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Enhancing Breast Cancer Recognition in Histopathological Imaging Using Fine-Tuned CNN

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Abstrak

Statistik Kanker Global melaporkan bahwa dari 2,3 juta kasus kanker payudara di seluruh dunia, 600.000 di antaranya berakhir dengan kematian. Faktor-faktor yang berkontribusi terhadap kanker payudara pada wanita mencakup pengaruh genetik dan gaya hidup. Salah satu metode untuk mengenali kanker payudara adalah melalui citra histopatologi. Belakangan ini, pembelajaran mendalam (deep learning) telah mendapatkan perhatian besar dalam dunia pembelajaran mesin karena kemampuannya yang kuat dalam memodelkan data kompleks, seperti citra. Dalam penelitian ini, kami melakukan klasifikasi kanker payudara dengan melatih model Convolutional Neural Network (CNN) pada dataset citra histopatologi yang telah dianotasi dan divalidasi oleh para ahli, yang terdiri dari dua kelas. Kami mengusulkan strategi optimasi model CNN untuk meningkatkan kinerja pengenalan kanker payudara, dengan menerapkan strategi fine-tuning pada MobileNetV2 dan InceptionResNetV2 untuk mengevaluasi kinerja CNN dalam mengklasifikasikan kanker payudara pada citra histopatologi. Hasil eksperimen menunjukkan bahwa model mencapai kinerja optimal dengan akurasi sebesar 96,22%.

Kata kunci: *Breast Cancer, Convolutional Neural Network, Deep Learning, Fine-tuning, Histopathology Image*

Abstract

Global Cancer Statistics reports that of the 2.3 million cases of breast cancer worldwide, 600,000 result in death. Factors contributing to breast cancer in women include both genetic and lifestyle influences. One method for recognizing breast cancer is through histopathology images. Recently, deep learning has gained significant attention in machine learning due to its powerful capabilities in modeling complex data, such as images. In this study, we classify breast cancer by training a Convolutional Neural Network (CNN) model on a dataset of histopathology images annotated and validated by experts, containing two classes. We propose an optimization strategy for CNN models to enhance breast cancer recognition performance, applying a fine-tuning strategy to MobileNetV2 and InceptionResNetV2 to evaluate CNN performance in classifying breast cancer within histopathological images. The experimental results demonstrate that the model achieves optimal performance with an accuracy of 96.22%.

Keywords: *Breast Cancer, Convolutional Neural Network, Deep Learning, Fine-tuning, Histopathology Image*

1. Introduction

Breast cancer is a type of tumor that develops in the breast tissue. It is one of the fastest-growing diseases worldwide [1]. According to Global Cancer Statistics, of the 2.3 million cases of breast cancer, 600,000 result in death. In Indonesia, the mortality rate from breast cancer is also relatively high, with 17% of every 100,000 women affected. Therefore, early detection of breast cancer is essential, and can be enhanced through the use of deep learning to classify histopathological images.

The method used in image processing is the Convolutional Neural Network (CNN), an advancement of the Multi-Layer Perceptron (MLP). CNN has shown remarkable results in image recognition because it attempts to replicate the image recognition system of the human visual cortex, enabling it to process image information effectively [2]. The core concept of CNN is to incorporate invariant properties into artificial neural networks, creating a model that is resilient to certain input transformations. This approach addresses issues in MLPs, where all layers are fully connected, leading to a loss of spatial information from the input required for precise calculations [3]. CNN offers higher accuracy on image datasets compared to other data types, such as text or signal waves. This is due to CNN's convolutional processing, which uses a pixel-based matrix structure to map images, making CNNs particularly well-suited for image or matrix data [4]. Like other neural networks, CNNs have neurons with weights, biases, and activation functions. The layers that compose a CNN include the Convolution Layer, ReLU Activation Layer, Pooling Layer, and Fully Connected Layer [5]. This study applies a fine-tuning strategy and compares two CNN models, MobileNetV2 and InceptionResNetV2, to evaluate their performance in the breast cancer classification process.

