Breast Cancer Prediction Using Deep Learning

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ABSTRACT

Breast cancer remains a significant global health challenge, particularly affecting women, with early detection pivotal in controlling its impact and reducing mortality rates. While traditional machine learning techniques have provided valuable insights, deep learning—especially through Convolutional Neural Networks (CNNs)—has demonstrated superior performance in image classification tasks. This research leverages the advanced CNN model, EfficientNet, known for its scalability and enhanced efficiency. EfficientNet's design optimizes computing resources, making it particularly suitable for deployment in wireless and mobile computing environments where computational power and battery life are limited. This study explores the application of EfficientNet in breast cancer detection across histopathological images, aiming to enhance detection accuracy and expand the applicability of deep learning techniques in medical diagnostics. By conducting a comprehensive evaluation of EfficientNet's architecture against CNN model, we aim to validate its superiority in achieving higher accuracy with lower computational demand. The anticipated outcome is a robust, efficient deep learning solution that not only improves breast cancer detection but also is feasible for implementation in mobile health applications, contributing significantly to early diagnosis and mobile health advancements.

KEYWORDS

Convolutional Neural Networks (CNNs), Histopathological Imaging, Image Classification, EfficientNet

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1 INTRODUCTION

Breast cancer (BC) affects approximately 8% of women during their lifetimes and stands as the second leading cause of cancer-related deaths globally. This prevalence persists across both developed and developing regions. Medical images can be obtained using a variety of techniques, including MRI scans, mammography, ultrasound, thermography, computed tomography scans, and histopathology. Among these methods, the histopathology test is the gold standard for the clinical diagnosis of cancers [9]. For pathologists, the classification of breast cancer into categories—primarily binary classification into benign or malignant—is crucial [5]. This systematic and objective classification aids in providing reliable prognostics and directing appropriate treatment strategies.

Conventional diagnostic methods for breast cancer face challenges in accuracy due to inherent variations in histopathological images and limitations in feature extraction techniques. Deep learning (DL), drawing inspiration from the human brain's neural networks, has emerged as a promising solution. This advanced machine learning approach uses multi-layer neural architectures capable of complex image analysis tasks, automatically learning and extracting features without requiring prior domain knowledge. Despite significant advancements, the performance of current algorithms still highlights a need for improvement. Ongoing research is focusing on leveraging DL to enhance the detection and classification of breast cancer, showing potential for notable breakthroughs in medical diagnostics [9].

Convolutional Neural Networks (CNNs) are a specialized kind of neural network used in deep learning that performs convolutional operations directly on raw data. Renowned for their effectiveness in various fields such as speech recognition, sentence modeling, and image classification, CNNs have recently been adapted for medical imaging tasks, including breast cancer diagnosis. A typical CNN architecture comprises three key layers: a convolutional layer for detecting features, a pooling layer for dimensionality reduction, and a fully connected layer for classification. This layered structure allows CNNs to automatically extract and learn features from complex datasets [10]. Prominent CNN models that have significantly advanced the field include EfficientNet, VGG, AlexNet, and GoogleNet, each contributing unique architectural improvements that enhance performance across diverse applications. This robust framework makes CNNs ideally suited for improving the accuracy and efficiency of breast cancer detection systems [7].

In this paper, we utilize the EfficientNet model, a state-of-the-art convolutional neural network. Addressing the challenge of model scaling to enhance accuracy without excessive computational demands, EfficientNet introduces a novel compound scaling method. This method systematically adjusts the network's depth, width, and resolution through fixed scaling coefficients, significantly improving efficiency and accuracy. For the purpose of breast cancer detection [8], we apply the EfficientNet model to histopathological image datasets, leveraging its structured scaling strategy. This allows for optimized performance within computational constraints, making the EfficientNet model highly suitable for precise and efficient medical image analysis, specifically in identifying breast cancer from complex histopathological images.

