Performance vs Computational Costs: A Study of Trade-offs in Deep Learning Models for Breast Cancer Detection

Lakshay Garg  
 School of Computer Science Engineering & Technology,  
Bennett University,Greater Noida, India

[E22CSEU1245@bennett.edu.in](mailto:E22CSEU1245@bennett.edu.in)

Ananya Nair   
 School of Computer Science Engineering & Technology,  
Bennett University,Greater Noida, India

[E22CSEU1243@bennett.edu.in](mailto:E22CSEU1243@bennett.edu.in)

Gourav Mahajan  
 School of Computer Science Engineering & Technology,  
Bennett University,Greater Noida, India

[E22CSEU1566@bennett.edu.in](mailto:E22CSEU1566@bennett.edu.in)

Ankit Yadav\*  
School of Computer Science Engineering & Technology,  
Bennett University,Greater Noida, India  
[ankit4607@gmail.com](mailto:ankit4607@gmail.com)\*

Sanya Gupta  
 School of Computer Science Engineering & Technology,  
Bennett University,Greater Noida, India

[E22CSEU1750@bennett.edu.in](mailto:E22CSEU1750@bennett.edu.in)

*Abstract*—This study investigates the tradeoff between performance and computational cost in deep learning models for breast cancer detection from medical images. We analyze five common architectures: DenseNet121, ResNet18, EfficientNet, XceptionNet, and MobileNet, using a variety of performance and computational measures. Model performance is measured by accuracy, precision, recall, and F1-score, while computational cost measures parameters, multiply-accumulate operations (MACs), and floating-point operations per second (FLOPs). Evaluating on the BreakHis dataset, XceptionNet has the best accuracy at 96.83%, followed by MobileNet at 94.79% and EfficientNet at 92.55%. The most computationally expensive model is ResNet18 with 25.6 million parameters, followed by XceptionNet with 22.9 million. MobileNet (4.2 million parameters) and EfficientNet (5.3 million parameters) are the smallest and most efficient architectures. The best model is MobileNet, which balances performance and computational economy. Despite having the fewest parameters, it has the second-highest accuracy.

Keywords—Breast Cancer Classification, Histopathological Image Analysis, Deep Learning in Medical Imaging, BreakHis Dataset

# Introduction

Breast cancer is one of the most commonly and dangerous type of cancer which spreads to the tissue of the breast and the cells breed without any control. In reality, the first mention of the breast cancer was recorded by the Egyptians around 1600 BC, but treatments for it were not recorded in a vivid way[1]. Since then a number of studies in medical research, diagnostic techniques and awareness campaigns have contributed to offering improved detection and treatment options. Breast cancer, despite everything, is still one of the most common causes of cancer death in women. According to the latest statistics worldwide, breast cancer makes up approximately 12–13% of all newly diagnosed cases of cancer each year and there are more than 2.3 million new cases and well over 680 000 deaths worldwide in 2020[2]. As a result, there is a high incidence rate, thus, further advances in early detection and diagnosis.

## AI and Machine Learning Application in Breast Cancer Diagnosis

AI and ML have significantly improved the diagnoses carried out in healthcare and, more specifically, in cancer. The techniques of image analysis enabled by AI could contribute to an early and accurate detection of breast cancer, which are identified as key elements for improving survival rates[3][4][5]. Machine learning models have been successfully used for finding patterns and anomalies in mammograms, ultrasound images, and histopathological samples that even human radiologists might miss[3]. Recent vision models have brought capabilities in this purpose and have been successful in forming a new discipline in this diagnosis of breast cancer. In resource constrained environments, MobileNet, with its compact architecture, has shown great promise in such domains[6].

### Key Vision Models for Breast Cancer Detection

***DenseNet121:*** A DenseNet121 model uses the densely connected architecture, which improves information flow between network layers. It helps in detailed feature extraction through complex breast tissue images. This model has been found highly effective in the identification of cancerous lesions associated with mammograms, where even subtle variations indicate early-stage cancers [4].

***ResNet18:*** The skip connections in ResNet18 do not produce vanishing gradients, which lead to a network that becomes more and more accurate with depth. This model has been especially helpful for radiologists who identify very hard-to-focus areas by the human eye in the early-stage detection of breast cancer on medical images [3].

