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Computational Efficiency and Accuracy of Deep Learning Models for Automated Breast Cancer Detection in Ultrasound Imaging

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ABSTRACT This study explores the trade-off between diagnostic performance and computational efficiency in deep learning models for the classification of breast cancer in ultrasound images. To this end, we evaluate three contemporary CNN architectures EfficientNetB7, EfficientNetV2-Small, and RexNet-200 in a multiple comparative study with standardized performance and complexity metrics. Our evaluations provide evidence that all three models achieved an identical high accuracy of 95.00%, but there were sizeable differences in the computational resources required to achieve that accuracy. RexNet-200 demonstrated tremendous computational efficiency, achieving identical performance with the least amount of resources (13.81M parameters; 3.05 GFLOPs) required compared to EfficientNetB7 which is much more computationally intensive. An examination of the confusion matrix for the models enhances the models clinical validity, as there are no malignant lesions misclassified as normal. Ultimately, our study clearly demonstrates that diagnostic accuracy is not a good metric for practical clinical deployment. RexNet-200, by representing high performance, with minimal resource utilization, is the most pragmatic and clinically applicable model, creating the opportunity to develop scalable and accessible CAD systems in resource-limited settings.

KEYWORDS
Breast cancer
Breast ultrasound
Deep learning
Computational efficiency
RexNet-200

INTRODUCTION

Breast cancer represents one of the most prevalent malignancies among women globally, characterized by the uncontrolled proliferation of epithelial cells within the breast tissue (Kim *et al.* 2025; Xiong *et al.* 2025). The etiology of the disease is rooted in a complex interplay of genetic predisposition with hormonal, environmental, and lifestyle factors (Obeagu and Obeagu 2024). As early detection significantly enhances treatment success and survival rates, the development of effective screening and diagnostic methodologies is of paramount importance. In this context, non-invasive medical imaging modalities assume a fundamental role in identifying pathological changes within the tissue (Kiani *et al.* 2025; Alshawwa *et al.* 2024; Begum *et al.* 2024). Although mammography is the cornerstone of standard screening, its diagnostic efficacy can be diminished, particularly in women with dense breast tissue, underscoring the need for supplementary imaging techniques (Katsika *et al.* 2024; Trentham-Dietz *et al.* 2024; Abeelh and AbuAbeileh 2024).

Owing to advantages such as its non-ionizing nature, widespread accessibility, and cost-effectiveness, ultrasonography is regarded as a valuable instrument for evaluating breast lesions (Iacob *et al.* 2024). It provides distinct benefits in clarifying suspicious mammographic findings, differentiating between cystic and solid masses, and guiding biopsy procedures, enhancing the characterization of lesions in women with dense parenchyma (Gordon *et al.* 2025). Nevertheless, its utility is constrained by certain limitations, including operator dependency, inter-observer variability in interpretation, and an inadequate capacity to detect microcalcifications. These challenges necessitate the development of more objective and standardized methodologies for the interpretation of ultrasound images (Vogel-Minea *et al.* 2025; Rana *et al.* 2024).

Recently, artificial intelligence (AI), and specifically deep learning (DL) techniques, have prompted a paradigm shift in the analysis of medical images (Karaman *et al.* 2023; Pacal *et al.* 2025; Pacal and Attallah 2025a; Zeynalov *et al.* 2025). Architectures such as Convolutional Neural Networks (CNNs) are delivering groundbreaking results in fields like radiology and pathology, attributed to their capacity to autonomously extract hierarchical features from large-scale datasets (Pacal 2024; Ozdemir *et al.* 2025; Lubbad *et al.* 2024b). In the context of breast cancer, DL models have demonstrated high success rates in the detection, classification, and segmentation of lesions across various imaging modalities, including mammography, ultrasound, and MRI (Pacal and Kılıcarslan 2023; COŞKUN *et al.* 2023; İnce *et al.* 2025; Lubbad *et al.* 2024a).