2 RELATED WORK

In the advancement of breast cancer diagnosis technologies, this study [2] introduces a deep learning model, BC-CNN, designed to classify breast cancer into eight distinct categories ranging from benign conditions to various malignant forms. Utilizing a dataset from Kaggle, the research employs both the proposed BCCNN model and five other pre-trained models—Xception, InceptionV3, VGG16, MobileNet, and ResNet50—fine-tuned on the ImageNet database. Each model was evaluated across different magnifications (40X, 100X, 200X, 400X, and Complete Dataset) of MRI images, enhanced by GAN techniques to enrich the dataset. The evaluation metrics included F1-score, recall, precision, and accuracy, demonstrating that the highest detection accuracies were achieved at 400X magnification, attributed to higher image resolution. This study underscores the significant impact of dataset boosting, preprocessing, and balancing in enhancing the performance of deep learning models in the precise classification of breast cancer.

[6] This research explores breast cancer detection using Convolutional Neural Networks (CNN) and transfer learning on mammographic images from the MIAS and DDSM databases. The study evaluated three methods: training a CNN from scratch, utilizing a pre-trained VGG-16 model for feature extraction, and fine-tuning VGG-16. It was found that using the VGG-16 model for feature extraction was nearly as effective as fine-tuning, achieving similar classification accuracies with significantly reduced computational time. Specifically, the feature extraction method was chosen for further tests, achieving an average validation accuracy of about 90.5% in distinguishing between benign, malignant, and normal cases with 10-fold cross-validation, demonstrating the efficiency and potential of transfer learning in medical image analysis for breast cancer detection.

[9] This study evaluates the effectiveness of deep learning (DL) systems, enhanced by transfer learning, for detecting breast cancer in histopathological images. Utilizing the BreaKHis database, which comprises 7909 images from 82 patients, the research applied image processing techniques followed by transfer learning across multiple convolutional network architectures, including ResNet, ResNeXt, SENet, Dual Path Net, DenseNet, NASNet, and Wide ResNet. The findings highlight that models like ResNext-50, ResNext-101, DPN131, DenseNet-169, and NASNet-A achieved exceptional accuracies, surpassing 99%, thus demonstrating significant advancements over prior methods in the field. These results support the use of advanced DL models in aiding pathologists with more accurate and early diagnoses of breast cancer.

[3] This study presents a convolutional neural network (CNN)-based method for enhancing the detection of breast cancer through the analysis of ductal carcinoma tissue in whole-slide images (WSIs). Utilizing a dataset of approximately 275,000 RGB image patches, the research compares the performance of various CNN architectures against traditional machine learning (ML) algorithms. The findings indicate that the CNN method outperforms ML algorithms, achieving an accuracy of 87%, which is 9% higher than the ML benchmarks. This improvement underscores the potential of CNNs to reduce human errors in the diagnostic process of breast cancer.

3 METHODOLOGY

3.1 Dataset

We utilized a comprehensive publicly accessible dataset from the Kaggle open-access database [1]. It includes 162 whole mount slide images of breast cancer (BCa) specimens, each scanned at a 40x magnification level. This extensive collection was subdivided into 277,524 image patches, each measuring 50 x 50 pixels. These patches include 198,738 classified as IDC-negative and 78,786 as IDC-positive, providing a balanced representation for robust analysis.

Each image patch is uniquely identified by a filename structured as u_xX_yY_classC.png. Here, u represents the patient ID (e.g., 10253_idx5), X and Y denote the x and y coordinates from which the patch was extracted within the whole mount slide, and C signifies the class designation, where 0 indicates non-IDC and 1 indicates IDC. An example filename, 10253_idx5_x1351_y1101_class0.png, illustrates this naming convention, facilitating systematic tracking and analysis of specific tissue sections relative to their spatial orientation and cancer status.