The choice of the MobileNetV2 model is based on its high accuracy and its efficiency in terms of computational resources. Unlike other CNN architectures, MobileNetV2 has a smaller number of training parameters, making it less demanding computationally [6]. MobileNetV2 also features an inverted residual block and bottleneck layers, which reduce the number of calculations compared to the original MobileNet model. Additionally, MobileNetV2 supports input images larger than 32x32 pixels, allowing it to handle larger images more effectively [7]. InceptionResNetV2 combines the strengths of Inception and Residual architectures. Both ResNet and Inception are CNN architectures known for their strong image recognition performance and low computational cost. Inception ResNetV2 brings together the advantages of these two architectures, resulting in improved performance [8]. This model is a successor to Inception ResNetV1, which achieved excellent results in the 2015 ImageNet Large Scale Visual Recognition Challenge (ILSVRC), and follows GoogleNet, the winning architecture at ILSVRC 2014 [9]. These qualities make MobileNetV2 and Inception ResNetV2 ideal for use in this study.

This study proposed the application of a fine-tuning strategy that adjusts learning rates and optimizers to enhance the performance of CNN models, specifically MobileNetV2 and InceptionResNetV2, for breast cancer classification using histopathology images. While these models have been widely used in various image recognition tasks, the integration of a tailored fine-tuning approach, which includes learning rate adjustment and optimizer optimization, is relatively underexplored in the context of medical image classification. By comparing the effects of different optimizers, including Adamax and SGD, and varying learning rates, this study aims to improve model accuracy and efficiency, particularly for breast cancer detection. This fine-tuning strategy offers a more refined and adaptable approach to CNN model training, making it a promising contribution to the field of deep learning in medical diagnostics.

2. Proposed Method

In this section, the proposed method is presented. We designed a CNN model to recognize breast cancer using histopathology images. The first stage is a fine-tuning strategy based on learning rate adjustments. The second stage involves training the CNN model using two models, MobileNetV2 and InceptionResNetV2. The third stage is model testing. The fourth stage is model evaluation to assess the performance of each model.

The learning rate is a critical parameter that controls the size of weight updates during each iteration of CNN training. In this study, learning rate-based fine-tuning is designed to dynamically adjust the learning pace. This strategy allows the model to begin training with larger updates to accelerate convergence and gradually reduce the update size to achieve optimal results, particularly when dealing with complex histopathology datasets. The adjustment of the learning rate, combined with appropriate optimizers, ensures training efficiency and mitigates issues such as loss oscillation or suboptimal convergence. This combination enables models like MobileNetV2 and InceptionResNetV2 to effectively extract relevant features from histopathology images, thereby improving breast cancer recognition accuracy.

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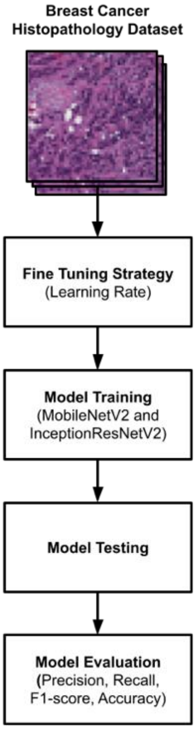

Figure 1. Proposed Method for Breast Cancer Recognition

2.1 Dataset

In this study, the breast cancer dataset was sourced from a public dataset available on Kaggle. This dataset comprises a total of 277,524 images, including 78,786 images labeled as Positive Breast Cancer and 198,738 images labeled as Negative Breast Cancer. For this stugdy, 70% of the dataset is used as training data, while the remaining 30% is allocated for testing. Figure 2 illustrates sample images from this dataset.

