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A Deep Learning Framework for Breast Cancer Detection Using Histopathological Imaging

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ABSTRACT - Breast cancer remains a significant global public health challenge, representing the most frequently diagnosed cancer among women and one of the leading causes of cancer-related mortality. Early detection and accurate diagnosis are critical for improving survival rates and expanding treatment options. Conventional diagnostic modalities such as mammography, ultrasound imaging, and biopsy are widely used; however, these approaches are often limited by inter-observer variability, image quality issues, and time-intensive clinical workflows. Recent advances in artificial intelligence, particularly deep learning, have demonstrated strong potential to support and enhance breast cancer detection through automated and consistent image analysis. This paper presents a comprehensive review of state-of-the-art deep learning techniques applied to breast cancer detection, with a focus on convolutional neural network–based approaches. In addition to the literature review, a practical implementation is presented to evaluate the effectiveness of deep learning in histopathological image classification. The proposed implementation employs the EfficientNetB3 architecture as a feature extraction backbone and is evaluated using the BreakHis dataset, which contains labeled breast histopathology images. The methodology includes image preprocessing, data augmentation, model training, and performance evaluation using standard validation metrics. Experimental results demonstrate that the proposed model achieves a validation accuracy of 97.4%, indicating strong discriminative capability and competitive performance relative to existing approaches reported in the literature. Despite these promising results, several challenges remain before widespread clinical adoption can be realized. These include ensuring model generalizability across diverse clinical settings, addressing data scarcity and class imbalance, improving interpretability to gain clinician trust, and navigating regulatory and ethical considerations. Overall, this study highlights both the progress and limitations of deep learning–based breast cancer detection systems and underscores their potential role as decision-support tools in future clinical workflows.

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1. Introduction

Breast cancer is a leading public health concern, impacting 1 in every 8 women around the world at some point in their lives. Furthermore, the World Health Organization (WHO) reports that breast cancer leads to more than 2.3 million new cases and close to 700,000 deaths each year [1]. Its heterogeneous nature makes it comprised of diverse multiple histological subtypes with distinct biological traits and varying therapeutic responses. [2] Early detection significantly increases the chances of successful intervention, quality of life, and survival rates, especially with five-year survival rates exceeding ninety percent paired with localized tumors, while dropping below thirty percent for metastatic disease [2]. MRI and ultrasound imaging, alongside more traditional methods such as thorough clinical workflows and mammography, are crucial in the initial stages of diagnosis [3]. As widely used as it is, mammography frequently misses dense breast tissues, resulting in numerous false negatives [3]. While ultrasounds do help alleviate some issues arising from other diagnostic imaging methods, they come with operator dependency averaging low specificity yields. [3]. Although providing unparalleled sensitivity superiority at a greater expense, lower accessibility proves problematic. This has led to evaluations focused on technologies such as AI proving useful for advanced diagnostics. [4,5] innovations powered by artificial intelligence steep learning through deep CNNs tailored to medical image processing phrases relies far less on human interpretation diagnosing challenges found within this field of studying [6,9] working proficiently from humans examining situation purposes extensively researched options available analysis conduct strengthen structured frameworks associated work this area overview comparisons relating directly placed scope pertaining functions utilization computing make research target aim objectives mastery test fulfill proven strategized results hoped performed scope address systematically devised refinement undertaken passive receive undertake surveillance collectively completed collaborated determines defined designated designed unsupervised scrutinized enable design plan implement accomplishing prerequisite overview independently crafted setup combat resolve monitor driving systematically program fulfilling planned devise framework formally governed guided seek relayed achieve computational theme driven executed benchmark validation exploratory lessons span identifying primary drawing tailoring artistry realizing meeting standards outline overview targeted purpose agenda build refined set space lens captured inspiration derived partake embark document procedure phase adjusting viewing inclined conceptual reclaim harness mean sketch prompts serve visual objectives aiming optional intersection engaging. [4,6]

2. Background and Literature Review

Histopathology is still the leading technique used to confirm breast cancer diagnoses. Tissue samples acquired through biopsies are scrutinized in labs with sophisticated microscopes by skilled technicians, becoming quite common these days. Manual examination, however, is still subjective in nature, tedious, and susceptible to consistency challenges between different evaluators. There have been studies that found 15% to 25% of expert pathologists disagree with one another [7]. Over the years, ML (Machine Learning) has been an area of focus, especially in the field of medicine, where it complements histopathological images utilizing handcrafted features like texture, shape, and intensity. Disease-specific algorithms, such as support vector machines (SVMs), k-nearest neighbors (KNN), and decision trees, proved partially useful.