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The present study aims to enhance the effectiveness and accuracy of early breast cancer diagnosis through DL-based analysis of ultrasound images (Pacal and Attallah 2025b; Cakmak *et al.* 2024; Kurtulus *et al.* 2024; Bayram *et al.* 2025; Pacal 2025). Accordingly, a comparative performance evaluation is conducted by training three modern CNN architectures EfficientNetB7, EfficientNetv2-Small, and RexNet-200 on a publicly available breast ultrasound dataset. The ultimate objective of this research is to identify the architecture that offers the highest efficiency and performance for this specific diagnostic task (Pacal 2022; Cakmak and Pacal 2025).

The field of medicine is undergoing a profound transformation through the integration of artificial intelligence (AI) and its sub-disciplines, machine learning (ML) and deep learning (DL) (Obuchowicz *et al.* 2024; Koçak *et al.* 2025). These technologies present groundbreaking opportunities across a broad spectrum, from the early diagnosis of diseases to the personalization of treatment protocols and from drug discovery to the decryption of complex biological data (Li *et al.* 2024; Islam *et al.* 2024). The domain of medical imaging, in particular, holds significant potential due to the capacity of AI algorithms to detect subtle patterns beyond human perception and to rapidly analyze vast volumes of data (Chambi *et al.* 2025; Meng *et al.* 2024). Disciplines such as radiology, pathology, and oncology are swiftly adopting AI-powered systems for their potential to enhance diagnostic accuracy and improve patient outcomes. In the management of prevalent health issues like breast cancer, the fusion of AI with accessible imaging modalities such as ultrasound (US) opens new horizons for advancing early detection capabilities (Rajkumar *et al.* 2024).

Current research in the literature is focused on both developing integrated clinical decision support systems for breast cancer diagnosis and enhancing model performance through hybrid approaches. For instance, Gagliardi et al. proposed a holistic system that provides radiologists with both a segmentation mask and a classification result, reporting clinically valuable outcomes on the BUSI dataset with over 90% accuracy, 92% precision, and 90% recall (Gagliardi *et al.* 2024). In a different approach, Abhisheka et al. achieved an accuracy of 89.02% and an AUC of 0.8717 with a hybrid model (HBCPS) that combines deep learning (ResNet50) and handcrafted (HOG) features, using an SVM as the classifier (Abhisheka *et al.* 2025). Along similar lines, Latha et al. leveraged an EfficientNet-B7 architecture augmented with advanced data augmentation and interpretability (XAI) techniques like Grad-CAM, attaining a superior classification accuracy of 99.14%, particularly in recognizing minority classes (Latha *et al.* 2024).

Other lines of investigation are directed towards exploring segmentation performance, computational efficiency, and the potential offered by next-generation architectures like Mamba. In this context, Umer et al. focused on the segmentation task with a U-shaped autoencoder featuring a multi-attention mechanism, achieving high Dice scores of 90.45% and 89.13% on the UDIAT and BUSI datasets, respectively (Umer *et al.* 2024). With the objective of reducing computational cost, Cai et al. developed SC-Unext, a lightweight architecture, demonstrating the importance of model efficiency with 97.09% accuracy and a 75.29% Dice score (Cai *et al.* 2024). Finally, Sarvi et al. revealed that Mamba-based architectures can deliver significant performance gains over traditional CNNs and Transformers up to a 1.98% increase in AUC and 5.0% in accuracy by better capturing long-range dependencies in limited data scenarios (Nasiri-Sarvi *et al.* 2024). These collective efforts indicate that the field is in a state of continuous evolution towards more accurate, efficient, and innovative models.

MATERIALS AND METHODS

Dataset

For this study, we utilized the publicly available dataset "Breast Ultrasound Images Dataset" provided by sabahesaraki on Kaggle, for classifying breast ultrasound (US) images (Kaggle 2025). This dataset contains pathologically proven breast lesions with three basic classes of benign, malignant, and normal breast tissue. The heterogenous dataset serves as a valuable resource to evaluate deep learning models' ability to differentiate tissues with different morphologies and lesion types.

To ensure standardization and reproducibility in the model development and evaluation phases, the collection of 780 images (437 benign, 210 malignant, 133 normal) was methodically partitioned into training, validation, and testing subsets. This division allocated 70% of the collection (545 images) for model training, 15% (115 images) for the validation process, and the remaining 15% (120 images) for the test phase to impartially assess final model performance. This strategic partitioning aims to facilitate model training on sufficient data while reliably measuring generalization capabilities and mitigating the risk of overfitting. Furthermore, potential model bias towards any specific class was addressed by ensuring that the class distribution within each subset mirrored the proportions of the original dataset. Accordingly, the training, validation, and test sets were structured to contain (305B, 147M, 93N), (65B, 31M, 19N), and (67B, 32M, 21N) samples, respectively. A schematic of this dataset partitioning is also visualized in Figure 1.