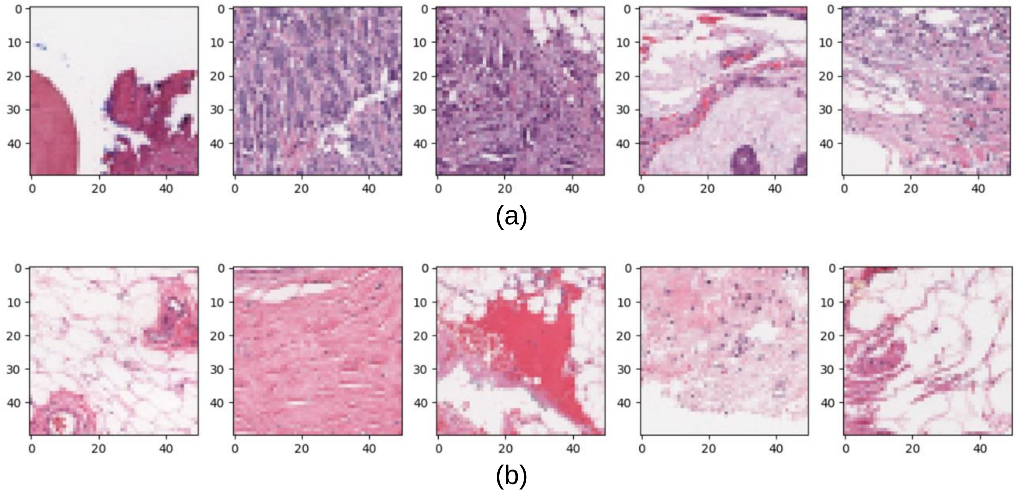

Figure 2. Sample of Breast Histopatology Images. (a) Cancerous Images, (b) Non-Cancerous Images (https://www.kaggle.com/datasets/paultimothymooney/breast-histopathology-images)

Table 1. Number of images from each class

Classes	#Images
Cancerous	78,786
Non-cancerous	198,738

2.2 Fine-tuning Strategy

Fine-tuning refers to training a model on a specific task using a pre-trained model that has already been trained on a large dataset [10]. This process allows the network to learn more specific features from the new dataset rather than relying solely on the general patterns learned from the original data [11]. In this study, we fine-tuned the model using three variations of learning rates to achieve optimal performance. This strategy was applied to two models: MobileNetV2 and InceptionResNetV2. Table 2 presents the details of the fine-tuning strategy.

Table 2. Learning Rate and Optimizers variation on Deep Learning Models

Model	**Fine-tuning Strategy**	
	Learning Rate	**Optimizer**
MobileNetV2	0.01	Adamax
	0.001	Adamax
	0.0001	Adamax
InceptioneResNetV2	0.01	Adamax
	0.001	Adamax
	0.0001	Adamax
MobileNetV2	0.01	SGD
	0.001	SGD
	0.0001	SGD
InceptioneResNetV2	0.01	SGD
	0.001	SGD
	0.0001	SGD

Optimizers are essential components in training CNN models, as they rrmine how the model's weights are updated to minimize the loss function. In this study, the selection and adjustment of optimizer parameters are crucial to improving training efficiency and ensuring convergence. Fine-tuning these parameters enables the model to better adapt to the complexity of histopathology image data, mitigating challenges such as slow convergence or suboptimal performance.

This study employs Adamax and SGD optimizers due to their distinct and complementary features. Adamax, an extension of the Adam optimizer, is selected for its adaptive learning rate capabilities and robustness in handling noisy gradients, making it well-suited for complex, high-dimensional datasets. In contrast, SGD is chosen for its simplicity and its ability to provide precise control over the training process via fixed learning rates and additional techniques such as momentum. The variation in learning rate significantly impacts the training process. A larger learning rate facilitates faster convergence but risks overshooting the optimal solution, whereas a smaller learning rate ensures finer weight updates at the expense of increased training time. Adamax's adaptive learning rate dynamically adjusts step sizes to stabilize training in noisy gradient regions, while SGD relies on manually tuned learning rates to balance convergence speed and stability. By experimenting with varying learning rates for each optimizer, this study aims to identify the optimal configuration for enhancing the performance of CNN models in breast cancer detection.

2.3 Model Training

In our model training, we applied a Transfer Learning strategy to both the MobileNetV2 and InceptionResNetV2 models. Each model was trained for 100 epochs with varying learning rates (LR) of 0.01, 0.001, and 0.0001. This study utilized an NVIDIA A100 GPU with 32GB of memory for training. Figures 3 and 4 illustrate the architectures of MobileNetV2 and InceptionResNetV2, respectively.

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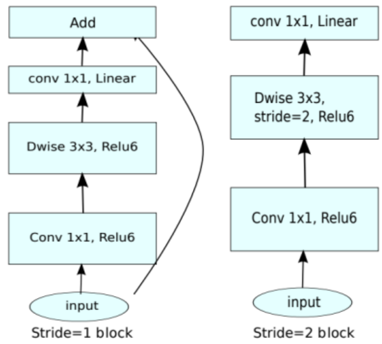
Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

(a)



(b)

Figure 3. MobileNetV2 architecture. (a) MobileNetV2 network architecture, (b) MobileNetV2 convolution block

Figure 3(a) depicts the design of MobileNetV2, where each row represents a sequence of identical layers (with variations in stride) repeated *n* times. In each sequence, the output channels (*c*) remain consistent across all layers, with the first layer having a stride of *s* and subsequent layers using a stride of 1. Every spatial convolution uses a 3×3 kernel. Figure 3(b) shows a MobileNetV2 convolution block composed of two types of blocks: the final block with a stride of 1 and an optimized block with a stride of 2. Each block contains three layers. The first layer is a 1×1 convolution with ReLU6 activation, the second is a depthwise convolution, and the third layer, which has no non-linearity, is another 1×1 convolution. When ReLU is applied to non-zero volume output, it ensures the deep network retains linear classification capabilities on the active output domain.