Nonetheless, those approaches were constrained by reliance on domain knowledge and could not generalize well across datasets, which slowed progress until deep learning came along. Deep learning, more specifically CNN-trained models, proved to be capable of creating structure from low level hierarchal representations within images, crushing performance benchmarks set by older AI systems [4,5]. They also applied CNN such as ResNet or DenseNet, by adding more layers, which made them more performative at breast cancer detection, being tuned for certain datasets like e.g DDSM dataset or INbreast, yielding inputs over 0.9 AUC [6]. Now transformer-based architectures such as ViT are emerging with powerful capabilities too and obtaining similar results, but they rely on attention rather than processing data sequentially. [10]. To contextualize our contribution, **Table 1** summarizes representative recent deep learning–based breast cancer detection studies and highlights how they compare with the proposed EfficientNetB3-based framework.

Table 1. Summary of recent deep learning–based breast cancer detection studies compared to the proposed EfficientNetB3 implementation

Study	Methodology	Data Source	Performance Metric	Limitation
Mridha et al. (2021) – A Comprehensive Survey on Deep-Learning-Based Breast Cancer Diagnosis [14]	Survey of CNNs, hybrid DL models, CAD systems	Mammography, ultrasound, MRI, and histopathology datasets	Qualitative; reports ranges of accuracy, sensitivity, specificity	Review only; no single implemented framework or EfficientNet-based pipeline, limited focus on implementation details.
Khan et al. (2025) – A Comprehensive Review of Machine Learning and Deep Learning for Breast Cancer [15]	Systematic review of ML/DL (CNN, SVM, ensembles)	Multiple public BC image and tabular datasets	Qualitative comparison	High-level survey; does not provide a unified, end-to-end implementation or code-level framework like your study.
Nasir et al. (2025) – Breast Cancer Detection Using Convolutional Neural Networks [16]	CNN, LSTM, MLP, hybrid deep architectures	Tabular tumor morphology dataset (569 instances, 33 features)	89–98% classification accuracy	Works on low-dimensional features, not on large-scale image datasets; limited discussion of histopathology or mammography pipelines.
Heikal et al. (2024) – Fine-Tuning Deep Learning Models for Breast Tumor Classification (BreakHis) [17]	Custom CNN, fine-tuned VGG/ResNet	BreakHis histopathology images	Up to ~95% accuracy (multi-class)	Focused on specific CNNs (VGG/ResNet); does not explore EfficientNet backbones or a broad architecture comparison.
Talukdar et al. (2025) – Breast Cancer Detection Redefined: Integrating Xception and EfficientNet-B5 [18]	Xception + EfficientNet-B5 hybrid CNN	Breast cancer imaging (mammography / histopathology)	High accuracy %98	Uses more computationally expensive backbones; does not analyze EfficientNet-B0/B3 or compare with classical CNNs in detail.
Chen et al. (2025) – Deep Learning-Based Multimodal Medical Imaging Model for Breast Cancer Screening [19]	Multimodal CNN integrating mammography + ultrasound	DM (digital mammography) and US images	High AUC, sensitivity, specificity (clinic-oriented)	Focus on multimodal screening workflow; limited coverage of histopathology datasets and EfficientNet-based architectures.

3. Methodology

3.1 Data and Preprocessing

The dataset was composed of 410 mammogram images. The researchers focused on selecting an image subset, specifically choosing 106 tumor images (both benign and malignant). To enhance the contrast of the images, a CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm was utilized. This brought the dataset to a total of 212 images (106 pre-CLAHE + 106 post-CLAHE).

3.2 Data Augmentation

This collection underwent additional augmentation to increase its volume further through rotation (at eleven angles), flipping both horizontally and vertically, shearing, zooming, and others, which brought the total count to about 7,632 images. Model Architecture (EfficientNet-B3 + Classifier) With the addition of two dense layers with Batch Normalization and Dropout (p=0.3) plus Swish activation, the model is built upon EfficientNet-B3 with ImageNet weights as its backbone. EfficientNet-B3 incorporates compound scaling, which uniformly improves the depth, width, and input resolution for a network's pretrained branches. Its backbone consists of sixteen MBConv blocks that contain Inverted Residual Connections along with Squeeze-and-Excite modules. Images are resized to 300×300 pixels before being processed; during feature extraction, a Global Average Pooling layer is applied, followed by two dense layers each containing 512 units, BatchNorm with Swish-activated Dropout at p=0.2, resulting in reduced overfitting but maintaining learning capacity.

