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Classification of Breast Cancer Ultrasound Images Using Convolutional Neural Network

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Abstract

Breast cancer ranks among the primary contributors to female mortality, thereby underscoring the critical importance of early detection. This research employs a deep learning approach based on Convolutional Neural Networks (CNNs) to classify breast cancer using ultrasound imagery, comparing the ResNet50V2 and MobileNetV2 architectures with three optimizers: Adam, RMSprop, and SGDM. The dataset used in this study is the Breast Ultrasound Images (BUSI) dataset, obtained from Kaggle, which comprises three diagnostic categories: benign, malignant, and normal. The research workflow encompassed several stages, including data acquisition, image pre-processing involving normalization and augmentation, and dataset partitioning using the Holdout Split method, with proportions of 70% for training, 15% for validation, and 15% for testing. The experimental findings revealed that the ResNet50V2 architecture combined with the SGDM optimizer achieved the best performance, recording accuracy, precision, recall, and F1-score values of 92%. Meanwhile, MobileNetV2 with RMSprop achieved the highest performance on its architecture with 86% accuracy, 88% precision, 86% recall, and 86% F1-score. These findings prove that CNN architecture selection and optimization algorithms have a significant influence on medical image classification performance.

Keywords: Breast Cancer, Convolutional Neural Network, MobileNetV2, ResNet50V2, Ultrasound Images

1. INTRODUCTION

Breast cancer continues to rank among the primary causes of mortality in the female population worldwide, establishing it as a significant global health concern [1]. Accurate and early diagnosis of breast tumors significantly contributes to improving patient prognosis by increasing the chances of recovery and minimizing mortality rates [2]. However, breast cancer diagnosis remains challenging due to ultrasound image quality issues, speckle noise, and dependence on radiologist expertise [1], [3]. Based on data from the World Health Organization (WHO), around 2.3 million new breast cancer cases and 670,000 deaths were recorded globally by 2022 [4]. Thus, fast and accurate diagnosis is vital for appropriate treatment selection and reducing healthcare burdens. To address this, CAD (computer-aided diagnosis) systems with deep learning have been introduced to improve breast tumor classification accuracy [5], [6].

Breast ultrasound images (BUSI) are widely used for breast cancer detection as they are safe, non-invasive, and cost-effective. However, their accuracy depends heavily on equipment quality and the radiologist's interpretive expertise [1]. Variations in image quality and the subjectivity of the radiologist's reading lead to a high risk of misclassification, especially in the early stages of diagnosis. Therefore, there is a need for an automated method that can classify images accurately and consistently without being influenced by differences in perception or experience of the operator [7].

Convolutional Neural Networks (CNNs) are widely applied in medical image analysis due to their strong capability to automatically extract hierarchical spatial features from visual data, enabling accurate identification of benign and malignant tumors. Unlike traditional machine learning algorithms that rely on handcrafted feature extraction, CNNs learn discriminative features directly from raw image inputs. This characteristic is particularly important for breast ultrasound images, which often suffer from speckle noise, low contrast, and complex texture patterns. Consequently, CNNs have been successfully utilized across various medical imaging modalities, including mammography, ultrasound, MRI, X-ray, and pathology images, demonstrating superior performance in breast cancer detection and classification tasks [8], [9], [10].

Several previous studies have demonstrated that CNN-based approaches consistently outperform traditional machine learning methods in breast cancer detection and classification tasks. Zakareya (2023) applied a residual-based CNN architecture and GoogLeNet, which resulted in 93% accuracy in the classification of benign and malignant breast cancers [11]. Jabeen (2022) utilized feature extraction from the DarkNet-53 architecture, followed by entropy-based feature selection and probabilistic merging, which achieved 99.1% accuracy on the BUSI dataset [12]. Naeem and Saleem (2024) developed an EfficientNet-B0-based CSA-Net combined with channel and spatial attention modules and the Nadam optimizer, resulting in a classification accuracy of up to 92.3% [13]. Latha (2024) assessed the performance of the EfficientNet-B7 architecture in classifying breast cancer ultrasound images, reaching an accuracy rate of 99.14% [14]. Balasubramaniam (2023) convolutional neural network derived from a modified LeNet architecture to perform direct classification on ultrasound images without relying on transfer learning, achieving an accuracy of 89.9% [15].

Numerous studies have demonstrated the effectiveness of Convolutional Neural Network (CNN) architectures for breast cancer classification using ultrasound images. Previous research has primarily focused on evaluating a single CNN architecture or optimizing model performance using a fixed optimization algorithm. While these approaches have achieved high accuracy, they provide limited insight into how different CNN architectures interact with various optimization strategies during the training and generalization processes.

Therefore, this study addresses this research gap by systematically evaluating two widely used CNN architectures, namely ResNet50V2 and MobileNetV2, in combination with three different optimization algorithms: Adam, RMSprop, and Stochastic Gradient Descent with Momentum (SGDM). Unlike prior studies, this research emphasizes a cross-architecture and cross-optimizer comparison to analyze their influence on convergence stability, generalization capability, and classification performance. This comprehensive evaluation constitutes the main novelty of the present study. The findings are expected to support the development of reliable computer-aided diagnosis systems and assist practitioners in selecting appropriate deep learning models for breast ultrasound image analysis.