This structured approach to data collection and naming ensures precise traceability and aids in the systematic analysis of the aggressiveness of IDC, thereby supporting the development of automated diagnostic tools aimed at enhancing the accuracy and efficiency of pathological assessments. Figure 1 and 2 are the samples of the dataset.

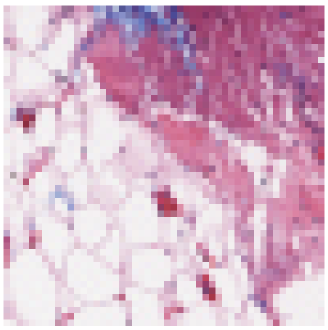


Figure 1: Dataset: IDC - negative

Figure 2: Dataset: IDC - positive

3.2 Pre-processing

To ensure effective training and validation of our deep learning models, including a CNN and EfficientNet, we implemented several pre-processing techniques tailored to optimize the whole performance.

We normalized images to align with EfficientNet's training conditions , and for the CNN model, we scaled pixel values to a range of 0 to 1 to enhance feature processing from raw intensities. Data augmentation techniques such as rotations, flips, and translations were applied to introduce variability and help the models generalize better across different imaging scenarios. We also processed images in small batches to manage resources efficiently and ensure smooth model training.

Additionally, we resized images to meet the specific input requirements of each model—224x224 pixels for EfficientNet and adjusted dimensions for the CNN—to maintain data integrity and network compatibility. These pre-processing steps were crucial in preparing the dataset for successful application in breast cancer detection, facilitating high accuracy and computational efficiency.

3.3 Training Model

EfficientNet is the foundational model designed to optimize performance and efficiency through a methodical scaling of its architecture. It is structured around Mobile Inverted Bottleneck Convolution (MBConv) blocks that vary in type, such as MBConv1, MBConv3, and MBConv6, depending on the expansion factor and kernel size [4].

A key feature of EfficientNet is the use of Squeeze-and-Excitation (SE) blocks within the MBConv blocks. These SE blocks adaptively recalibrate channel-wise feature responses by assigning different importances to each channel, thus enhancing the model's capacity to focus on relevant features within the histopathological images.

The architecture also incorporates depthwise separable convolutions, which reduce the computational load without sacrificing depth or accuracy. Inverted residual connections help maintain information flow across the network, and the Swish activation function is used to ensure smoother training dynamics.

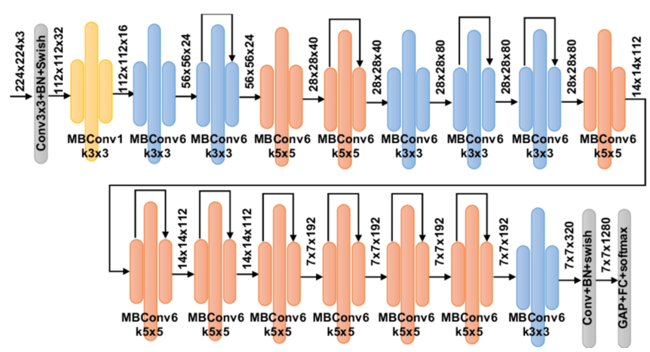


Figure 3: EfficientNet Architecture

Overall, EfficientNet is engineered to provide high accuracy with fewer parameters and reduced computational demand, making it ideal for detailed image analysis tasks such as detecting breast cancer from histopathological images, where precision and efficiency are paramount.

In this project, EfficientNet was trained using the TensorFlow framework, which offers extensive support for deep learning operations and GPU acceleration. The training was executed on a split dataset consisting of 70% training and 30% validation data to monitor over fitting and model performance continuously.

The model was trained using the Adam optimizer, with a carefully selected initial learning rate and adjustments made via a learning rate scheduler based on the performance on the validation set. We employed binary cross-entropy as the loss function, suitable for the binary classification task at hand. The training process was monitored by evaluating the model on a validation dataset, which helped in fine-tuning the parameters to avoid over fitting and under fitting.