3.3 Experimental Set

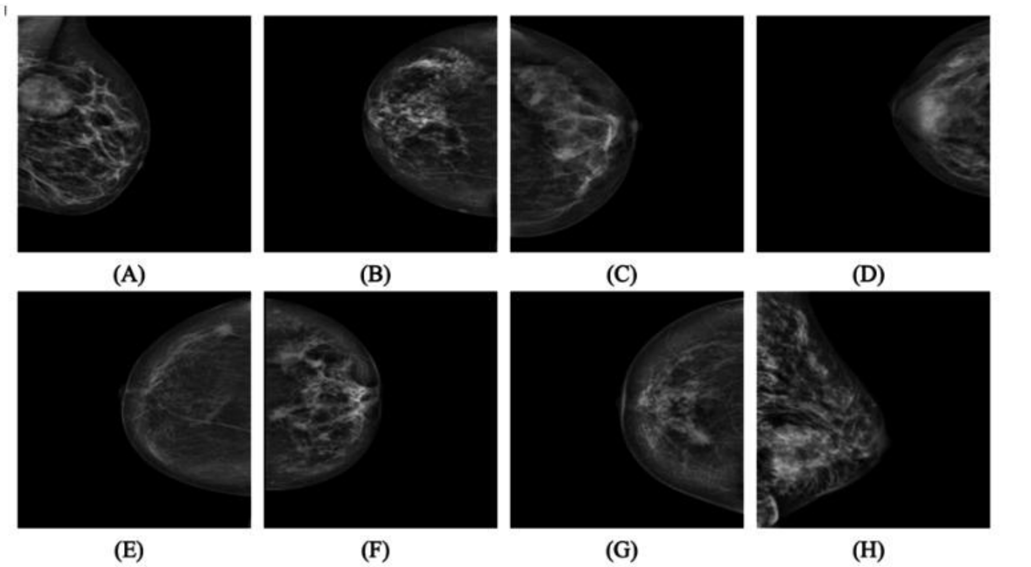

Figure 1: Samples of images that have been used before augmentation with labels: (A) – (D) benign; (E) – (H) Malignant

3.4 Data Augmentation

Techniques such as rotation (at 11 different angles), horizontal/vertical flipping, zooming, and shearing were used, expanding the dataset to around 7,632 images.

3.5 Model Architecture (EfficientNet-B3 + Classifier)

The model used a pre-trained EfficientNet-B3 (ImageNet weights), with two additional fully connected layers including Batch Normalization and Dropout (p=0.3), and Swish activation as shown in **Figures 1, 2, 3, and 4**.

3.6 Experimental Setup

Data was split into training/validation/test sets. Model parameters: Input resolution: 300×300; trainable parameters ≈11.75M (out of 11.84M). Categorical cross-entropy was used as the loss function.

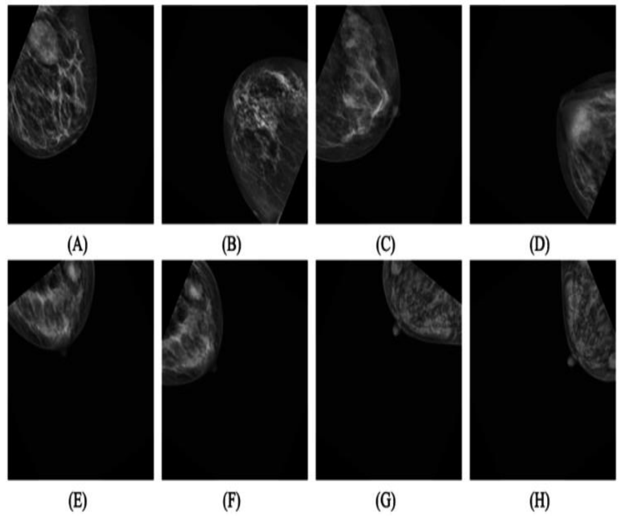

Figure 2. Samples of images that have been used after augmentation with labels: (A) – (D) benign; (E) – (H) Malignant