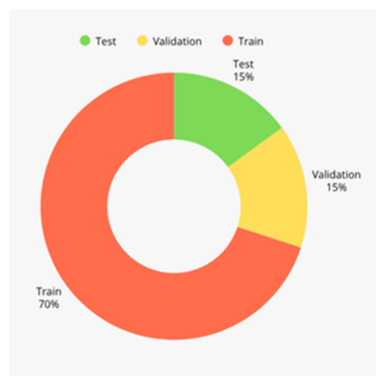

Figure 1 The Breast Ultrasound Images dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing.

To elucidate the composition of the dataset and the visual distinctions among its classes, representative ultrasound images for each category (benign, malignant, and normal) are presented in Figure 2. Upon examination, benign lesions typically exhibit well-defined contours and a homogeneous internal structure. In contrast, malignant lesions often display morphological characteristics such as irregular borders, spiculated margins, and a heterogeneous internal echo pattern. Normal breast tissue, for its part, reflects characteristic fibroglandular and adipose tissue patterns. These examples not only highlight the morphological differences between the classes but also expose the inherent challenges associated with ultrasound imaging, such as speckle noise and low contrast. This visual presentation provides a valuable context for understanding the key distinguishing features that the models must learn to identify, and for appreciating the diversity encapsulated within the dataset.

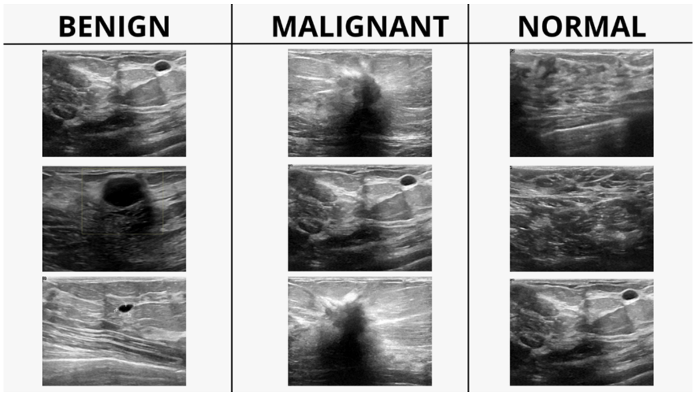

Figure 2 Sample ultrasound images from the dataset belonging to the benign, malignant, and normal classes.

Data Augmentation

To enhance the generalization performance of the deep learning models and mitigate the risk of overfitting a prevalent challenge in limited datasets typical of medical imaging this study incorporated a suite of on-the-fly data augmentation techniques into the training pipeline. As the focus of the task was on classification, the segmentation masks (mask.png) included in the original dataset were excluded from the analysis. The primary augmentation strategies applied to each image during the training loop included the following: images were first subjected to a "Random Resized Crop," where they were randomly cropped to a scale of 8% to 100% of the original area with an aspect ratio between 0.75 and 1.33, and subsequently resized to 224x224 pixels using a random interpolation method. Additionally, a random horizontal flip was applied with a 50% probability. To introduce color diversity, "Color Jitter" was employed, randomly altering the brightness, contrast, and saturation of the images by a factor of 0.4. Vertical flipping was not utilized in this work. This on-the-fly augmentation methodology ensures that the model encounters diverse variations of the data in each training epoch. This approach is designed to prevent the model from becoming overly dependent on the specific artifacts of the training set, thereby fostering a more robust and reliable performance on unseen data (Wang *et al.* 2024; Mumuni *et al.* 2024).