4 RESULTS AND ANALYSIS

Our study implemented the EfficientNet model for the detection of breast cancer from histopathological images, analyzing 277,524 image patches derived from 162 whole mount slide images. The study primarily focused on binary classification, distinguishing IDC-positive from IDC-negative cases.

4.1 Key Findings

(1) **High Accuracy and Efficiency:** The EfficientNet model excelled in accuracy, harnessing its compound scaling method that optimally balances model depth, width, and resolution to enhance performance within computational limits.
(2) **Superior Performance:** Compared to CNN model, EfficientNet delivered superior accuracy and efficiency, particularly in resource-limited settings, affirming its design merits.
(3) **Robust Generalization:** The model demonstrated strong generalization across varied imaging conditions, attributed to comprehensive pre-processing and data augmentation techniques like image normalization, scaling, rotations, flips, and translations.

4.2 Model Evaluation

4.2.1 *Training Process:*

EfficientNet was subjected to a rigorous training regimen over 40 epochs. The accuracy and loss curves, depicted in Figures 4 and 5 respectively, indicate a consistent improvement in model performance with minimal overfitting.

4.2.2 *Accuracy Metrics:*

The classification report in Figure 6 highlights the model's precision, recall, and F1-score. EfficientNet achieved a high accuracy rate of 96%, significantly outperforming the traditional CNN, which recorded an accuracy of 94.2%.

4.2.3 *Model Test:*

Fig 7 displays the test images alongside their predicted and actual labels, illustrating the model's accuracy in real-world

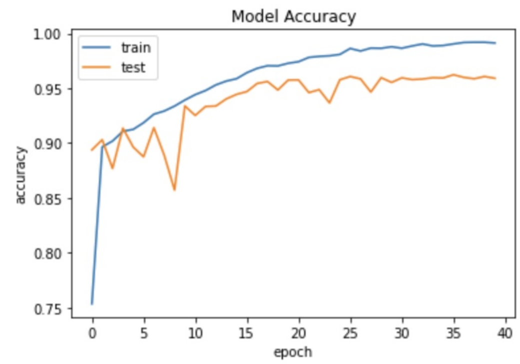


Figure 4: Model of Accuracy

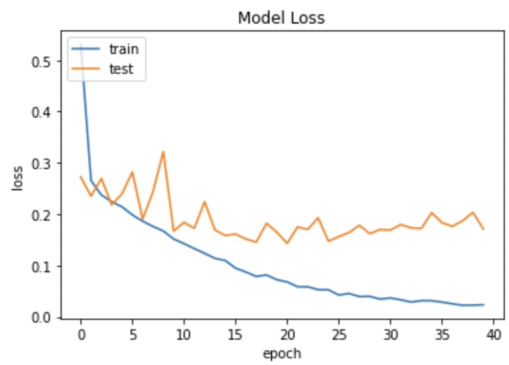
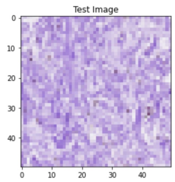


Figure 5: Model of Loss

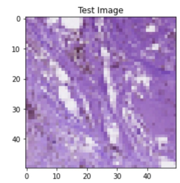
	precision	recall	f1-score	support
Class 0	0.98	0.98	0.98	6343
Class 1	0.86	0.87	0.86	1091
accuracy			0.96	7434
macro avg	0.92	0.92	0.92	7434
weighted avg	0.96	0.96	0.96	7434

Figure 6: Classification Report

scenarios. These figures supports the model's capability to accurately identify and differentiate between IDC-positive and IDC-negative cases. The images demonstrate the effectiveness of the proposed models in correctly identifying the absence and presence of breast cancer. For each test image, the predicted class label generated by the model is shown alongside the actual truth label. It is evident from the figure that the models have high accuracy in identifying the absence and presence of breast cancer, as the predicted labels are the same as the actual labels for most of the test images. This high accuracy results from the models' ability to capture the relevant features of the biopsy images through transfer learning from the pre-trained models and data pre processing techniques to address data imbalances and enhance model performance.