***MobileNet:*** Deep learning model specifically designed for mobile and embedded devices is called MobileNet. It achieves high accuracy by being computationally efficient involving use of depth wise separable convolutions[6]. In low resource environments or portable medical devices where computational resources are limited MobileNet is particularly useful for breast cancer detection [5].

***Xception:*** The Xception model is better than Inception architectures. Its superior pattern capturing capacity afforded by its cameras is superior to that of traditional methods, it is an useful tool for breast cancer imaging image analysis, especially identifying subtle abnormality in histopathological image [7].

Fig. The accuracy (Y-axis) vs number of parameters (X-axis) vs MAC (size of bubble) comparison of models. The best performing model (highest on Y-axis) is XceptionNet. The model with the most parameters (rightmost on X-axis) is ResNet.

***EfficientNet:*** This architecture has also been evaluated for its computationally efficient design utilizing scaling in that the network depth, width, and resolution are balanced. As a result, it is a good option for large scale breast cancer imaging because it maintains high accuracy in the mammogram analysis, with little computational overheads[1].

## Comparative Performance of Models in Breast Cancer Detection

Each of these vision models has been considered for the above key metrics. Such models are crafted to be highly efficient as well as accurate in the analysis of images concerning detection in breast cancer. While MobileNet and Xception are effective at capturing complex patterns, they could be applied in multi-modal imaging approaches. ResNet18 may be more balanced between its cost in computation and accuracy, supporting it in real-time analysis within clinical settings[3][5][7]

## Role of AI in Early Detection and Diagnostic Accuracy

Early and accurate diagnosis plays a crucial role in breast cancer treatment because, traditionally, the success of the treatment process largely depends on early-stage cancer detection. AI models have emerged as a critical component in overcoming these issues of early detection because they reduce diagnostic delays, minimize human errors, and standardize interpretation across different clinical environments. Such models can be used with radiologists to pinpoint areas of concern and thus assist in faster and more reliable diagnostic workflow[3][5][1].

Challenge with breast cancer image analysis Indeed, the variability of the appearance of the tumor, differences in imaging modalities, and subtle expression characteristics of early-stage cancer make challenges in breast cancer imaging. AI and ML are unique in handling such challenges because they can be trained to recognize diverse imaging patterns, improve specificity in the identification of the cancerous lesion, and adapt to the diverse nature of images. All of these capabilities make vision models a hub tool in breaking the limits of traditional diagnostic methods.

## Clinical Impact and Real-World Applications

Currently, we are seeing proofs of concept that AI models are having real benefit in breast cancer screening and diagnosis. For example, DenseNet121 and EfficientNet have been used to perform large-scale mammogram analyses using state-of-the-art detection accuracy without using traditional methods[4][1]. In addition, research on MobileNet and Xception indicate their promise in multi modal imaging and brings a more detailed and expansive view of disease progression[6]. However, these are not just better diagnostics; they also establish the confidence that even complicated cases may be detected. However, these models are already making a significant difference to the way healthcare professionals manage high risk cases and complex imaging situations while still in their early integration into real world clinical settings[3][5][1].

# Literature Review

Tan et al. (2019) proposed a new scaling method for CNNs called EfficientNet which achieved superior performance than other models within fewer parameters and FLOPs. This work highlighted on reasons on how model scaling can lead to efficient results in deep learning. As compared to other architectures such as ResNet and DenseNet net, EfficientNet attains higher accuracy at less computational expense which makes it the new standard for efficient architectures.

He et al. (2016) proposed Residual Networks (ResNets) in which one bypasses the vanishing gradient problem by adding shortcuts between layers to allow gradients to flow freely in deep frameworks. ResNets brought about a huge improvement in the depth of the Neural Networks in addition to the performance of the deep networks. Compared to EfficientNet, ResNet employs deeper layers for representation learning; on the other hand, EfficientNet achieves a global balance of depth, width and resolution scales.

In Huang et al. (2017), the authors developed DenseNet that formed feed-forward connections between all layers. This approach optimizes the model by the reuse of features, it gets rid of redundancy, and produces compact models. With respect to the efficiency of parameters, it is clear that the DenseNet forms better structures for the required images even if it does not significantly best the ResNets in accuracy of the resultant structure. While the EfficientNet model focuses on the right scaling strategy, there is DenseNet which focuses on the gradient flow and sharing of parameters.

In MobileNetV2 (Sandler et al., 2018), inverted residuals and linear bottlenecks are introduced to reduce resource requirements for networks featuring deep structures in low resource devices and mobile setting. EfficientNet shares low computational cost with MobileNetV2 but has a different, mobile vision task optimized architecture.