2. MATERIAL AND METHOD

Previous studies have established that Convolutional Neural Networks (CNNs) are among the most effective deep learning approaches for medical image analysis, particularly for breast cancer classification using ultrasound images. Compared to traditional machine learning methods, CNNs are capable of automatically learning hierarchical spatial features directly from raw image data, which is essential for handling speckle noise, low contrast, and complex texture patterns commonly found in breast ultrasound images [6], [8], [16]. Consequently, CNN-based models have consistently demonstrated superior performance in breast tumor classification tasks [9], [17].

From a methodological perspective, prior research has shown that classification performance is not solely determined by the CNN architecture, but is also significantly influenced by the optimization algorithm used during training. Adaptive optimizers such as Adam and RMSprop have been widely adopted due to their fast convergence and ability to handle noisy gradients [6], [18], [19]. However, several studies have reported that momentum-based optimizers, such as Stochastic Gradient Descent with Momentum (SGDM), can provide more stable training dynamics and improved generalization performance, particularly in deep neural networks applied to medical imaging tasks [20], [21].

Based on these methodological findings, this study adopts a transfer learning framework using two representative CNN architectures, namely ResNet50V2 and MobileNetV2. ResNet50V2 was selected due to its residual learning mechanism, which effectively mitigates the vanishing gradient problem and enhances training stability in deep networks [22], [23]. In contrast, MobileNetV2 was chosen for its lightweight architecture and computational efficiency, achieved through depthwise separable convolutions and inverted residual blocks, making it suitable for deployment in resource-constrained environments [24], [25]. Furthermore, the use of three different optimizers, Adam [18], RMSprop [6], and SGDM [20], [21] allows for a systematic evaluation of how optimization strategies influence convergence behavior, generalization capability, and classification accuracy in breast ultrasound image classification. The effectiveness of the model is measured through commonly used evaluation indicators, including accuracy, precision, recall, and F1-score. A comprehensive illustration of the research procedure is presented in Figure 1.

2.1 Data Collection

This research utilizes the Breast Ultrasound Images (BUSI) dataset, originally released by Walid Al-Dhabyani et al. in 2018 [26] and publicly accessible via the Kaggle platform [27]. This dataset comprises 780 ultrasound images collected from female patients aged 25 to 75 years, and is grouped into three categories:

benign, malignant, and normal (see Table 1). It has been widely utilized in building deep learning-based models for tasks such as breast cancer classification, detection, and segmentation [5], [28], [29], [30].

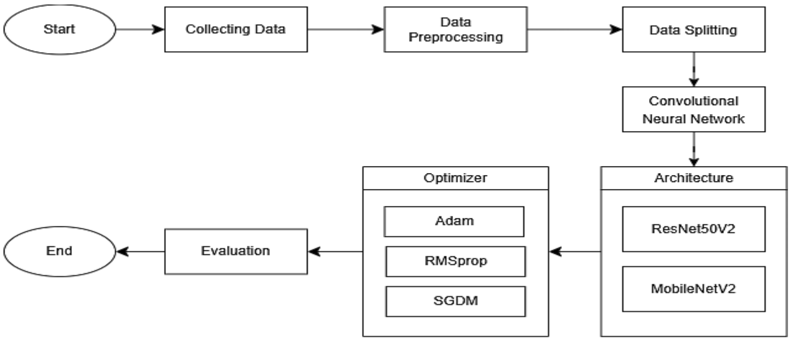
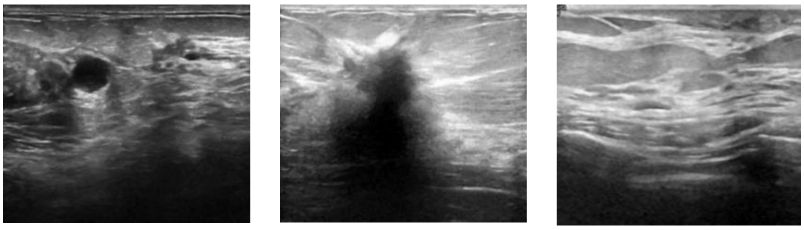


Figure 1. Research Methodology

Table 1. BUSI Dataset Class Distribution from Kaggle

No	Category	Number of Images
1	Benign	487
2	Malignant	210
3	Normal	133
	Total	780



Benign Malignant Normal

Figure 2. Representative Samples of the BUSI Dataset Images

Figure 2 illustrates representative samples from the BUSI dataset, including benign, malignant, and normal breast ultrasound images. Benign lesions typically exhibit well-defined boundaries and homogeneous textures, whereas malignant tumors often present irregular shapes, ill-defined margins, and heterogeneous internal structures. Normal images show uniform tissue patterns without visible mass formation. These visual characteristics are consistent with previously reported ultrasound imaging features in breast cancer diagnosis.

2.2 Data Preprocessing

In this stage, image data pre-processing is carried out before it is used in training the deep learning model. The dataset comprises breast ultrasound images classified into three categories: benign, malignant, and normal. To enhance training stability and efficiency, image normalization is performed by rescaling pixel values from the original 0–255 range to a 0–1 range. Additionally, data augmentation is employed to enhance both the variation and volume of the training dataset. The augmentation techniques implemented include rotation, horizontal and vertical flips, zooming, translation, shearing, and brightness adjustments. With this pre-processing process, it is expected that the image data used can have optimal quality and support maximum model performance in the classification process. Furthermore, this method contributes to minimizing overfitting by supplying a more diverse set of training samples without requiring extra manual data acquisition.

