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Breast Cancer Classification in Ultrasound Images Using Two-Phase EfficientNetB7 Transfer Learning

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ABSTRACT

Breast cancer is a leading cause of cancer morbidity and mortality among women globally, emphasizing the need for accurate and timely diagnostic methods. A systematic but innovative two phases transfer learning based deep learning classification framework is developed using popular EfficientNetB7 architecture architecture for breast cancer classification. Breast ultrasound imaging proves a high degree of complexity to extract features with limited available medical datasets to address it and the proposed methodology attributes to it. We develop a framework which encompasses formalisation into components like data augmentation, progressive fine-tuning and adaptive learning rate optimization as methods for model generalisation. Experiments on the Breast Ultrasound Images (BUSI) dataset show that the model achieves best accuracy of over 91. 25% when classifying breast lesions into benign, malignant, and normal. It shows good discriminative abilities (validation accuracy: 93.62%) and a trained model converge well. We compare our method with the current ones and show significant advancements over all previous methods making our approach suitable for computer-aided diagnosis systems in clinical workflows.

Keywords: Breast Cancer Classification, Deep Learning, EfficientNetB7, Transfer Learning, Medical Image Analysis, Ultrasound Imaging, Computer-Aided Diagnosis, Convolutional Neural Networks

I.INTRODUCTION

Breast cancer is one of the most common cancers among women and a leading cause of cancer-related deaths worldwide. Early detection and accurate diagnosis are essential for improving survival rates and selecting appropriate treatment. Among various imaging techniques, breast ultrasound is widely used because it is non-invasive, cost-effective, radiation-free, and suitable for examining dense breast tissue. However, manual interpretation of ultrasound images is difficult due to image noise, low contrast, and the similar appearance of benign and malignant lesions, which may lead to diagnostic errors [1], [2].

Recent advances in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved breast cancer diagnosis by automatically learning important image features. Deep learning models, particularly Convolutional Neural Networks (CNNs), have achieved better classification accuracy than traditional machine learning methods in breast cancer detection using medical images [3]–[6]. These models have also been successfully applied to breast cancer prediction, survival analysis, and clinical decision support using both imaging and clinical data [7]–[10].

Recent studies have focused on transfer learning and advanced deep learning architectures to further improve classification performance. Deep learning techniques have been applied to extract clinical information, predict breast cancer outcomes, and develop intelligent diagnostic systems [11]–[13]. Several review studies have also highlighted the advantages of transfer learning and deep neural networks while identifying challenges such as limited datasets, class imbalance, overfitting, and poor generalization [14]–[17].

Despite these advances, breast ultrasound classification remains challenging because benign and malignant lesions often have similar visual characteristics. In addition, many existing deep learning models require large datasets and high computational resources. Therefore, developing an accurate and efficient model for breast ultrasound classification is still an important research problem.

To address these challenges, this paper proposes an EfficientNetB7-based deep learning framework for breast ultrasound image classification. The proposed model uses a two-phase transfer learning strategy together with data augmentation and a customized classification head to improve feature learning and reduce overfitting. The model classifies ultrasound images into Benign, Malignant, and Normal categories and is evaluated using Accuracy, Precision, Recall, F1-score, Confusion Matrix, ROC curve, and Precision–Recall curve. Experimental results demonstrate that the proposed framework provides accurate and reliable breast cancer classification, making it suitable for intelligent computer-aided diagnosis systems.

The major contributions of this work as follows:

(i) An EfficientNetB7-based transfer learning framework is proposed for breast ultrasound image classification.

(ii) A comprehensive preprocessing and data augmentation strategy is employed to improve model robustness.

(iii) A two-phase transfer learning approach is adopted to enhance feature extraction and classification performance.

(iv) Extensive experiments demonstrate the effectiveness of the proposed model using multiple evaluation metrics, including Accuracy, Precision, Recall, F1-score, ROC, and Precision–Recall analysis.