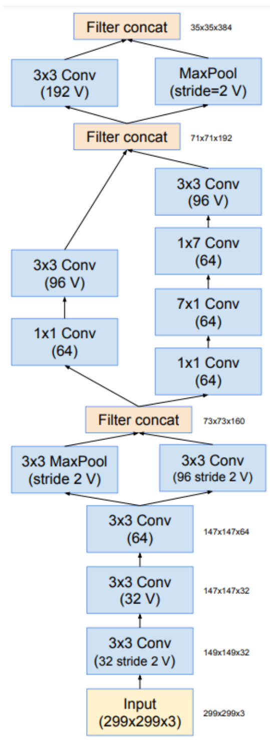


Figure 4. InceptionResNetv2 network architecture

Figure 4 shows the InceptionResNetV2 architecture, where the core component is the Residual Inception Block. Each block is followed by a 1×1 convolution filter expansion layer, which increases filter dimensionality before addition to match input depth. This architecture uses batch normalization in conventional layers but is 164 layers deep overall, handling images sized

299×299 pixels. The Residual Inception Block combines various-sized convolutional filters with residual connections, reducing training time and mitigating degradation in deeper networks.

2.4 Perfomance Evaluation

In this section, we evaluate the performance of each model across different scenarios. Several metrics are used to assess model performance, including the confusion matrix, accuracy, recall, precision, and F1 score [12]. The evaluation focuses on measuring classification performance based on recall, precision, F1-score, and accuracy. Each model's performance will be assessed under various fine-tuning strategies applied during the training process.

3. Literature Study

The Convolutional Neural Network (CNN) is a Deep Learning architecture widely used for image classification tasks across various domains. CNNs have shown remarkable success in handling complex image-based classifications, which has led to their application in diverse fields. For instance, in [13], MobileNet was proposed for classifying Balinese carving motifs, where a data augmentation strategy improved model accuracy by up to 16.2%. This study demonstrated how augmenting data could enhance CNN performance in specific classification tasks.

In the medical domain, CNNs have become crucial for diagnosing diseases through image analysis. Multiple studies highlight CNN's effectiveness in classifying diabetic retinopathy, a leading cause of blindness. For example, ResNet-50 and DenseNet121 were applied to develop a diabetic retinopathy classification model, achieving an accuracy of 95.58% [14]. Another study used the MobileNet model for the same purpose, reaching an impressive accuracy of 98% [15]. Further studies employed models such as ResNet50, InceptionV3, Xception, Dense121, and Dense169 to capture rich features for classifying different stages of diabetic retinopathy, enhancing classification precision [16].

Similarly, CNNs have been employed in breast cancer detection, with studies showing promising results. In [17], VGG16, DenseNet, and ResNet18 were proposed for breast cancer classification, yielding an accuracy of 92%. Transfer learning strategies with ResNet50, VGG19, and InceptionV3 have also been applied to enhance performance by leveraging pre-trained models and adapting them to specific tasks [18]. Additionally, Bilgic [19] proposed a CNN model specifically for breast cancer recognition, further confirming CNN's potential in medical image diagnostics.

MobileNetV2 is a lightweight convolutional neural network (CNN) architecture designed for efficiency and performance, particularly in resource-constrained environments. It builds upon the original MobileNet by introducing depthwise separable convolutions, which significantly reduce computational complexity and memory requirements. The hallmark of MobileNetV2 is the use of inverted residual blocks with linear bottlenecks, which allow the network to maintain high representational power while minimizing the number of parameters. This design is highly advantageous for tasks involving high-dimensional input data, such as histopathology images, where computational efficiency is crucial. In addition to its lightweight design, MobileNetV2 is known for its strong feature extraction capabilities. The network balances efficiency and accuracy by focusing on reducing redundant computations without sacrificing performance. This makes MobileNetV2 suitable for applications requiring real-time processing or deployment on devices with limited computational resources. In this study, MobileNetV2 is utilized to assess its ability to effectively extract relevant features for breast cancer detection while maintaining a fast and efficient training process.