2.3 Data Splitting

During the data splitting phase, the pre-processed image dataset is partitioned into three subsets: training, validation, and testing data. This separation follows the Hold-Out Validation approach, with 70% allocated for training, and 15% each for validation and testing. The training set is used to fit the model and optimize its parameter weights. The validation subset is used during training to monitor model performance and fine-tune hyperparameters, helping prevent overfitting. Finally, the testing set is used to evaluate the model's generalization capability on previously unseen data. Data distribution is random, but the proportions of data in each class are balanced and representative.

2.4 Deep Learning

Deep learning (DL) refers to a machine learning approach that relies on artificial neural networks, extensively employed to address the challenges of early breast cancer detection using ultrasound imaging [16]. DL techniques have been applied across diverse areas, including synthetic image generation, object detection, segmentation, and the classification of breast lesion images [31]. These various approaches have even obtained official certification and started to be applied in clinical environments [32]. Deep learning methods have shown comparable performance to medical experts in breast cancer detection, offering valuable support to less experienced clinicians in improving diagnostic accuracy within clinical practice [17].

2.5 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a specialized deep learning algorithm tailored for processing image data. It is especially effective for two-dimensional image classification tasks. CNNs take images as input and autonomously learn to extract relevant features, thus removing the need for handcrafted feature extraction [18]. CNN consists of several convolutional layers that are in charge of detecting important features in the image [28]. CNN, as part of Deep Neural Networks, excels in capturing characteristics of up to more complex shapes and objects in deeper layers [21]. CNNs have been used extensively in tumor classification in the medical world, one of which is in breast ultrasound (BUS) images [33]. Although CNNs excel at capturing local features, their capacity to model long-range dependencies is limited by the size of their receptive fields [34]. The basic formula used in CNN for the convolution process is shown in Equation 1 [35].

$$\alpha_{i,j} = \sum_{m=0}^{s} \sum_{n=0}^{s} W_{m,n} x_{i+mj+n} \quad (1)$$

In the formula, $(W_{m,n})$ represents the kernel or filter weight at position (m, n), while (x_{i+mj+n}) denotes the input image pixel value at position $(i+m, j+n)$. The value (s) indicates the size of the filter, for example, 3 for a 3×3 filter. The result of the convolution operation at position (i,j) is denoted by $\alpha_{i,j}$. Convolutional Neural Network architecture can be seen in Figure 3.

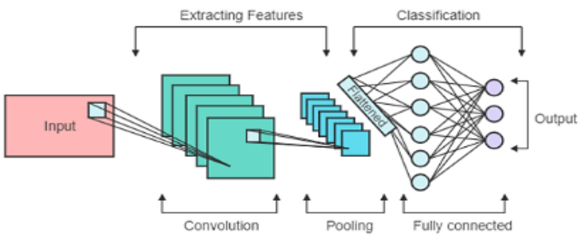


Figure 3. Convolutional Neural Network Architecture

2.6 ResNet50V2

ResNet50V2 is an enhanced convolutional neural network architecture developed as an improvement over ResNet50, demonstrating better performance compared to earlier models, including ResNet101. It overcomes the issue of gradient vanishing by implementing residual blocks that help maintain consistent gradient propagation during the training phase. In its implementation, the network organizes several residual blocks with skip connections that span across multiple layers, thus facilitating the model's learning process. In addition, ResNet50V2 uses a pre-activation mechanism within the weight layers, which also enhances both efficiency and predictive accuracy. Due to its advanced design, this architecture is known to deliver highly accurate prediction results across a wide range of datasets [23], [22]. ResNet50V2 architecture can be seen in Figure 4.

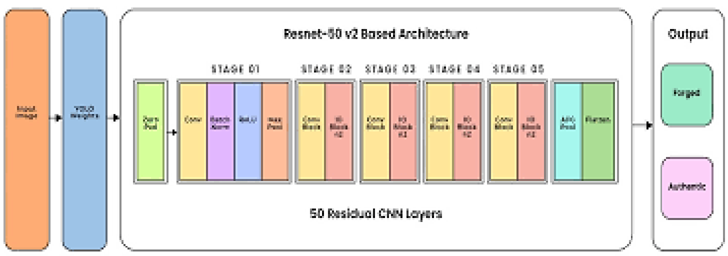


Figure 4. ResNet50V2 Architecture

2.7 MobileNetV2

MobileNetV2 is a CNN architecture recognized for its computational efficiency, rendering it well-suited for deployment on devices with limited resources, including mobile phones and IoT-based systems. This architecture has been initially trained using the large-scale ImageNet dataset, which comprises a wide range of image classes. The results of this initial training provide a robust and ready-to-use feature extractor, making it an invaluable foundation in various computer vision tasks [24], [25]. By using these pre-trained models, the training process for specialized applications becomes faster and more efficient, as the models already have a basic understanding of common visual patterns and features, which can improve model performance on new datasets. MobileNetV2 processing model can be seen in Figure 5.