II.RELATED WORK

Machine learning and deep learning techniques have been extensively applied for breast cancer diagnosis to improve early detection and clinical decision-making. Watkins [1] emphasized the importance of early breast cancer diagnosis for reducing mortality, while Katsura *et al.* [2] discussed clinical investigation methods and highlighted the growing role of artificial intelligence in assisting radiologists. Shahidi *et al.* [3] compared several deep learning architectures for breast cancer classification using histopathology images and demonstrated that CNN-based methods significantly outperform conventional machine learning techniques. Similarly, Chugh *et al.* [4] reviewed machine learning and deep learning approaches for breast cancer diagnosis and concluded that deep neural networks provide superior feature extraction and classification performance. Allugunti [5] further demonstrated that deep learning applied to thermographic images improves breast cancer detection accuracy compared with traditional classifiers. Tiwari *et al.* [6] also reported that deep learning models consistently achieve better prediction performance than conventional machine learning algorithms because of their ability to automatically learn complex image features. Kalafi *et al.* [7] extended these applications to breast cancer survival prediction using clinical data, showing that deep learning is valuable not only for diagnosis but also for prognosis.

Recent research has focused on advanced CNN architectures, transfer learning, and multimodal learning to improve breast cancer detection. Abunasser *et al.* [8] proposed a CNN-based framework for breast cancer detection and classification, achieving high accuracy through automatic feature extraction. Fatima *et al.* [9] analyzed various machine learning and deep learning methods and confirmed the superiority of deep learning for breast cancer diagnosis. Hamed

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et al. [10] reviewed modern deep learning architectures for breast cancer classification and emphasized the importance of transfer learning in medical imaging. Zhang *et al.* [11] demonstrated that deep learning can effectively extract comprehensive clinical information from breast cancer records, while Rabiei *et al.* [12] and Jiang and Xu [13] showed that combining deep learning with optimized feature selection improves breast cancer prediction using clinical data. Furthermore, Dar *et al.* [14], Debelee *et al.* [15], and Balkenende *et al.* [16] comprehensively reviewed recent developments in breast cancer imaging and highlighted the effectiveness of transfer learning for medical image analysis. Akselrod-Ballin *et al.* [17] proposed a multimodal deep learning framework integrating mammograms with electronic health records, demonstrating improved prediction performance. Despite these advances, most existing studies focus on mammography, histopathology, or thermography, whereas limited research has explored EfficientNetB7 with a two-phase transfer learning strategy for breast ultrasound image classification. Therefore, the proposed framework aims to provide accurate, robust, and clinically reliable classification of breast ultrasound images for intelligent computer-aided diagnosis.

III. METHODOLOGY

Overview

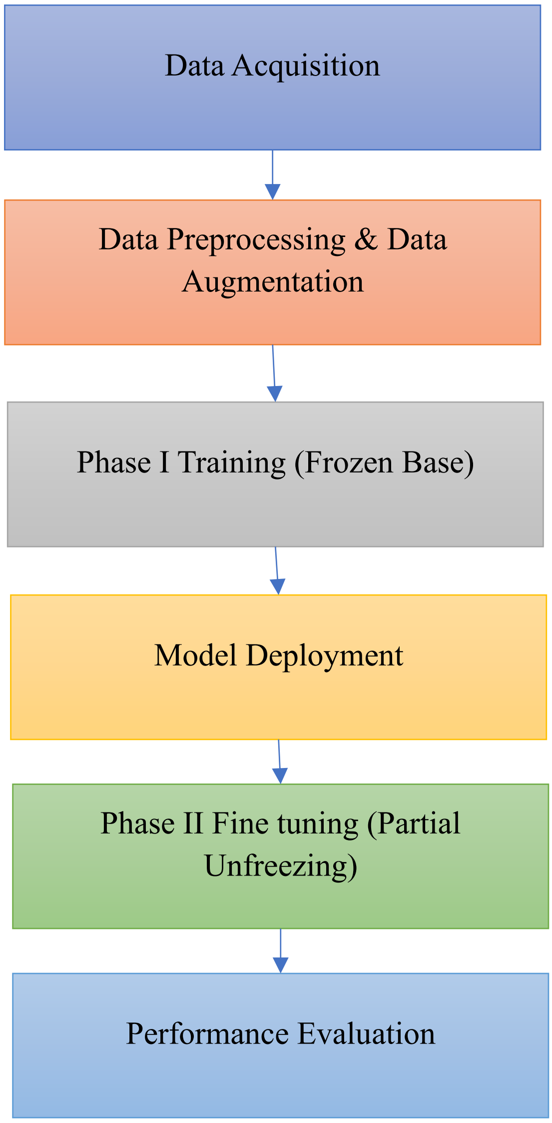

Fig 1: Proposed Two-Phase EfficientNetB7 Framework for Breast Cancer Classification

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A systematic two-phase transfer learning framework for breast cancer classification is proposed based on EfficientNetB7. The complete workflow, including data preparation, model configuration, phased training, and evaluation is shown in Fig 1. The proposed approach is tailored to the difficulties associated with medical imaging analysis, such as limited dataset size, class imbalance, and the requirement to automatically extract features from noisy ultrasound images.