The Used Algorithms

In this research, we use deep Convolutional Neural Network (CNN) architectures, which have been shown to be effective in the computer vision research literature, to automatically classify breast ultrasound (US) images. In fields like medical imaging where there tends to be a small amount of labelled data, the advantage of transfer learning - as opposed to training a model from scratch - is considerable. By using transfer learning in particular fields, it is possible to leverage the feature extraction ability of models pre-trained on large data sets like ImageNet, and then challenge those features in a smaller and more specific target dataset. The use of a transfer learning approach is also intended to facilitate quicker convergence, better generalization, and a reduced chance of overfitting. For our project, all the CNN architectures we used were loaded with pre-trained weights from a model trained on ImageNet, and then we fine-tuned the models on our target breast ultrasound dataset.

The first set of architectures considered includes the EfficientNet family. EfficientNet families of architectures changed how researchers think about model scaling. Tan and Le proposed these architectures that scale model dimensions (Depth, Width, and Resolution) in a systematic way using what they call 'compound scaling' rather than just scaling in a random way. This principle allows for higher efficiency and accuracy using fewer parameters. EfficientNetB7, being a large and performant member of the family and the largest and most performant of the versions (that was scaled in this compound fashion) stands as a baseline for image classification tasks. The second architecture considered, EfficientNetV2-S, is a next-generation architecture that builds on the first and offers both faster training and a more efficient parameter.zip. It uses both MBConv and Fused-MBConv blocks and improved its training strategy to optimally achieve a good balance of speed and accuracy, especially for the S (Small) version (Tan and Le 2019, 2021).

RexNet-200, another modern architecture that we evaluated, was created for addressing the 'representational bottleneck' problem raised by standard designs. Rank eXpansion Networks (RexNets), as introduced by Han et al., are based on the idea that in standard convolutional blocks, channel narrowing-and-widening operations can lose information. RexNets work around this issue by providing blocks for networks to preserve and build the 'rank' of inter-layer channel representations, or the amount of unique information. This construction can facilitate a fuller and more varied flow of features between the layers, and thus increase the model's representational capabilities. RexNet-200, which we used in the study, is a higher-performing type of this architecture (with a 2.0 scaling factor) (Han *et al.* 2021).

Three distinct and contemporary CNN architectures EfficientNetB7, EfficientNetV2-S, and RexNet-200 were chosen to compare their respective performance in classifying breast ultrasound image classes as benign, malignant, and normal. Each model has its own design philosophies and contributions, including compound scaling, training optimization, and overcoming representational bottlenecks, which provides a broad view of the variability in CNN approaches to this complex medical classification task. The models are evaluated using comprehensive metrics to derive meaningful conclusions regarding the most suitable architecture for this task.

Performance Metrics

Measuring the performance of deep learning models is a critical step for assessing the practical value of these models, justifying methodological choices, and allowing data-driven choices. Relying on performance measures can have different purposes, such as evaluating the effectiveness of a model, guiding the optimization process, guarding against data errors or biases, allowing for an objective comparison between models, and identifying phenomena such as overfitting. The current paper adopts conventional evaluation criteria that are established and accepted in the academic literature that is specific to the issue of breast cancer classification.

The primary metrics employed within this project accuracy, precision, recall, and F1-score are indicators of central importance not only in deep learning evaluations but also in other disciplines. Accuracy, which offers an initial impression of general performance, is the ratio of correct predictions to the total number of instances. Precision, which measures the exactness of positive predictions, reflects the reliability of the model's positive labeling; high precision implies a low false positive rate. Recall, which measures the model's ability to identify all actual positive cases, indicates its success in detecting events that should not be missed. The F1-score, which combines these two metrics into a single measure, is the harmonic mean of precision and recall, serving as a balanced performance criterion that reflects the trade-off between false positives and false negatives. Conceptually, these definitions may also be formulated through the mathematical expressions presented below.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

RESULTS AND DISCUSSION

The comparative analysis, as detailed in Table 1, reveals that the three evaluated architectures each achieved an identical accuracy of 95.00% in classifying breast ultrasound images. Behind this uniform accuracy score, however, lie significant divergences in other performance and complexity metrics. While EfficientNetV2-Small led in precision at 94.89%, EfficientNetB7 yielded the best results for recall and F1-score, at 95.38% and 94.41%, respectively. A striking paradox emerges when these performance data are considered alongside the computational costs of the models: EfficientNetB7, despite possessing some of the highest metrics, is the most resource-intensive model with 63.79 million parameters and 10.26 GFLOPs. In contrast, RexNet-200 attains the same high accuracy with only 13.81 million parameters and 3.05 GFLOPs, proving to be a remarkably efficient alternative that requires approximately 4.6 times fewer parameters and 3.4 times less computational power.