(a) Test Image 1: Index - 100



(b) Test Image 2: Index - 3890

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Predicted Value using EfficientNet model 0
True Value 0
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(c) Predicted and True label for Test image 1

```
Predicted Value using EfficientNet model 1
True Value 1
```

(d) Predicted and True label for Test image 2

Figure 7: Test Images and Predictions

4.2.4 *Confusion Matrix Analysis:*

The confusion matrix (Figure 8) provides a crucial insight into the model's performance by displaying the counts of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions made by the EfficientNet model. The matrix reveals the model's strengths in distinguishing between IDC-positive and IDC-negative cases, with a high number of true positives and true negatives indicating robust diagnostic capabilities. The low number of false positives and false negatives highlights the model's precision and recall balance, ensuring both sensitivity and specificity in breast cancer detection. This analysis of the confusion matrix confirms the model's efficacy in clinical settings, promoting confidence in its deployment for medical diagnostics, where accuracy is paramount.

4.2.5 *Comparative Analysis:*

Table 1 presents a comparative analysis of accuracy between the CNN model and the EfficientNet model. The EfficientNet model demonstrates a superior accuracy of 96%, while the CNN model records an accuracy of 94.2%. This highlights EfficientNet's enhanced capability in handling complex image classification tasks, benefiting from its advanced architectural optimizations.

The results underscore the potential of advanced deep learning model - EfficientNet in enhancing the diagnostic processes for breast cancer. The high accuracy and efficiency

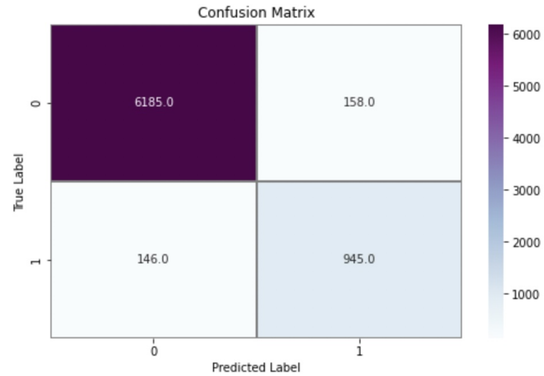

Figure 8: Confusion Matrix

Model	Accuracy
CNN	94.2%
EfficientNet	96%

Table 1: Compartive Analysis

of the model not only boost confidence in the use of automated systems for medical diagnostics but also suggest that similar approaches could be replicated for other types of medical image analyses.

The generalization ability of the model across varied conditions and its superior performance against CNN model mark a significant step forward in the application of deep learning technologies in healthcare.

5 MOBILE AND WIRELESS INNOVATIONS IN BREAST CANCER DETECTION

The integration of deep learning technologies in mobile and wireless computing is revolutionizing healthcare by facilitating the deployment of advanced diagnostic tools. Our project, centered on the EfficientNet model, exemplifies this innovation. EfficientNet, known for its computational efficiency and scalability, stands out as an ideal candidate for future mobile health applications, compared to traditional CNN models.

EfficientNet's design incorporates a novel compound scaling method that systematically optimizes depth, width, and resolution, which enhances performance without substantial increases in computational demand. This attribute makes it exceptionally well-suited for environments where computational resources are limited, such as mobile devices. In contrast, traditional CNN models often require significant computational power and may not perform optimally on mobile platforms due to their intensive processing needs.