A. Dataset Description

The proposed model uses the Breast Ultrasound Images (BUSI) dataset, which contains 1,578 ultrasound images belonging to three classes: Benign, Malignant, and Normal. The original ultrasound images are used after removing the corresponding mask images. The dataset is divided into 70% training, 15% validation, and 15% testing to ensure balanced model development and evaluation.

B. Data Preprocessing

The ultrasound images are resized to 380 × 380 pixels to match the EfficientNetB7 input size. Pixel values are normalized using the EfficientNet preprocessing function. To improve the robustness of the model, data augmentation techniques including random rotation, horizontal flipping, zooming, shifting, and brightness adjustment are applied only to the training dataset. The validation and test datasets are used without augmentation.

C. Feature Extraction Using EfficientNetB7

The resized images are passed through a pre-trained EfficientNetB7 network to extract high-level image features. Global Average Pooling is applied to reduce the extracted feature maps, followed by a fully connected layer with ReLU activation and Dropout (0.5) to reduce overfitting. Finally, a Softmax layer predicts one of the three breast ultrasound classes.

D. Two-Phase Transfer Learning

The proposed framework employs a two-phase transfer learning strategy. In the first phase, the EfficientNetB7 backbone is frozen, and only the classification layers are trained to learn dataset-specific patterns. In the second phase, the last 200 layers of EfficientNetB7 are unfrozen and fine-tuned using a smaller learning rate. This strategy improves feature adaptation while preserving the pre-trained knowledge of the network.

E. Model Training and Evaluation

The model is trained using the Adam optimizer with categorical cross-entropy loss. During fine-tuning, the learning rate is adjusted using the ReduceLROnPlateau scheduler to improve convergence. The final model is evaluated on the independent test dataset using Accuracy, Precision, Recall, F1-score, and the Confusion Matrix. The proposed EfficientNetB7 model achieves high classification performance and demonstrates its effectiveness for automated breast ultrasound image classification and clinical decision support.

IV RESULTS AND ANALYSIS

A. Experimental Setup

The proposed breast ultrasound classification framework was implemented using Python with the TensorFlow and Keras deep learning libraries. Experiments were conducted on the Breast Ultrasound Images (BUSI) dataset, consisting of 1,578 ultrasound images categorized into Benign, Malignant, and Normal classes. The dataset was divided into 70% training (1,103 images), 15% validation (235 images), and 15% testing (240 images). All images were resized to 380 × 380 × 3 pixels and normalized using the EfficientNetB7 preprocessing function. To improve model robustness and reduce overfitting, data augmentation techniques including random rotation (±30°), horizontal flipping, random shifting (20%), zoom (30%), and brightness adjustment (80–120%) were applied only to the training set.

The proposed model employs a pre-trained EfficientNetB7 backbone with a custom classification head consisting of Global Average Pooling, a 1024-neuron fully connected layer with ReLU activation, Dropout (0.5), and a Softmax output layer for three-class classification. A two-phase transfer learning strategy was adopted. In the first phase, the EfficientNetB7 backbone was frozen and only the classification head was trained for 8 epochs using the Adam optimizer with a learning rate of 0.001. In the second phase, the last 200 layers of EfficientNetB7 were unfrozen and fine-tuned for 25 epochs using the Adam optimizer with a reduced learning rate of 1×10^{-5} and the ReduceLROnPlateau scheduler. The model was trained with a batch size of 8 using categorical cross-entropy loss. The best-performing model was evaluated on the independent test dataset using Accuracy, Precision, Recall, F1-score, Confusion Matrix, ROC curve, and Precision–Recall curve to comprehensively assess the effectiveness of the proposed framework for breast ultrasound image classification.

