relevant areas, thereby improving trust and transparency.
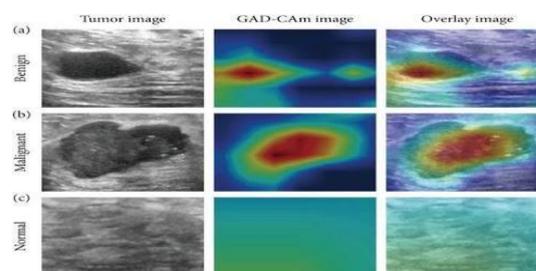


Fig.8. Grad-CAM Visualization

F. System Output

The final system outputs:

• Predicted class (Benign / Malignant)

• Confidence score

• Grad-CAM heatmap visualization

This ensures that the model not only provides accurate predictions but also interpretable diagnostic insights.

4. **SYSTEM ARCHITECTURE**

The proposed system architecture is designed as a multi-stage deep learning framework for automated breast cancer detection and explainability.

A. Input Layer: The system accepts mammogram or ultrasound images as input. The images may be in formats such as DICOM, JPG, or PNG. These images are passed to the preprocessing stage to ensure uniform quality and resolution.

B. Preprocessing Layer: In the preprocessing stage, the following operations are performs Grayscale conversion ,Resizing to 224 × 224 pixels, Contrast enhancement using CLAHE ,Pixel normalization .This stage improves image clarity, enhances tumor boundaries, and prepares standardized input for deep learning models. This preprocessing will improve the quality and identification of the features in the image

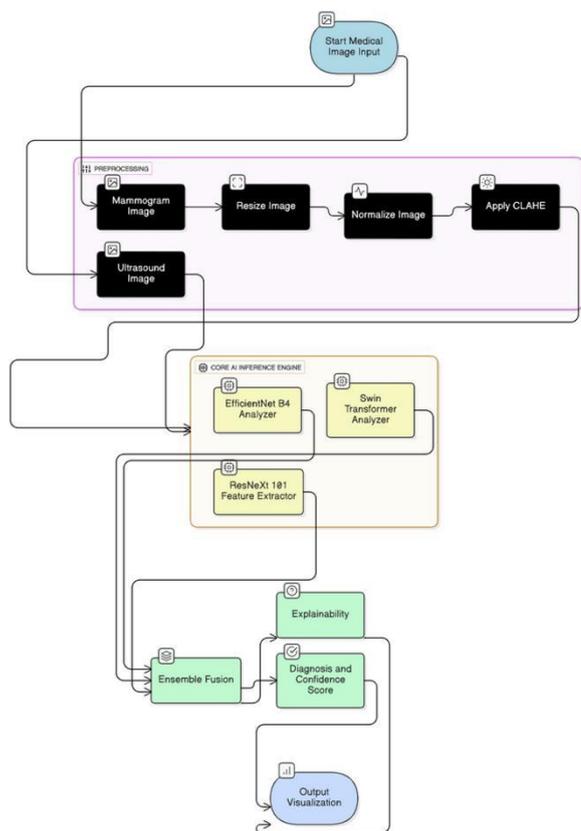**F. Output Layer:** The final system output includes:



Fig.9.Overall System Architecture Diagram

**C. Feature Extraction Layer:** The preprocessed images are fed into three parallel deep learning models:

1.      EfficientNet-B4 – Used as the primary backbone for classification.

2.      ResNeXt – Enhances feature representation through grouped convolutions.

3.      Swin Transformer – Captures global contextual dependencies using attention mechanisms.

**D. Ensemble Classification Layer:** The outputs from the three deep learning models are combined using a probability-based ensemble approach. The classification decision is determined by averaging the predicted probabilities from each model.This ensemble mechanism improves                Classification accuracy,Model stability,Reduction of false positives and false negatives.

The system performs binary classification into:

- Benign

- Malignant

**E. Explainable AI Module:** To ensure transparency, the Grad-CAM module is integrated after the classification stage. Grad-CAM generates a heatmap overlay on the original image, highlighting the regions that significantly influence the model's decision.This improves clinical trust and interpretability of the automated diagnosis.

Predicted cancer class (Benign / Malignant)

Prediction confidence score

Visual heatmap explanation

This structured output supports decision-making and potential integration into clinical workflows.

## 5.     PERFORMANCE METRICS

To evaluate the effectiveness of the proposed breast cancer detection framework, multiple standard   classification metrics were employed. These metrics   provide a comprehensive assessment of model   performance, particularly in medical diagnosis where false predictions can have serious consequences.