In 2017, Chollet et al. used Xception a CNN architecture that takes advantage of depthwise separable convolutions to boost model performance and efficiency. Inception models with a simplified and optimized architecture can be thought of as being an extension of Xception. Under comparing with EfficientNet, Xception is designed to optimize layer operation, not just scaling model dimension.

In Spanhol et al. (2016) they explored breast cancer histopathological image classification using CNNs. The variability of histopathological images made it a challenge to classify them and robust feature extraction was deemed important. This work highlights the need for efficient and accurate modeling — such as EfficientNet — for medical imaging.

Gradient descent optimization algorithms have been overviewed by Ruder (2017) who, among other things, analyzed the pros and cons. The work also include Adam and RMSprop, which helps improve training stability. Finally, such optimizations help in model training — not in its architecture, as the study does not explicitly address this — but they provide benefits when training EfficientNet.

However, Loshchilov et al. (2017) suggested to escape on the convergence trap by applying SGDR (Stochastic Gradient Descent with Warm Restarts), which periodically restarts the learning rate. This presumably allows enhancement of the convergence efficiency during training for other types of architectures like that of EfficientNet.

In the paper of YIn et al. (2024) they proposed a model based on multimodal fusion to combine different imaging modalities to obtain a better segmentation accuracy for breast tumor segmentation using ultrasound imaging modalities. In comparison to this work focuses on multimodal integration rather than network scaling; however, EfficientNet's principles could be applied to such tasks.

In their recent work, Elsabawy et al. (2023) explore ensemble machine learning techniques for breast cancer detection. However, by combining multiple models, our study found that prediction accuracy is improved. In ensembles, EfficientNet can be a base model, because it is a high efficiency and accuracy model.

In (2017) Howard et al. introduced MobileNets, a low cost CNN architecture for mobile and embedded systems. As with EfficientNet, the core principle of this architecture is efficiency, but depthwise separable convolutions are used as the primary design principle.

Practical recommendations for training deep architectures using gradient based methods were provided by Bengio et al. (2012). In particular, the paper outlined the problems of common training such as overfitting, initialization and learning rate schedule. These recommendations work out as fairly well with EfficientNet via the use of advanced techniques such as learning rate warmups and proper initialization during training.

Pereira (2024) indicated that medical imaging is also dependent on perception research and how perceptions influence improving diagnostic models. However, as it turns out, this research makes it clear that EfficientNets like CNNs need to virtually mimic human feature perception and analysis well, at least in domains like breast cancer imaging.

# Methodology

This work compares five state of the art deep learning models: DenseNet121, ResNet18, MobileNet, Xception, and EfficientNet in predicting benign or malignant histopathological images of breast cancer that are present in BreakHis dataset. The section starts with the description of the dataset, followed by the description the loading and preprocessing of the data, the type of the model, the training procedure, the evaluation metrics and other methodological aspects that are required for the conducting experiments in an efficient manner. and analysis of results.

## Dataset: BreakHis

The BreakHis dataset is an open-source collection of 7,909 histopathological images from benign and malignant breast tumors. Captured at four magnification levels: 40x, 100x, 200x, and 400x, each sample is annotated as either benign or malignant. Its heterogeneity is very high; images come from multiple patients and diverse imaging conditions, making it a complete testbed for assessing model robustness in breast cancer classification[8]. As shown in ***Fig:1***, these images exhibit diverse structural and histological patterns.

*Class Distribution***:** The dataset has an imbalance; there are more images within the malignant class. Stratified sampling was used to preserve such a distribution in all different splits of training, validation, and test sets.

*Scale-Level Analysis:* The various scales allow for a range of structural information. Models were tested at both individual scale levels and the combined dataset to investigate performance over multiple scales[8].

A collage of cells under a microscope

Description automatically generated

Fig. Some samples of breast cancer images.

## Data Loading and Preprocessing

Data loading and preprocessing is important when working with high resolution histopathological images especially with deep learning models like MobileNet and Xception. The following were done:

*Image Resizing:* All images were resized to 224x224, the input size supported by MobileNet and Xception[5][1].

*Normalization:*Images were normalized using ImageNet mean [0.485, 0.456, 0.406] and std [0.229, 0.224, 0.225]. This step aligns the dataset’s pixel intensity distribution with the expectation of pre-trained MobileNet and Xception models for better transfer learning[5][1].