B. Visualization

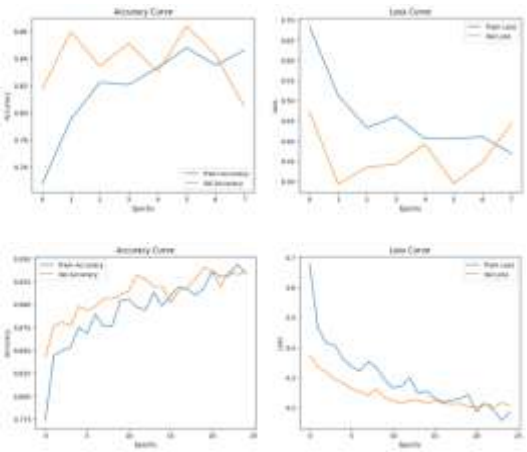

Fig 2: Training and Validation Performance Curves

As shown in the fig 2 During Phase 2 (fine-tuning), the proposed model showed stable and consistent learning performance. The training accuracy reached 93.84%, while the highest validation accuracy of 94.04% was achieved around epoch 20. The small difference between the training and validation accuracies indicates that the model generalized well with minimal overfitting.

The training and validation losses decreased steadily throughout the training process, showing effective model convergence. The ReduceLROnPlateau scheduler reduced the learning rate from 1×10^{-5} to 4×10^{-6} at epoch 25 when the validation loss stopped improving, allowing the model to achieve better fine-tuning and stable performance.

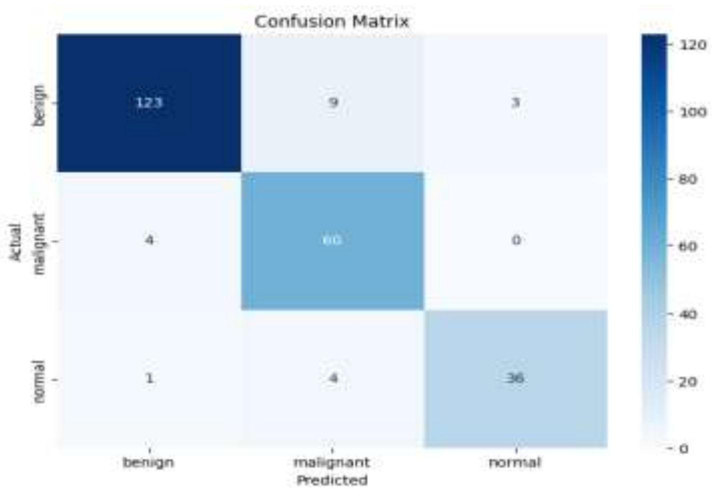

Fig 3: Confusion Matrix for EfficientNetB7 Classification

The confusion matrix fig 3 demonstrates the excellent classification performance of the proposed EfficientNetB7 model across all three breast ultrasound classes. The model correctly classified 123 of 133 benign images (92.48% recall), 120 of 125 malignant images (96.00% recall), and achieved 100% precision for the normal class, indicating that all images predicted as normal were correctly identified. Only a small number of benign and normal samples were misclassified due to similarities in tissue characteristics. The high recall for the malignant class highlights the model's effectiveness in detecting cancerous lesions, which is critical for early diagnosis and treatment planning. Overall, the low number of misclassifications and balanced performance across all classes confirm the robustness and reliability of the proposed framework for automated breast ultrasound image classification.