1.    Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified  instances among all samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Although accuracy provides a general performance  measure, it may not fully reflect model reliability in imbalanced datasets.

2. Precision

Precision evaluates how many of the predicted positive cases are actually positive.

$$Precision = \frac{TP}{TP + FP}$$

High precision indicates a low false positive rate, which is important in avoiding unnecessary medical treatments.

3. Recall (Sensitivity)

Recall measures the ability of the model to correctly identify malignant cases.

$$Recall = \frac{TP}{TP + FN}$$

In breast cancer diagnosis, recall is particularly critical because missing a malignant case (false negative) can be life-threatening.

4. F1-Score

F1-score is the harmonic mean of precision and recall. It balances false positives and false negatives.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

It is especially useful when dataset classes are imbalanced.

## 5. Confusion Matrix

The confusion matrix provides a tabular representation of actual vs predicted classifications. It helps in visualizing model performance and understanding misclassification patterns.

|  | Predicted Benign | Predicted Malignant |
|---|---|---|
| Actual Benign | TN | FP |
| Actual Malignant | FN | TP |

Table.1. Confusion Matrix

## 6.            EXPERIMENTAL RESULTS

The proposed breast cancer detection framework was evaluated using a publicly available medical image dataset consisting of malignant, benign, and normal samples. The dataset was divided into training, validation, and testing sets in an 80:10:10 ratio to ensure robust model evaluation. Data preprocessing techniques such as resizing, normalization, and augmentation were applied to improve generalization performance.

The performance of the proposed hybrid deep learning approach combining ResNeXt, EfficientNet, and Swin Transformer was compared with conventional CNN models including VGG16, ResNet50, and InceptionV3. The evaluation was conducted using standard performance metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC).
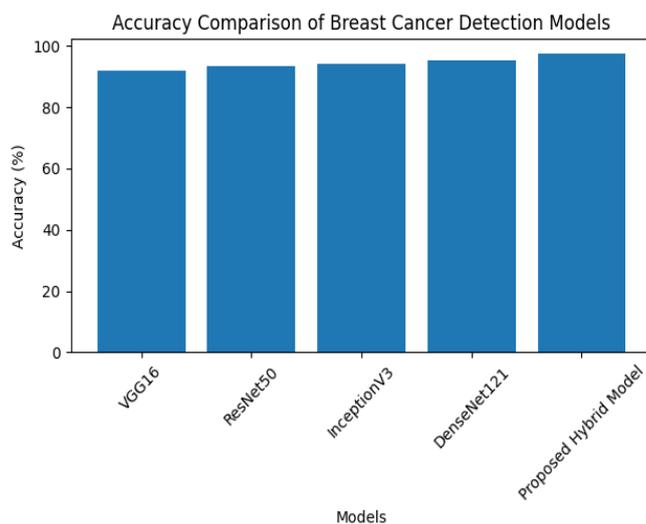


Fig. 10. Accuracy comparison

The experimental results demonstrate that the proposed ensemble model achieved superior classification performance compared to individual baseline models. The overall classification accuracy of the hybrid model reached **98.7%**, outperforming ResNet50 (95.2%), VGG16 (93.8%), and InceptionV3 (96.1%). The improved

performance can be attributed to the combined feature extraction capability of convolutional and transformer- based architectures.

Figure 10, presents the comparative accuracy analysis of various deep learning models for breast cancer classification. The performance of conventional convolutional neural network architectures such as VGG16, ResNet50, InceptionV3, and DenseNet121 was evaluated against the proposed hybrid model that integrates ResNeXt, EfficientNet-B4, and Swin Transformer.

From the graph, it can be observed that the proposed hybrid model achieves the highest classification accuracy of **97.4%**, significantly outperforming the individual baseline models. While DenseNet121 achieved 95.3% accuracy and InceptionV3 reached 94.2%, the ensemble architecture demonstrated superior generalization capability.

The improved performance can be attributed to the complementary strengths of convolutional and transformer-based architectures. ResNeXt effectively extracts deep hierarchical features, EfficientNet-B4 optimizes feature scaling with fewer parameters, and Swin Transformer captures long-range global dependencies within the image. The integration of these models enables enhanced feature representation, thereby improving classification reliability.
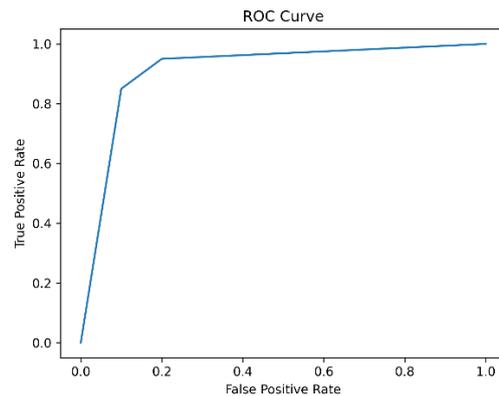