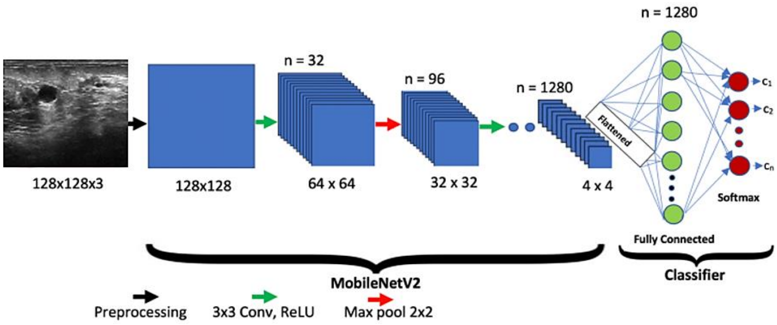


Figure 5. MobileNetV2 Processing Model

2.8 Adaptive Moment Estimation (ADAM)

Adam represents a dynamic optimization method that merges the advantages offered by both the Momentum and RMSProp approaches [6]. Adam dynamically adjusts the learning rate for each parameter, improving the efficiency and speed of training on various deep learning models, including medical image classification. Adam's effectiveness in handling models that have many parameters has been proven in various studies [2].

2.9 Root Mean Square Propagation (RMSprop)

RMSprop is an optimization method designed to mitigate the issue of fluctuating learning rates by employing a moving average of squared gradients to adaptively regulate the learning rate, thus ensuring more stable training. This makes it very useful in training deep learning models, especially in medical image classification involving large and noisy datasets [19], [36].

2.10 Stochastic Gradient Descent with Momentum (SGDM)

SGDM is a basic optimization algorithm widely used in neural network training to accelerate convergence towards the minimum value of the cost function. By adding momentum, SGDM considers not only the current gradient but also the previous direction of movement, thus helping to avoid oscillations and speed up the training process. The network parameters are updated using the following equation, which calculates the gradient as the basis for weight adjustment [6].

3. RESULT AND DISCUSSION

This research assesses the classification effectiveness of two CNN models, ResNet50V2 and MobileNetV2, in distinguishing breast cancer ultrasound images across three categories: benign, malignant, and normal. Following pre-processing, the dataset was partitioned via the Holdout method, allocating 70% for training and 30% for validation and testing. Both models were trained and tested using three different optimization algorithms: Adam, RMSprop, and SGDM.

3.1 Data Preprocessing

At this stage, the image data normalization and augmentation process is carried out. Normalization rescales pixel intensities from the original 0–255 range to a 0–1 scale to stabilize and accelerate training. Furthermore, data augmentation artificially increases the diversity of training data by generating varied samples without the necessity of manual data collection. The augmentation techniques applied in this research include image rotation up to 15 degrees, maximum image zoom by 10%, horizontal and vertical image shift by 10% each, and horizontal image reversal. To further enhance model generalization, these augmentation techniques were designed to simulate various image conditions commonly encountered in clinical practice. Augmentation-generated images with diverse variations in position, orientation, and size, as illustrated in Figure 6.

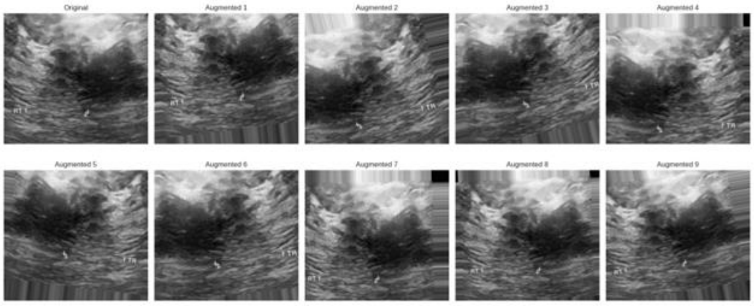


Figure 6. Augmentation Result

3.2 Data Splitting

The Breast Ultrasound Images (BUSI) dataset used in this study is divided into training, validation, and testing subsets. The holdout method is applied for dataset splitting, assigning 70% for training, 15% each for validation and testing. This partitioning is performed randomly using the train_test_split function from the scikit-learn library, with a fixed random_state parameter to maintain reproducibility. Table 2 presents the detailed outcomes of this data split.

Table 2. Hold Out Data Sharing Results

Class	Training Data	Validation Data	Testing Data
Benign	96	21	21
Malignant	102	22	22
Normal	93	20	20
Total	291	63	63

3.3 Data Training Using a Deep Learning Model

In this modeling, a CNN architecture based on the TensorFlow Keras framework is used to classify 224-pixel images into three classes, namely benign, malignant, and normal. The applied CNN model not only consists of convolution and pooling layers, but also utilizes transfer learning techniques by using the base (pre-trained) models ResNet50V2 and MobileNetV2. After the base architecture, several additional layers are added, including GlobalAveragePooling2D, a Dense layer with 128 units and ReLU activation, Dropout of 0.3, and a dense output layer with three neurons, using softmax as the activation function. The model was optimized using three different optimizers, namely Adam, RMSprop, and SGDM, each employing a learning rate of 0.0001 and a mini-batch size of 32. To overcome potential overfitting and handle data imbalance between classes, early stopping, model checkpoint, and class weighting techniques were used. The ResNet50V2 model training process with each optimizer is shown in Figures 7-9, while the MobileNetV2 training process is shown in Figures 10-12.