InceptionResNetV2 is a deep CNN architecture that combines the strengths of Inception modules and residual connections. It builds on the original Inception architecture by integrating residual connections, which help mitigate the vanishing gradient problem in very deep networks. The Inception modules allow the model to capture multi-scale features by performing convolutions of different sizes in parallel, while residual connections improve gradient flow during backpropagation. These characteristics make InceptionResNetV2 highly effective for handling complex image datasets, such as histopathology images, where feature diversity is critical. Despite its high computational complexity, InceptionResNetV2 achieves state-of-the-art accuracy in various computer vision tasks. Its ability to capture intricate patterns in data makes it particularly useful for fine-grained image classification problems like cancer detection. In this study, InceptionResNetV2 is employed to evaluate its capability to extract diverse and detailed features from histopathology images, aiming to improve the accuracy of breast cancer recognition.

Building on these related studies, our study proposes a fine-tuning strategy to improve CNN model performance in breast cancer recognition. This fine-tuning involves optimizing learning rates and experimenting with different optimizers during the model training process, aiming to achieve higher accuracy and robust classification capabilities in detecting breast cancer.

4. Result and Disccussion

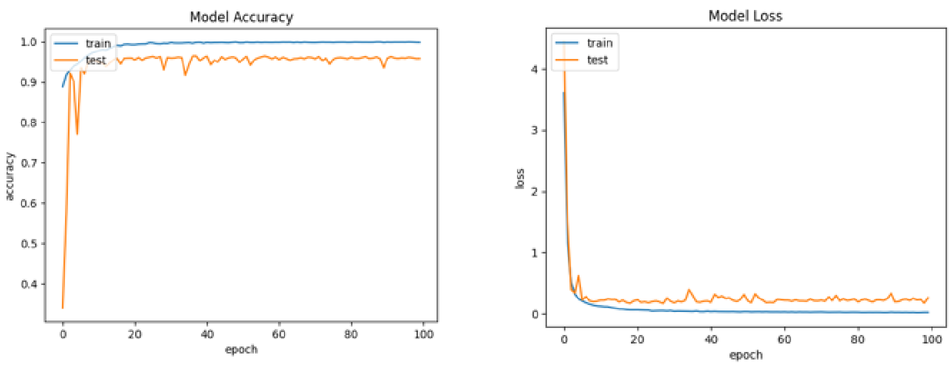
In this section, we discuss the results of each stage to compare the performance of the models across different scenarios. We present the outcomes of the MobileNetV2 and InceptionResNetV2 models, highlighting the effects of various fine-tuning strategies on their performance.

4.1 MobileNetV2

The fine-tuning strategy was applied to the MobileNetV2 model to achieve optimal results. In this experiment, MobileNetV2 reached a highest validation accuracy of 96.22% using a learning rate of 0.001 with the SGD optimizer. Additionally, the Adamax optimizer demonstrated even better performance, achieving an accuracy of 98.57% on MobileNetV2. Table 3 presents the detailed results of the fine-tuning strategy applied to the MobileNetV2 model.

Table 3. Fine-tuning strategy result on MobileNetV2

Learning Rate	Optimizers	Training		Validation	
		Accuracy	Loss	Accuracy	Loss
0.01	SGD	0.9981	0.0208	0.9579	0.2588
0.001	SGD	0.9987	0.0212	**0.9622**	0.1870
0.0001	SGD	0.9988	0.0389	0.9570	0.1955
0.01	Adamax	0.9995	0.0156	0.9756	0.1584
0.001	Adamax	0.9997	0.0127	**0.9857**	0.1265
0.0001	Adamax	0.9992	0.0245	0.9648	0.1647



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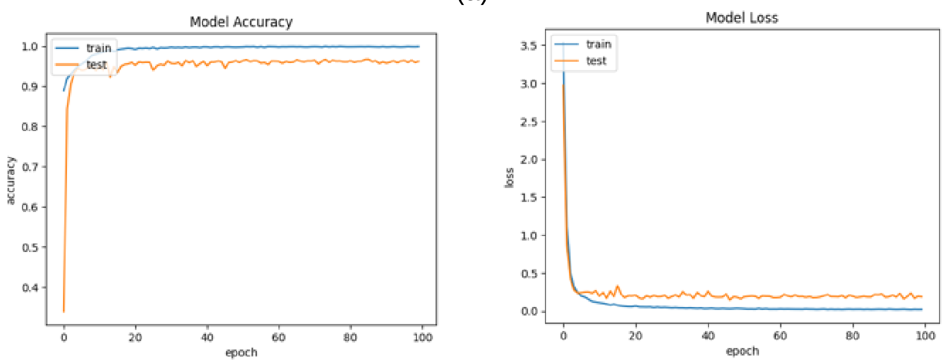