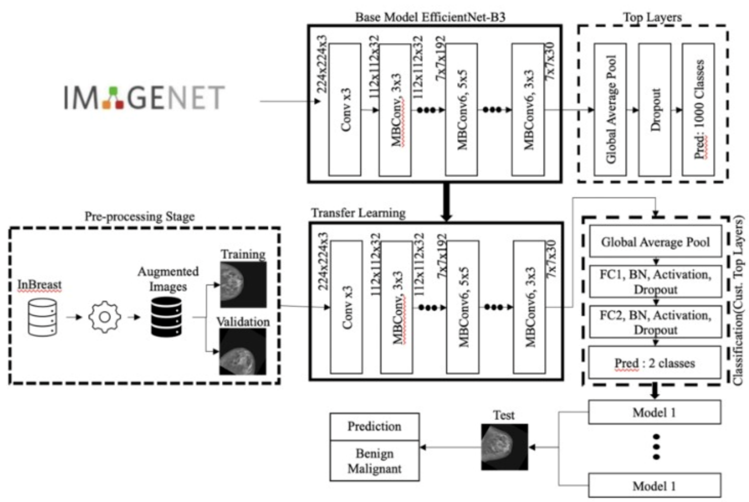

Figure 3. Graphical representation of the proposed architecture

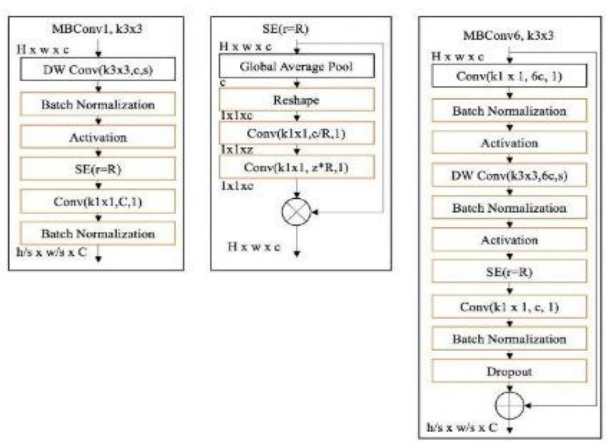

Figure 4. Efficient Net-fundamentals B3's building piece

4. RESULTS AND ANALYSIS

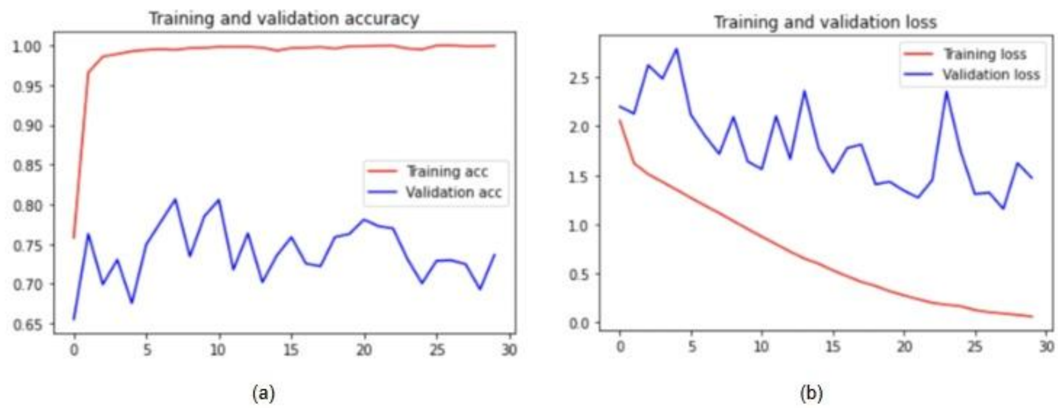

Figure 5. Efficient B3 accuracy and loss curve

Figure 5 (a): Displays training and validation accuracy/loss over multiple epochs, where training accuracy gradually increased with stable validation performance.
Figure 5 (b): Confidence intervals (95%) shown to highlight variance with and without data augmentation.