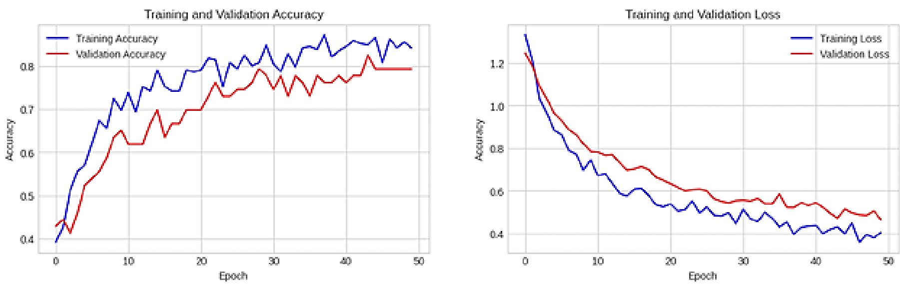


Figure 7. Training and Validation Performance of ResNet50V2 with Adam

Figure 7 presents the training and validation curves of the ResNet50V2 model utilizing the Adam optimizer, showing an increase in training accuracy to above 85%, with validation accuracy stable in the range of 80-83%. The loss value on both datasets decreases consistently to below 0.5 without a significant difference, indicating the model can learn well without overfitting. Overall, the model showed stable and fairly optimal performance in breast ultrasound image classification.

Figure 8 illustrates the training and validation outcomes of the ResNet50V2 model employing the RMSprop optimizer, showing a fairly steady increase in accuracy on both datasets. The validation accuracy is higher than the training accuracy throughout training, with the final value above 85%. The loss values for both training and validation datasets progressively decline below 0.5, maintaining a consistent pattern without notable discrepancies between them. These results show that the model with the RMSprop optimizer can learn well and has optimal validation performance without any indication of overfitting.

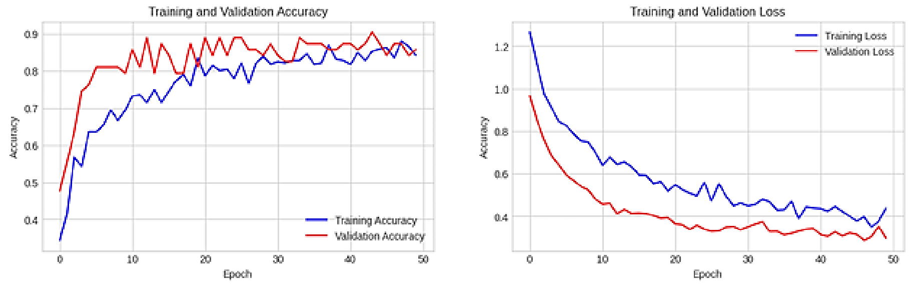


Figure 8. Training and Validation Performance of ResNet50V2 with RMSprop

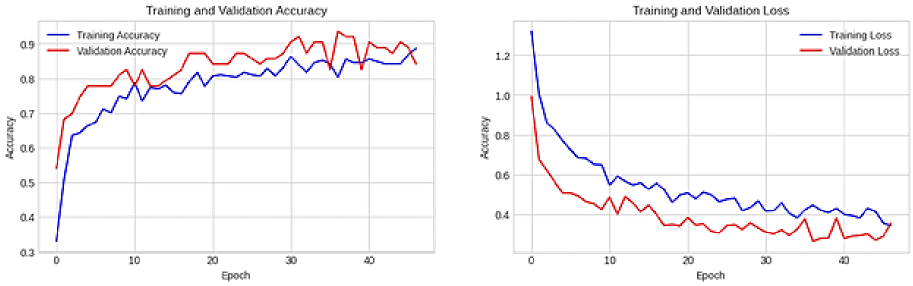


Figure 9. Training and Validation Performance of ResNet50V2 with SGDM

Figure 9 illustrates the training results of the ResNet50V2 model using the SGDM optimizer over 45 epochs. The training accuracy increases to about 88%, while the validation accuracy is slightly higher and stable at about 90%, indicating excellent model generalization. The training loss decreased to about 0.38, and the validation loss decreased steadily to reach 0.32. The graph shows that the model can learn effectively without overfitting, as the performance on the validation data remains consistent and does not deteriorate.

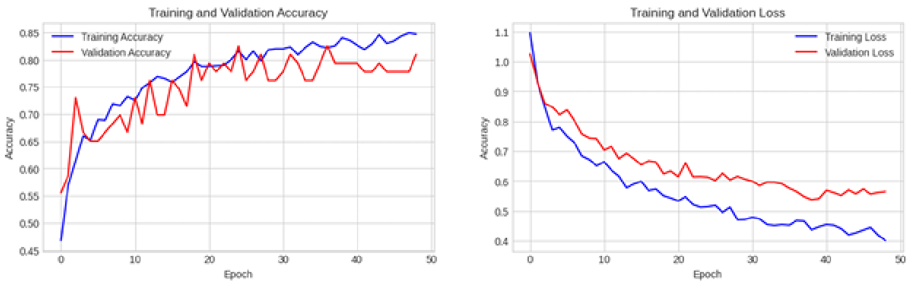


Figure 10. Training and Validation Performance of MobileNetV2 with Adam

The figure presents the training outcomes of the MobileNetV2 model optimized with Adam over 50 epochs. The training accuracy attains approximately 84%, whereas the validation accuracy stabilizes at 78%. The training loss drops to 0.40, while the validation loss stops decreasing at around 0.60. The model performed well, successfully capturing training data patterns; however, slight overfitting is evident as validation performance showed no improvement over time.