The main advantages for this model in mobile integration are:

(1) **Reduced Computational Load:** EfficientNet's ability to achieve high accuracy with fewer parameters directly translates into reduced computational load. This reduction is critical in mobile contexts where hardware capabilities are inherently constrained.
(2) **Scalability:** The scalable architecture of EfficientNet allows it to adapt seamlessly across different devices with varying processing powers. This scalability ensures that the model remains effective whether deployed on high-end servers or integrated into mobile health applications.
(3) **Accessibility:** Mobile computing allows breast cancer detection tools to be used anywhere, providing access to high-quality diagnostics in under served regions.
(4) **Energy Efficiency:** Mobile devices operate under strict energy constraints. EfficientNet's efficient use of computational resources minimizes energy consumption, which is vital for prolonged operational periods in mobile applications, enhancing the feasibility of its deployment in remote patient monitoring systems.
(5) **Real-Time Data:** Wireless capabilities enable real-time data capture and analysis, facilitating immediate decision-making and early intervention.

While our focus has been on demonstrating the superiority of the EfficientNet model in controlled tests, the inherent characteristics of this model pave the way for transformative applications in mobile health. Its deployment could democratize access to advanced diagnostic tools, making them available directly on smartphones and tablets used by healthcare providers in diverse settings.

6 LIMITATIONS AND FUTURE WORKS

In advancing the application of the EfficientNet model for breast cancer detection, our research has highlighted several areas of limitation that warrant further discussion and consideration. Addressing these limitations is crucial for ensuring the model's robustness and applicability in real-world settings.

6.1 Limitations

One of the primary limitations observed in our study relates to the dependency of the EfficientNet model on the quantity and quality of the training data. Despite its advanced architecture, the model's performance is inherently tied to the representativeness and diversity of the input data. In scenarios where data is scarce or lacks variability, particularly from under-represented populations or less common cancer types, the model's ability to accurately generalize decreases. This limitation is critical, as it may affect the model's diagnostic accuracy in diverse clinical environments.

While EfficientNet has shown promising results in controlled tests, its ability to generalize to new, unseen medical cases remains a challenge. The histopathological images used in training may not fully encapsulate the variability encountered in everyday medical practice, where new patterns of cancer manifestation can emerge. This issue is compounded by demographic and genetic differences across populations, which may not be adequately represented in the training dataset.

6.2 Future Works

Looking ahead, there are several exciting directions for enhancing the capabilities of our EfficientNet-based system for breast cancer detection. First, integration with Internet of Things (IoT) healthcare devices could significantly amplify the model's effectiveness. By enabling continuous monitoring and real-time data collection, these devices can provide dynamic inputs that refine and improve model accuracy over time, adapting to patient-specific conditions and variations in tumor presentation.

Moreover, exploring alternative deep learning architectures that address some of EfficientNet's limitations could yield substantial benefits. Future research will consider architectures known for lower latency and better handling of unstructured data, which are critical for improving processing times and expanding the types of data the model can effectively analyze. This exploration is particularly pertinent as it may lead to more adaptive and faster diagnostic tools, thereby enhancing patient outcomes through timely and accurate diagnosis.

7 CONCLUSION

Throughout this project, we rigorously analyzed the performance of deep learning model Convolutional Neural Networks (CNNs) vs EfficientNet, focusing on their capacity to detect and predict breast cancer from histopathological images. Our findings consistently underline the exceptional capabilities of EfficientNet, which surpasses other models in terms of accuracy and computational efficiency.

EfficientNet's advanced architecture achieves an optimal balance between depth, width, and resolution, thereby reducing computational demands without compromising on model performance. This unique feature renders it exceptionally well-suited for deployment in resource-constrained environments, such as mobile health applications. The integration of EfficientNet into mobile platforms can transform breast cancer diagnostics, offering healthcare professionals tools that support real-time, accurate diagnosis right from their mobile devices. This can greatly increase the accessibility of high-quality healthcare services, particularly in remote areas or in regions where medical resources are limited.

By adopting EfficientNet, this project not only enhances the efficiency and accuracy of breast cancer screening but also sets the stage for a revolution in the early diagnosis and treatment of breast cancer. The potential of EfficientNet to improve patient outcomes and redefine the standards of care in oncology is immense, promising a future where advanced technology and healthcare converge to save lives.

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