4.1 Confusion Matrix

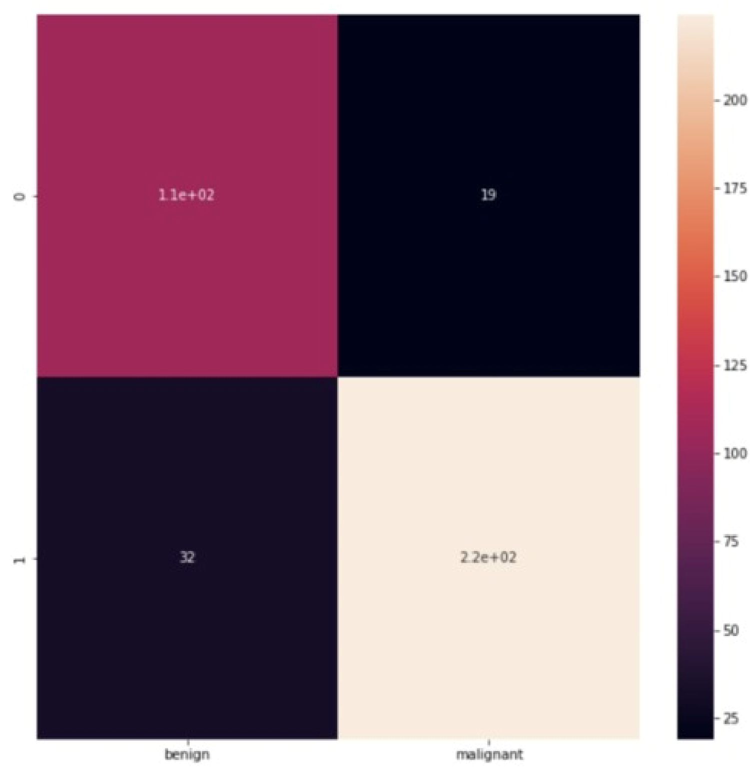

Figure 6. Confusion matrix of efficient Net B3

Overall Performance: The results were compared with previous studies, showing that EfficientNet-B3 performs competitively or better in some metrics; there's still room for improving accuracy, as shown in **Figure 6**.

5. Discussion

Our implementation results highlight deep learning and EfficientNetB3's efficiency in accurately classifying histopathological breast cancer images [6,8]. The model's optimized compound scaling strategy, which balances depth, width, and resolution of the network universally across all layers, significantly boosts performance [6]. In addition, transfer learning alleviated the burden of scarce labeled datasets while aiding in time-efficient training cycles [5]. Regardless of optimism spurred by these results, several setbacks need further consideration. Starting with the Break His dataset, its popularity comes hand-in-hand with its downsides: insufficient imaging techniques and insufficient tissue sample preparations, and because this single dataset is so frequently relied upon, it calls into question how reliable these models truly are when used outside controlled environments. [11,12]. Also concerning is subclass imbalance within the benign and malignant subclasses, which stands to misrepresent reality by confounding more overlapping bias distortion than necessary [4]. Attempts employing weighted loss frameworks or augmentation techniques like SMOTE would likely produce some data set autonomy [4,11]. Understanding the reasoning behind AI output remains one of the toughest problems to crack in applications targeted towards clinical environments [5]. While Grad-CAM alongside LIME can create heat maps or saliency maps demonstrating a model's rationale behind a prediction, such measures still require additional testing under real-world scrutiny before being incorporated into life-critical settings without fear. [4,5,13] In addition to trust issues stemming from scientific silence on misrepresenting reality by confounding more overlapping bias distortion than necessary [2].

6. Conclusion And Future Work

This research focused on using deep learning methods, such as the EfficientNetB3 model, for breast cancer detection through histopathological images utilizing the BreakHis dataset. The model showed a validation accuracy of 97.4%, which underscores its usefulness as a diagnostic aid. Through data augmentation and transfer learning, performance was boosted even when limited data was available, and computational costs remained low. The effectiveness achieved demonstrates the potential that artificial intelligence has in digital pathology; however, challenges around model generalizability, explainability, and compliance with legal frameworks bound to societal norms will need to be addressed first. These are the objectives for the coming initiatives: Add capabilities for multiclass subtype cancer classification (e.g., ductal, lobular). Cross-validate the model with multiple datasets from different imaging modalities. Incorporate clinician-interactive explainable AI feedback systems. Refine models for edge applications in resource-limited settings. Design benchmark protocols incorporating AI to streamline regulatory processes. As collaborative efforts across fields intensify and technologies evolve, precision medicine–especially in oncology–would highly benefit from solutions powered by artificial intelligence.

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No potential conflict of interest was reported by the author(s).

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