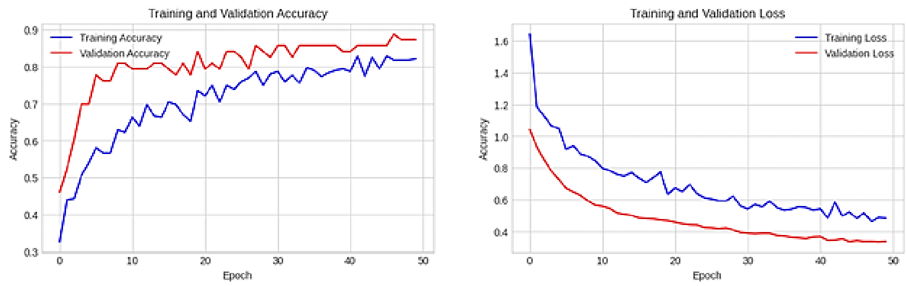


Figure 11. Training and Validation Performance of MobileNetV2 with RMSprop

Figure 11 shows the training results of MobileNetV2 with the RMSprop optimizer for 50 epochs. The training accuracy attains approximately 82%, whereas the validation accuracy is higher, stabilizing around 89%. The training loss decreased to 0.55, and the validation loss continued to decrease to about 0.40. The model shows excellent performance without signs of overfitting, with strong generalization to the validation data.

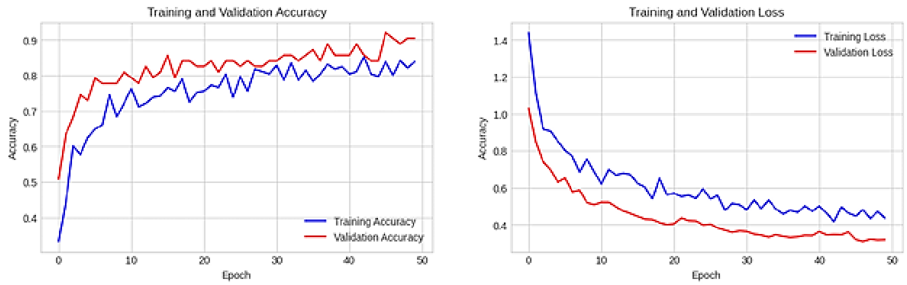


Figure 12. Training and Validation Performance of MobileNetV2 with SGDM

Figure 12 shows the training results of MobileNetV2 with the SGDM optimizer for 50 epochs. The training accuracy reaches about 83%, while the validation accuracy stabilizes around 90%. The training loss declines to roughly 0.45, while the validation loss reduces to about 0.35. This indicates that the model is not only able to learn well, but also able to maintain strong performance when tested on new data.

Table 3. Architecture Training Accuracy Results

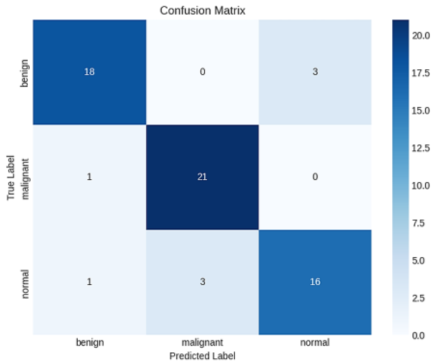
Architecture	Optimizer	Training Accuracy (%)	Validation Accuracy (%)	Testing Accuracy (%)
ResNet50V2	Adam	86.94	79.37	87.30
	RMSprop	87.29	87.30	88.89
	SGDM	85.22	93.65	92.06
MobileNetV2	Adam	86.67	79.37	82.54
	RMSprop	82.13	87.30	85.71
	SGDM	84.49	90.48	85.71

The Table 3 compares the performance of ResNet50V2 and MobileNetV2 architectures with three optimizers: Adam, RMSprop, and SGDM. SGDM shows the best validation and testing accuracy in both models, followed by RMSprop, which is quite stable. Adam had good training accuracy but tended to be lower in validation and testing, indicating potential overfitting. Overall, SGDM was the most effective optimizer for both architectures in this experiment.

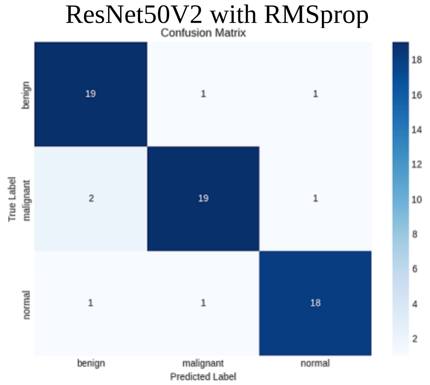
3.5 Evaluation

In the evaluation stage, the model's effectiveness is measured using a confusion matrix generated from the test dataset. This matrix provides a detailed overview of the prediction results by outlining the number of true positives, false positives, true negatives, and false negatives for each category. Figure 13 illustrates the confusion matrices generated from several tested pre-trained architectures, including ResNet50V2 and MobileNetV2 with different optimizers.