(b)

Figure 5. The best model's accuracy and loss during training process on MobileNetV2
(a) Learning Rate 0.001 and SGD optimizers, (b) Learning Rate 0.001 and Adamax optimizers

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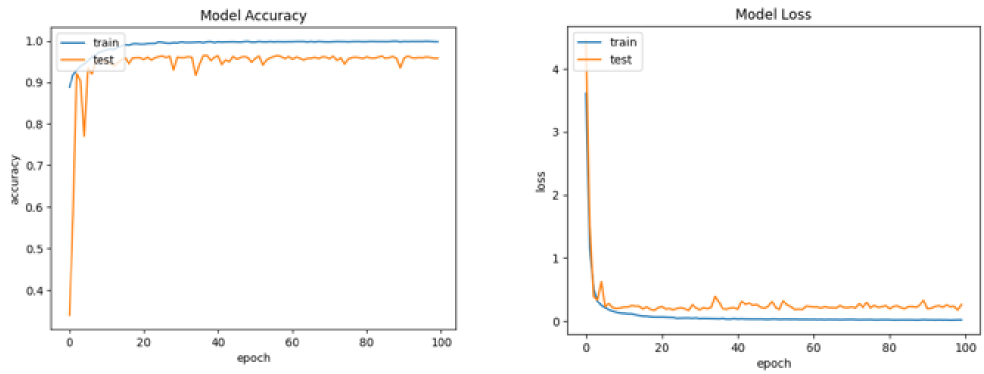
Figure 5 presents a comparison of the best model's accuracy and loss throughout the training process. The experimental results indicate that the testing accuracy aligns closely with the training accuracy at each epoch, demonstrating that the model converges effectively. This outcome suggests that the fine-tuning strategy applied to MobileNetV2 achieves high performance based on the evaluation metrics.

4.2 InceptionResNetV2

In this section, the fine-tuning strategy is applied to the InceptionResNetV2 model to achieve optimal results. In this experiment, InceptionResNetV2 reached a highest validation accuracy of 95.13% with a learning rate of 0.001 and the SGD optimizer. Additionally, the Adamax optimizer on InceptionResNetV2 yielded improved performance, achieving an accuracy of 97.35%. Table 4 presents the results of the fine-tuning strategy applied to the InceptionResNetV2 model.

Table 4. Fine-tuning strategy result on InceptionResNetV2

Learning Rate	Optimizers	Training		Validation	
		Accuracy	Loss	Accuracy	Loss
0.01	SGD	0.9929	0.0331	0.9298	0.2523
0.001	SGD	0.9964	0.0239	0.9319	0.2820
0.0001	SGD	0.9992	0.0321	**0.9513**	0.2123
0.01	Adamax	0.9968	0.0263	0.9472	0.2223
0.001	Adamax	0.9982	0.0217	0.9567	0.2353
0.0001	Adamax	0.9997	0.0126	**0.9735**	0.1826



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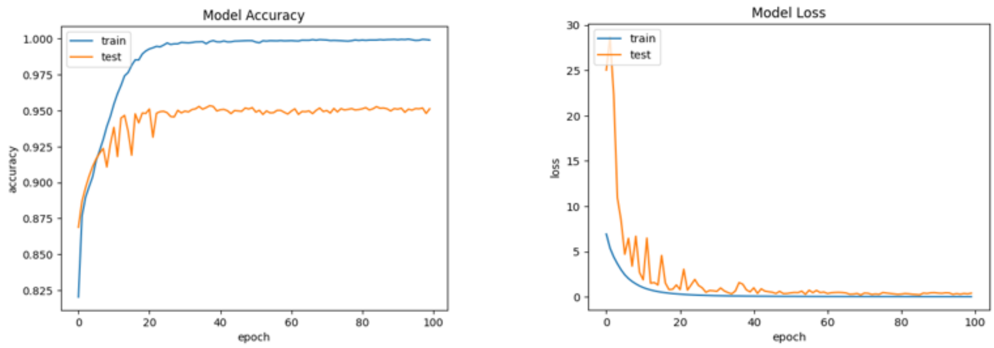