*Data Augmentation:* To improve model generalization and robustness the following augmentations were done:

* Random Flips (horizontal and vertical) and Random Rotation (-10° to +10°) to address orientation variability.
* Random Cropping and Zooming to focus on different parts of the image and help the models learn from different perspectives.
* Color Jitter, Gaussian Blur and Random Contrast Adjustments to simulate real world imaging variability.
* Elastic Deformation to make the models more sensitive to subtle texture changes in histopathological tissues which is important for classification[4][7].*Data Split:* The dataset was split into training (80%) and validation (20%) using stratified sampling. This way the benign to malignant ratio is consistent across all splits.

## Training Methodology

The pre trained architectures were pre-trained on ImageNet and then fine-tuned on BreakHis dataset. A comparative analysis of the computational requirements for each model architecture is shown in Table 2*.* For fine-tuning on the BreakHis dataset, we modified each model by replacing the final layer with a binary classifier for benign/malignant classification.

## Evaluation Metrics

To evaluate the performance of the deep learning models, we employed four key metrics: that is, accuracy, precision, recall, and F1 score. These metrics allow us to assess complete classification performance of histopathological images to benign and malignant classes. To ensure a well-rounded evaluation of the models, we report the results from our experiments in this form.

*Accuracy:*Accuracy measures the proportion of correctly classified samples out of the total samples. It is a general indicator of the model's performance:

*Precision:*Precision is the correctness of the model predicting positive cases correctly, i.e the ratio of true positives to all positive cases:

*Recall (Sensitivity):*Recall measures the ability of the model to identify true positives, i.e., the proportion of actual positive cases (malignant images) that the model correctly classifies:

*Recall* =

*F1 Score:*F1 score is defined as the harmonic mean of precision and recall, since it is balanced measure, especially if classes are imbalanced[7][1].

*F1 Score* =

F1 scores of EfficientNet and Xception were high, which means that these two models had balanced performance in finding true positives and minimizing both number of false positives and false negatives.

# Experimental Settings

An experimental setup was designed for training and evaluating deep learning models for reduced efficiency and reproducibility. The following settings were used:

*Loss Function:* The Binary Cross-Entropy Loss function was used as the objective metric since it is naturally achievable for a binary classification task. Predicted probabilities are classified as either benign or malignant breast cancer cases with minimum error between the predicted probabilities and ground truth labels, effectively classifying cases as benign or malignant breast cancer. BCE Loss is defined as:

where yi​ is the true label, ​ is the predicted probability, and N is the number of samples. BCE Loss is widely used in medical imaging tasks because of its ability to handle imbalanced datasets effectively.

*Optimizer:* The Adam Optimizer was used because of its adaptive learning rate capabilities, as well as efficient sparsity handling. This optimizer is particularly beneficial for training deep learning models on high dimensional medical imaged datasets[9].

*Learning Rate (LR):* A cosine annealing scheduler for the learning rate decay and an initial learning rate of 0.001 were used. The models attained more stable convergence throughout later training stages thanks to this scheduling strategy[3][10].

*Batch Size:* The balance between computational efficiency and the stability of gradient updates was obtained by choosing a batch size of 32. They were of a proper size for processing high resolution histopathological images[7][11].

*Epochs and Early Stopping:* Models were trained for 3 epochs in a rapid training – for computational efficiency. The amount of training that each of the models had was limited, and thus validation loss was monitored to confirm that the models were indeed learning during this training. No early stopping mechanisms were applied as the number of epochs was very small[12].

# Result & Disscussion

The five deep learning models Densetn121, Resnet18, EfficientNet, Xception, MobileNet are evaluated on histopathological breast cancer image classification. and the performance metric, Are Accuracy, Precision, Recall and F1 score. *Table 2* summarizes the results obtained by each of the models.

## Performance Comparison & Discussion

This section presents the performance of the five deep models. Table 1 shows the performance scores across four metrics: accuracy, precision, recall and F1-score.

Table Performance of models for Breast Cancer Classification

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** |
| DenseNet121 | 90.57 | 90.48 | 90.57 | 90.44 |
| ResNet18 | 87.14 | 87.26 | 87.14 | 86.61 |
| EfficientNet | 92.55 | 92.50 | 92.55 | 92.52 |
| Xception | 96.83 | 96.88 | 96.83 | 96.85 |
| MobileNet | 94.79 | 94.85 | 94.79 | 94.81 |

Fig. Accuracy comparison of models for breast cancer detection.