Table 1 A Comparison of Performance and Complexity in CNN Models for Classifying Breast Ultrasound Images

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)	Params (M)	GFLOPs
EfficientNetB7	95.00	93.58	95.38	94.41	63.79	10.26
EfficientNetV2-Small	95.00	94.89	93.75	94.28	20.18	5.42
RexNet-200	95.00	93.38	93.75	93.54	13.81	3.05

These findings demonstrate that for the evaluation of modern deep learning architectures, computational efficiency is a critical factor alongside diagnostic accuracy. RexNet-200, by achieving high accuracy with minimal resources, emerges as the most practical and convenient solution for Computer-Aided Diagnosis (CAD) systems intended for deployment in resource-constrained clinical environments or on local devices. With its high precision and balanced efficiency, EfficientNetV2-Small presents a strong option for scenarios where minimizing false positives is vital. On the other hand, despite its highest recall rate, the heavy computational burden of EfficientNetB7 significantly limits its scalability and practicality for real-world applications. This work clearly establishes the potential of efficient and lightweight architectures like RexNet-200 to enable the development of sustainable and accessible systems for the early diagnosis of breast cancer, without compromising on accuracy compared to their larger, more complex counterparts.

A detailed breakdown of the classification performance for the RexNet-200 model is provided in the confusion matrix presented in Figure 3. The concentration of values along the matrix's diagonal axis is an indicator of the model's success; it correctly classified a total of 116 samples (64 Benign, 31 Malignant, and 21 Normal). An analysis of the errors reveals that 2 Benign cases were misclassified as Malignant, and 1 Malignant case was misclassified as Benign. A particularly noteworthy finding that reinforces the model's clinical reliability is that no errors were made in the 'Normal' class, and crucially, no 'Malignant' case was overlooked as 'Normal' the most critical error scenario. This error profile corroborates the robust performance underlying the model's high accuracy rate.

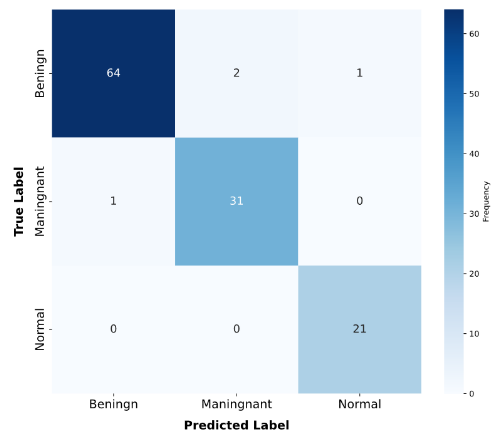

Figure 3 RexNet-200 model confusion matrix for breast ultrasound classification.

CONCLUSION

This study, by comparing three distinct deep learning models for the classification of breast ultrasound images, has demonstrated that computational efficiency is a decisive differentiating factor, even amidst an identical accuracy rate of 95.00%. The results beginning to clearly outline RexNet-200, a model that can know the diagnostic performance equivalent to a more complex architecture such as EfficientNetB7 according to leading metrics, but that comes with far less resource usage. Specifically, there is clearly a large resource-use advantage to the design of this architecture; the model operated with roughly 4.6 times fewer parameters than EfficientNetB7 and 3.4 times lower computational demands on the host system. More importantly, RexNet-200 was confirmed to be clinically robust based on the confusion matrix analysis, especially in terms of not misclassifying diagnoses of malignant as normal.

Thus, at minimum, this study provides evidence suggesting that simply pursuing the highest accuracy metric is not effective for the development of any future modern Computer-Aided Diagnosis (CAD) systems. However, one fundamental change is to move to architectures that maximize the trade-off between diagnostics accuracy and efficiency. Because of the success of RexNet-200 and the rest of our study, it is evident that it is possible to develop a system for the early diagnosis of breast cancer that is high-performance, scalable, sustainable, and can be used in settings where hardware resources are limited. There are several reasons why an efficient CAD model is best for the real world.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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