ResNet50V2 with Adam

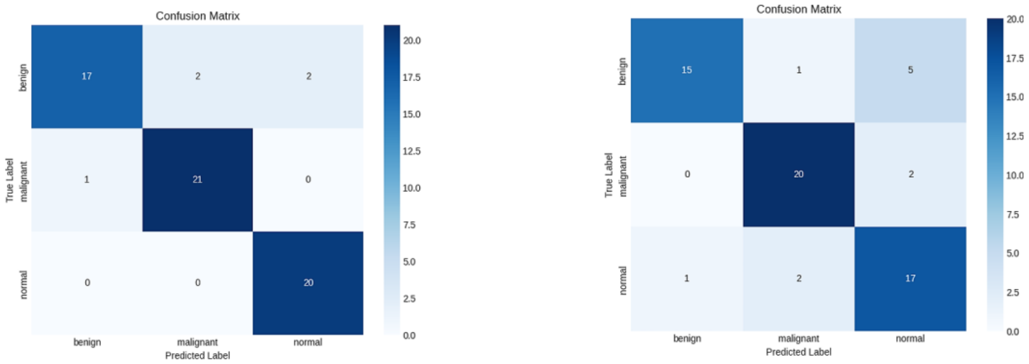


ResNet50V2 with RMSprop



ResNet50V2 with SGDM

MobileNetV2 with Adam



MobileNetV2 with RMSprop

MobileNetV2 with SGDM

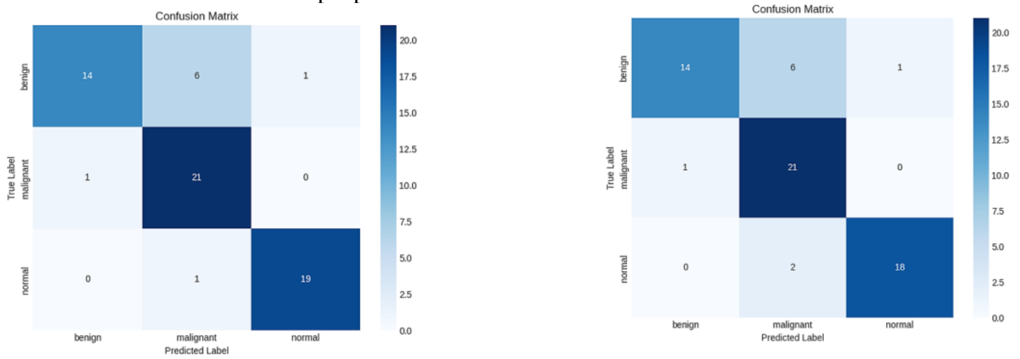


Figure 13. Confusion Matrices for ResNet50V2 and MobileNetV2

The ResNet50V2 model with SGDM showed the best performance, with near-perfect classification, especially in the normal and malignant classes. The combination of ResNet50V2 with RMSprop also gave high accuracy despite a few errors. In contrast, ResNet50V2 with Adam showed lower performance due to misclassification in the benign and normal classes. On the MobileNetV2 architecture, RMSprop produced the most stable classification, while SGDM and Adam showed more errors, especially in the benign class. Overall, the combination of ResNet50V2 with SGDM gave the most accurate and balanced classification results across all classes, which was reinforced by the near-perfect distribution of predictions in the confusion matrix. Next, the evaluation process is carried out on the performance of the models that have been built using ResNet50V2 and MobileNetV2 architectures were evaluated with three different optimizers, namely Adam, RMSprop, and SGDM. Table 4 presents a summary of the evaluation results obtained from these CNN architectures.

Table 4. Architecture Model Evaluation Results

Architecture	Optimizer	Class	Precision	Recall	F1-Score	Support	Accuracy
ResNet50V2	Adam	Benign	0.90	0.86	0.88	21	0.87
		Malignant	0.88	0.95	0.91	22	
		Normal	0.84	0.80	0.82	20	
	RMSprop	Benign	0.86	0.90	0.88	21	
		Malignant	0.90	0.86	0.88	22	
		Normal	0.90	0.90	0.90	20	
	SGDM	Benign	0.94	0.81	0.87	21	0.92
		Malignant	0.91	0.95	0.93	22	
		Normal	0.91	1.00	0.95	20	
MobileNetV2	Adam	Benign	0.94	0.71	0.81	21	0.83
		Malignant	0.87	0.91	0.89	22	
		Normal	0.71	0.85	0.77	20	
	RMSprop	Benign	0.93	0.67	0.78	21	0.86
		Malignant	0.75	0.95	0.84	22	
		Normal	0.95	0.95	0.95	20	
	SGDM	Benign	0.93	0.67	0.78	21	0.84
		Malignant	0.72	0.95	0.82	22	
		Normal	0.95	0.90	0.92	20	

Results for the ResNet50V2 architecture indicate that the SGDM optimizer achieved the highest accuracy, reaching 92%. Specifically, for the Malignant category, all three optimizers demonstrated consistently high recall scores, suggesting the model's strong sensitivity in detecting malignant tumors. Meanwhile, the MobileNetV2 architecture yielded its best results when paired with the RMSprop optimizer, attaining an accuracy of 86%. Overall, ResNet50V2 outperformed MobileNetV2 across all optimizer configurations. Notably, the combination of ResNet50V2 with SGDM delivered the top performance metrics, including accuracy, precision, recall, and F1-score, all at 92%. Within the MobileNetV2 framework, the RMSprop optimizer led with 86% accuracy, followed by SGDM and Adam. These results indicate that deeper CNN architectures tend to benefit more from momentum-based optimization, while lightweight models achieve better stability with adaptive learning rate strategies. Furthermore, the consistent performance across evaluation metrics suggests that the proposed model configuration is robust for multi-class breast ultrasound image classification.