Fig. F1-score comparison of models for breast cancer detection.

Fig. 3 and Fig. 4 present the visual comparison of accuracy and F1-score for models respectively.

*Xception* achieved the highest performance across all metrics, with an accuracy of 96.83% and an F1-Score of 96.85%, making it the best performing model for breast cancer classification in this study. This result highlights the effectiveness of Xception's architecture in capturing intricate patterns in histopathological images.

*MobileNet* also performed exceptionally well, achieving an accuracy of 94.79% and an F1-Score of 94.81%. Its lightweight design makes it the best candidate for deployment in real-time or resource-constrained environments without significant loss in accuracy.

*EfficientNet* struck a balance between computational efficiency and performance, with an accuracy of 92.55% and an F1-Score of 92.52%. Its compound scaling design enables the resource to be fully utilized for classification - whilst at the same time retaining stability.

*DenseNet121*, though little behind EfficientNet, performed a 90.57% accuracy by densely connecting the layers and hence effectively extracted the details in the histopathological images.

*ResNet18*, exhibited the lowest performance among the models, with an accuracy of 87.14% and an F1-Score of 86.61%. However, because of its basic structure and lightweight computation, it is reasonable for applications with restricted computation power.

## Computational Cost Comparison

This section presents the computational cost associated with each of the models. Three computational parameters have been evaluated for each model namely, number of parameters, MACs and FLOPs as presented in Table 2 and Fig. 5.

Table Computational cost comparison of models.

|  |  |  |  |
| --- | --- | --- | --- |
| **Models** | **No. of Params (millions)** | **MACs**  **(billions)** | **FLOPs**  **(billions)** |
| DenseNet121 | 7.98 | 2.8 | 5.6 |
| ResNet18 | 25.6 | 3.6 | 7.2 |
| Xception | 22.9 | 4.1 | 8.2 |
| MobileNet | 4.2 | 0.569 | 1.14 |
| EfficientNet | 5.3 | 0.390 | 0.78 |

# Conclusion, Challenges and Limiations & Future Work

## Conclusion

To evaluate the performance of the five deep learning models (DenseNet121, ResNet18, EfficientNet, Xception, and MobileNet) for breast cancer classification using histopathological images from the BreakHis dataset, this study. Accuracy, precision, recall and F1 Score - important values to measure the precision of these models in discovering malignancy effectively as well as assessing their robustness in doing so.

Out of all the models used, Xception proved most accurate to our problem, achieving 96.83% in accuracy and 96.85% in F1-Score. While the lightest model MobileNet was competing with a second-best accuracy of 94.79% and with an high F1-Score of 94.81%. It’s an appealing candidate for real time applications in resource constrained environments where computation efficiency is essential. On the other hand, EfficientNet achieved a good balance between accuracy and computational efficiency in large scale image analysis, and the results were solid. With an accuracy of 92.55% and an F1-Score of 92.52%, it proved both fit for high performance and resource efficient situations. Other robust models, such as DenseNet121 and ResNet18, were a bit worse than more advanced architecture.

## Challenges and Limitations

However, despite strong performance, the inherent variability of histopathological images has not been addressed to a satisfactory extent[13]. However, these images are often different for multiple reasons one of which is the use of different staining techniques and different magnification levels[14]. Additionally, the dataset may be imbalanced (more malignant than benign samples), which may also have impacted some performance metrics, like recall and precision[15]. To deal with this, we used data splitting using stratified sampling, but more advanced techniques like class weighting could still further increase model performance[15].

Fig. Comparison of computational cost of models.

## Future Work

Several avenues exist for improving the performance and applicability of these models:

* *Integration of Multi-modal Data:*Other imaging modalities such as mammography or MRI could be mixed with histopathological pictures in future studies to increase model robustness and accuracy[16].
* *Larger and More Diverse Datasets:*By testing on larger, more diverse datasets we can make a more thorough evaluation of generalizability of these models over other populations[11].
* *Ensemble Learning:*The strength of individual designs could be harnessed by combination of different models using ensemble approaches[17].
* *Addressing Dataset Bias:*In the last, we still need to do more work on how to resolve the dataset biases brought about by class imbalance and image quality variability to further improve the models’ performance in the real world clinical setting[18].

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