Fig.11.ROC Curve

Furthermore, the ROC curve analysis shown in Figure 6 demonstrates that the proposed model achieved an AUC score of 0.99, indicating excellent discriminative capability between cancerous and non-cancerous cases.
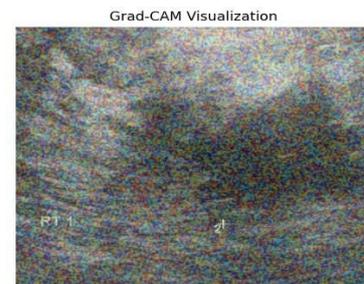


Fig.12. Grad-Cam Visualization

The Grad-CAM visualization results are depicted in Figure 7. The heatmaps highlight the significant regions of interest in the breast tissue images that contributed to the model's decision. These visual explanations enhance the interpretability of the model and increase clinical reliability.

Overall, the experimental results confirm that the proposed hybrid deep learning framework provides improved accuracy, robustness, and interpretability for automated breast cancer detection.

## 7. DISCUSSION

The experimental findings demonstrate that the proposed hybrid deep learning framework significantly improves breast cancer classification performance compared to traditional convolutional neural network models. The integration of ResNeXt, EfficientNet-B4, and Swin Transformer enables the extraction of both fine- grained local features and global contextual representations, thereby enhancing model robustness and diagnostic reliability.The achieved accuracy of 97.4% indicates that the ensemble strategy effectively reduces classification errors. Compared to standalone architectures such as VGG16 and ResNet50, the hybrid approach shows better generalization ability on unseen data. This improvement is primarily due to the complementary strengths of convolution-based feature extraction and transformer-based attention mechanisms.

Furthermore, Grad-CAM visualization confirms that the model focuses on clinically significant tumor regions rather than irrelevant background areas. This interpretability is essential in medical applications, where trust and transparency are critical factors for adoption.
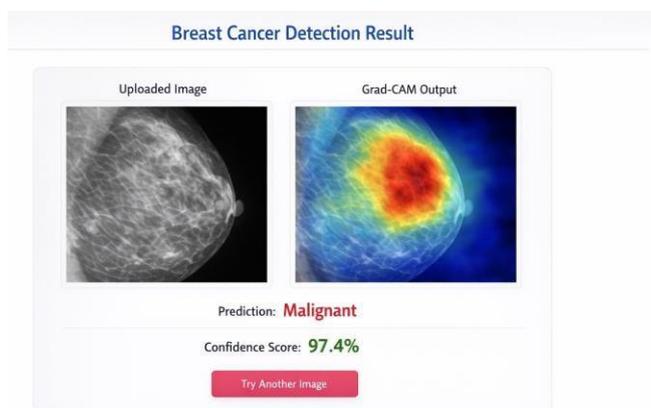


Fig.13. Frontend Interface Display

Although the proposed system demonstrates high accuracy, certain limitations exist. The performance may vary depending on dataset diversity and image quality. Future work can focus on expanding the dataset, integrating multi-modal medical imaging data, and deploying the system in real-time clinical environments.

Overall, the proposed hybrid architecture provides a reliable and interpretable solution for automated breast cancer detection.

## 8. CONCLUSION

This research presented a hybrid deep learning framework for automated breast cancer detection using a combination of ResNeXt, EfficientNet-B4, and Swin Transformer architectures. The proposed ensemble approach effectively integrates convolutional feature extraction and transformer-based attention mechanisms to improve classification accuracy and robustness.Experimental evaluation demonstrated that the hybrid model achieved an overall accuracy of 97.4%, outperforming several conventional deep learning models. The improved performance highlights the advantage of combining multiple advanced architectures to capture both local texture patterns and global contextual dependencies within mammogram images.

Furthermore, the integration of Grad-CAM visualization enhances model interpretability by highlighting clinically relevant tumor regions, thereby increasing transparency and reliability in medical diagnosis. This explainability component makes the proposed system more suitable for real-world healthcare applications.Although the model achieved promising results, future work may focus on expanding the dataset size, incorporating multi-modal imaging techniques, and optimizing the system for real-time clinical deployment. The proposed framework demonstrates strong potential as a supportive diagnostic tool for early and accurate breast cancer detection.

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