(b)

Figure 6. The best model's accuracy and loss during training process on InceptionResNetV2 (a) Learning Rate 0.001 and SGD optimizers, (b) Learning Rate 0.001 and Adamax optimizers

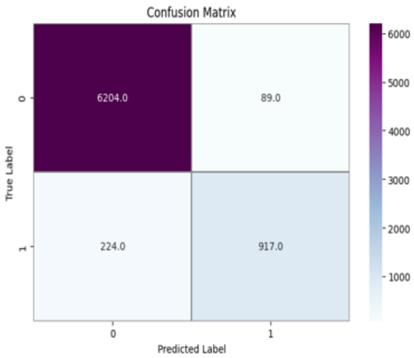
The experimental findings indicate that InceptionResNetV2 achieved relatively high performance compared to MobileNetV2. Figure 6 illustrates the comparison of the best model's accuracy and loss during the training process. The results show that testing accuracy aligns closely with training accuracy at each epoch, demonstrating that the model converges effectively.

4.3 Perfomance Comparison

In this section, we evaluate the model performance by comparing the results of each model, including a comparison table and confusion matrices. Table 5 presents the performance comparison of the MobileNetV2 and InceptionResNetV2 models, with MobileNetV2 achieving the highest validation accuracy of 98.57% using a learning rate of 0.001 and the Adamax optimizer. In this study, MobileNetV2 outperformed InceptionResNetV2 overall, indicating its robustness and effectiveness in this study.

Table 5. Perfomance Comparison

Model	Learning Rate	Optimizers	Training		Validation	
			Acc.	Loss	Acc.	Loss
	0.01	SGD	0.9981	0.0208	0.9579	0.2588
MobileNetv2	0.001	SGD	0.9987	0.0212	0.9622	0.1870
	0.0001	SGD	0.9988	0.0389	0.9570	0.1955
	0.01	Adamax	0.9995	0.0156	0.9756	0.1584
MobileNetv2	0.001	Adamax	0.9997	0.0127	**0.9857**	0.1265
	0.0001	Adamax	0.9992	0.0245	0.9648	0.1647
	0.01	SGD	0.9929	0.0331	0.9298	0.2523
InceptionResNetV2	0.001	SGD	0.9964	0.0239	0.9319	0.2820
	0.0001	SGD	0.9992	0.0321	0.9513	0.2123
	0.01	Adamax	0.9968	0.0263	0.9472	0.2223
InceptionResNetV2	0.001	Adamax	0.9982	0.0217	0.9567	0.2353
	0.0001	Adamax	0.9997	0.0126	**0.9735**	0.1826



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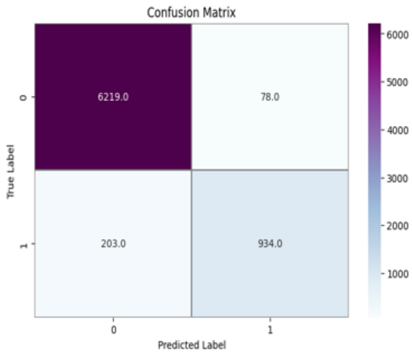

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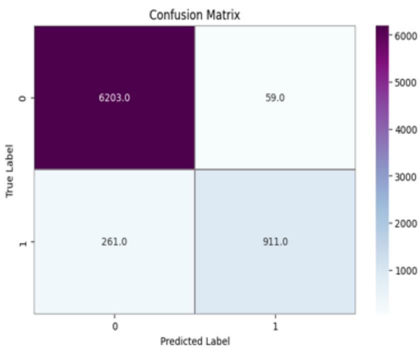
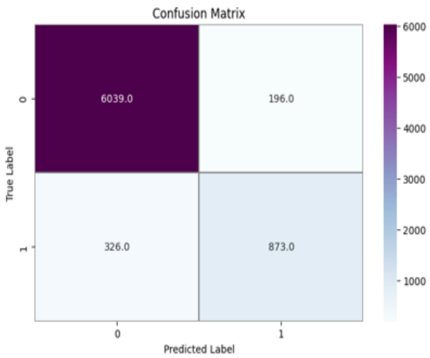


(c)

Figure 9. Comparison of confusion matrix on MobileNetV2. (a) Matrix learning rate 0.01, (b) learning rate 0.001, (c) Learning rate 0.0001 on Adamax optimizers.