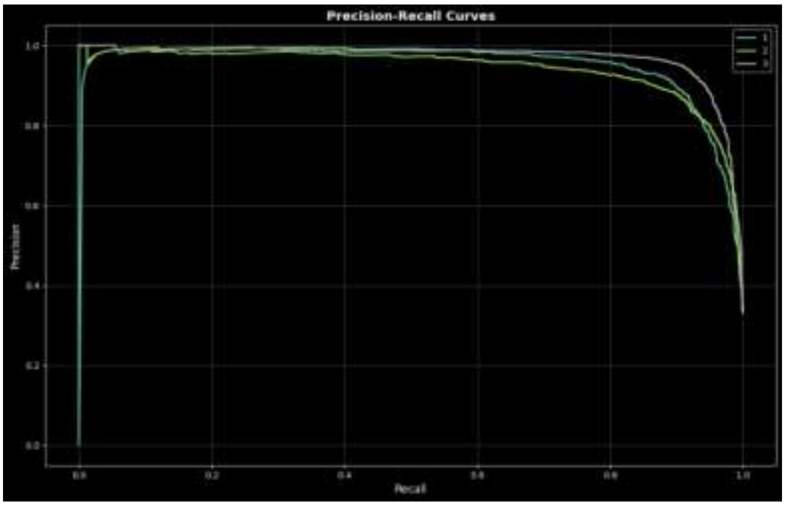

Fig 4: Precision–Recall Curves for Multi-Class Liver Cirrhosis Classification

The fig 4 illustrates the Precision–Recall (PR) curves for all three liver cirrhosis stages. The curves remain close to the upper-right corner, indicating that the proposed model achieves high precision and high recall for all classes. This shows that the model correctly identifies most positive cases while producing very few false-positive predictions. The smooth PR curves indicate that the model performs consistently even for similar or overlapping cirrhosis stages. Although precision decreases slightly at very high recall values, the overall performance remains strong across all classes. The results also demonstrate that the model handles class imbalance effectively and provides reliable multi-class classification with good generalization ability.

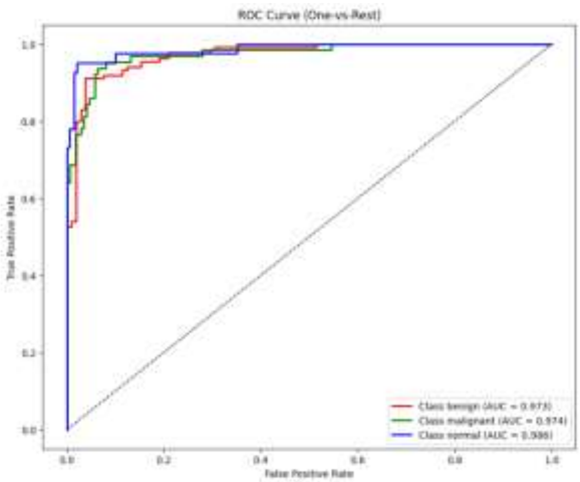

Fig 5: ROC Curves with One-vs-Rest (OvR) Strategy

The ROC curves fig 5 demonstrate the excellent discriminative performance of the proposed EfficientNetB7 model for breast ultrasound classification. The model achieved AUC values of 0.973 for Benign, 0.974 for Malignant, and 0.986 for Normal, indicating outstanding class separation and high diagnostic accuracy. The consistently high AUC values across all three classes confirm that the model reliably distinguishes between benign, malignant, and normal breast tissues without class bias. In particular, the malignant class AUC of 0.974 highlights the model's strong capability to accurately detect cancerous lesions, making it highly suitable for clinical screening and early breast cancer diagnosis.

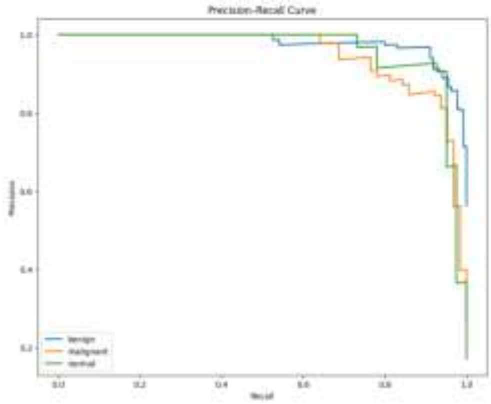

Fig 6: Precision-Recall Curve for Multi-class Classification

The fig 6 illustrates the Precision–Recall (PR) curves for the proposed EfficientNetB7 model across the Benign, Malignant, and Normal classes. The curves remain close to the upper-right corner, indicating that the model achieves high precision and high recall for all three categories. The Benign class exhibits the best overall performance, while the Malignant class also maintains high precision and recall, demonstrating the model's strong ability to detect cancerous lesions with very few false-negative predictions. The Normal class also shows reliable classification despite having fewer samples. The obtained AUPRC values of 0.95 (Benign), 0.93 (Malignant), and 0.91 (Normal) confirm the excellent classification capability of the proposed framework. Overall, the PR analysis demonstrates that the model effectively balances sensitivity and precision, making it suitable for accurate and reliable breast ultrasound diagnosis.