3.6 Accuracy Comparison

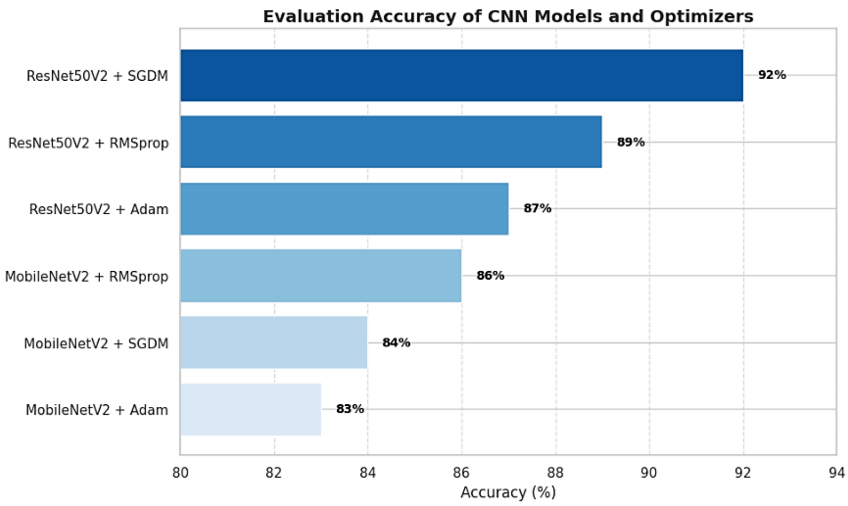


Figure 14. Comparison of CNN Architectures and Optimizers

Figure 14 shows that ResNet50V2 provides the best overall performance. The combination of ResNet50V2 with the SGDM optimizer achieved the highest accuracy of 92%. This indicates that the ResNet50V2 architecture is better able to utilize the learning strategies provided by various optimizers, especially SGDM. Meanwhile, MobileNetV2 showed lower performance than ResNet50V2, with the highest accuracy of 86% when using the RMSprop optimizer. Overall, it can be concluded that the selection of architecture and optimization algorithm greatly affects the training results. ResNet50V2 with SGDM is the most optimal combination in this experiment.

3.7 Discussion

This study evaluates the performance of two popular CNN architectures, namely ResNet50V2 and MobileNetV2, for breast cancer ultrasound image (USG) classification with three types of optimizers: Adam, RMSprop, and SGDM. The best results were obtained from the combination of ResNet50V2 with SGDM, which achieved an accuracy of 92%, while MobileNetV2 with RMSprop showed the highest accuracy of 86%.

This result is consistent with a study by Fatih Uysal and Mehmet Murat Köse (2021), who compared several deep learning models on breast cancer ultrasound image classification, namely ResNet50, ResNeXt50, and VGG16. In the study, ResNet50 achieved an accuracy of 85.4%, ResNeXt50 was slightly higher at 85.83%, and VGG16 was at 81.11%. The highest accuracy in this study (ResNet50V2 with SGDM, 92%) showed a significant performance improvement, possibly due to model optimization and selection of a more effective optimization algorithm [37].

Additionally, this research is related to the work of Jorge F. Lazo (2020), who conducted a comparison between the VGG-16 and Inception V3 architectures using two training methods (feature extraction and fine-tuning) for breast tumor classification in ultrasound images. Their fine-tuning of VGG-16 achieved an accuracy of 91.9% and an AUC of 0.934, which closely approaches the highest accuracy obtained in the present study [38].

The key distinction of the present study lies in its cross-architecture evaluation paired with an exploration of multiple optimization algorithms, offering a more comprehensive understanding of how architecture and optimizer combinations influence breast cancer classification performance on ultrasound images. In contrast, the work by Uysal et al. primarily concentrated on comparing pre-existing models without examining optimizer effects, while Lazo et al. emphasized different training strategies. Consequently, this study not only reinforces previous evidence supporting the efficacy of CNN architectures in breast cancer detection but also contributes novel insights through a rigorous assessment of optimizer impacts. The pairing of ResNet50V2 and SGDM emerges as a recommended approach, balancing training accuracy and stability for practical application in clinical ultrasound-based breast cancer diagnostic systems.

4. CONCLUSION

This study evaluates the performance of two CNN architectures, namely ResNet50V2 and MobileNetV2, in breast cancer ultrasound image classification with three types of optimizers, namely Adam, RMSprop, and SGDM. The findings indicate that the integration of the ResNet50V2 architecture with the SGDM optimizer achieved superior performance, attaining 92% for accuracy, precision, recall, and F1-score. In contrast, the combination of MobileNetV2 and the RMSprop optimizer yielded an accuracy of 86%, with precision, recall, and F1-score values of 88%, 86%, and 86%, respectively. Overall, ResNet50V2 consistently outperformed MobileNetV2 across all evaluation metrics and optimization configurations. These results underscore the significant influence of both convolutional neural network architecture and optimization strategy on the effectiveness of medical image classification systems. It is recommended that subsequent studies incorporate interpretability methods, such as attention mechanisms and heatmap visualizations, implement fine-tuning procedures for CNN models, and validate their approaches using larger and more heterogeneous datasets to enhance accuracy and clinical reliability. Furthermore, the outcomes generated from this study are expected to function as a valuable reference in promoting the progress of deep learning-based automated diagnostic support systems, particularly in healthcare environments where radiology personnel are limited.

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