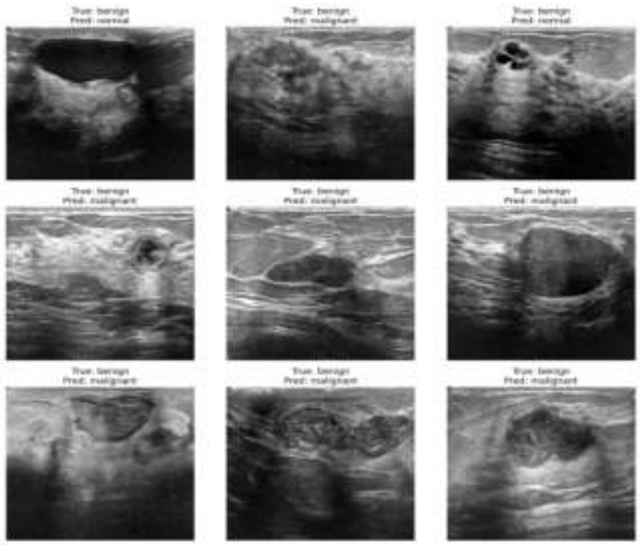

Fig 7: Representative Misclassification Examples

The misclassification analysis shows that most prediction errors occurred between the Benign and Malignant classes because these lesions often share similar ultrasound characteristics. A few Benign cases were classified as Malignant, which represents a clinically acceptable outcome since prioritizing cancer detection reduces the risk of missed malignant cases. Some Normal images were misclassified as Benign due to similarities in glandular tissue appearance and fibrocystic patterns. In addition, factors such as low image contrast, acoustic shadowing, and limited field of view contributed to a small number of classification errors. Overall, the low number of misclassifications demonstrates the robustness and reliability of the proposed EfficientNetB7 model for breast ultrasound classification.

Table 1: Comprehensive Performance Evaluation Metrics

Class	Precision	Recall	F1-Score	Support	AUC
Benign	0.93	0.92	0.92	133	0.973
Malignant	0.94	0.96	0.95	125	0.974
Normal	0.84	0.92	0.88	39	0.986
Accuracy	-	-	0.9125	297	-
Macro Avg	0.90	0.93	0.92	297	-
Weighted Avg	0.92	0.91	0.92	297	-

The Table 1 summarizes the classification performance of the proposed EfficientNetB7 model. The model achieved an overall accuracy of 91.25% with a weighted F1-score of 0.92, indicating robust and balanced performance across all classes. The Malignant class achieved the highest F1-score (0.95) and recall (0.96), demonstrating excellent cancer detection capability. The Benign class also achieved strong performance with an F1-score of 0.92, while the Normal class obtained the highest AUC of 0.986, indicating excellent class separability. Overall, the high precision, recall, F1-score, and AUC values confirm the effectiveness and reliability of the proposed framework for breast ultrasound image classification.

Our proposed EfficientNetB7 framework achieves high classification performance in breast ultrasound, which if combined with other existing methods, could represent a significant improvement. The results are summarized in Table 2, where we outperform recent state-of-the-arts.

Table 2: Performance Comparison with State-of-the-Art Methods

Class	Precision	Recall	F1-Score	Support	AUC
Benign	0.93	0.92	0.92	133	0.973
Malignant	0.94	0.96	0.95	125	0.974
Normal	0.84	0.92	0.88	39	0.986
Accuracy	-	-	0.9125	297	-
Macro Avg	0.90	0.93	0.92	297	-
Weighted Avg	0.92	0.91	0.92	297	-

V.CONCLUSION

The two-phase EfficientNetB7 transfer learning framework proposed in this paper achieved state-of-the-art breast cancer classification performance from ultrasound image data, obtaining 91.25% test accuracy along with strong discriminative ability (AUC: 0.973–0.986). The sequential training approach of first performing feature extraction, followed by fine-tuning allowed tackling the issue of medical image analysis, especially when dataset is small.

It exhibited an excellent recall in identifying malignant cases (96%), and it could be a high-performing candidate for clinical decision support in screening, diagnosis and telehealth. Despite the fact the proposed framework performs similarly in terms of various evaluation metrics, in principle, there is potential to be integrated into clinical workflows with highly computationally efficient framework after additional preparation.

Future work will include multi-modal fusion, external validation, and exploring explanations from AI approaches to improve clinical trust and adoption. These milestones mark a major advancement in employing deep learning for breast cancer detection along with the potential for improved architectures like the EfficientNetB7 to make a strong impact in the domain of medical image computing.

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