Figure 9 illustrates the confusion matrix for the MobileNetV2 model at different learning rates. With a learning rate of 0.01 (Figure 9a), the model correctly recognized 80.3% of the positive class and 98.5% of the negative class, demonstrating its ability to handle most classifications accurately even at a higher learning rate. At a learning rate of 0.001 (Figure 9b), the model showed improvement, correctly recognizing 77.7% of the positive class and an impressive 99.7% of the negative class, which may indicate better generalization with this configuration. Finally, at a learning rate of 0.0001 (Figure 9c), it correctly identified 82.14% of the positive class and 98.7% of the negative class, suggesting stability and fine-grained adjustment at lower learning rates



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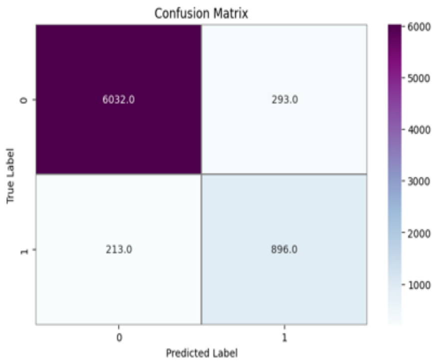

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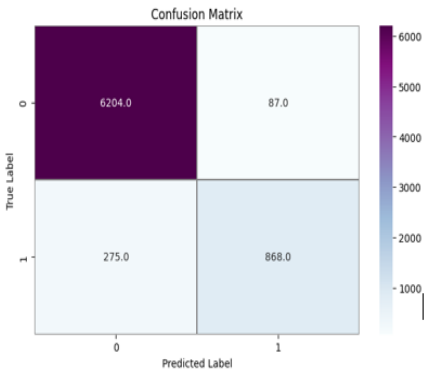

(c)

Figure 10. Comparison of confusion matrix on InceptionResNetV2. (a) Matrix learning rate 0.01, (b) learning rate 0.001, (c) Learning rate 0.0001 on Adamax optimizers.

Figure 10 shows the confusion matrix results for the InceptionResNetV2 model across various learning rates. At a learning rate of 0.01 (Figure 10a), the model correctly identified 77.7% of the positive class and 96.85% of the negative class, indicating relatively stable performance but a slight challenge in handling positive class detection. With a learning rate of 0.001 (Figure 10b), the model achieved 80.7% accuracy for the positive class and 96.74% for the negative class, showing some improvement and highlighting its sensitivity to fine-tuning. Finally, at a learning rate of 0.0001 (Figure 10c), the model recognized 75.9% of the positive class and 98.6% of the negative class, illustrating better performance in negative class detection while slightly reducing accuracy in the positive class.

These results suggest that MobileNetV2, with its optimized configuration, is better suited to this classification task than InceptionResNetV2, likely due to MobileNetV2's architecture, which is more adaptable to fine-tuning through learning rate and optimizer adjustments. The choice of learning rate and optimizer plays a crucial role in maximizing model performance and achieving a balance between positive and negative class detection accuracy.

5. Conclusion

Based on our experiments, we demonstrated a fine-tuning strategy to improve CNN model performance. We conducted experiments on two models, applying fine-tuning across various learning rates and optimizers. This fine-tuning approach yielded high performance in recognizing breast cancer based on histopathology images, a critical task where accurate classification directly impacts diagnosis and treatment planning. By optimizing learning rates and selecting effective optimizers, we were able to enhance model sensitivity and accuracy.

The MobileNetV2 model achieved superior results, outperforming InceptionResNetV2 with an accuracy of 98.57% when using the Adamax optimizer and a learning rate of 0.001. This significant result suggests that MobileNetV2's lightweight architecture, combined with Adamax's adaptive learning capabilities, provides an optimal balance for handling complex medical images without overfitting. This high accuracy highlights MobileNetV2's potential for clinical applications, where efficient processing and reliable performance are essential. Additionally, the success of this model with different fine-tuning strategies demonstrates the importance of tailored optimization techniques in medical imaging, as subtle adjustments can lead to substantial improvements in diagnostic accuracy.

These findings underscore the value of experimenting with various fine-tuning strategies, particularly in high-stakes fields like medical imaging, where precision is critical. Future work could explore further refinements, including advanced data augmentation techniques or ensemble models, to potentially increase performance and generalizability in real-world settings.

References

[1] G. P. Natakusumah and E. Ernastuti, "Implementasi Metode CNN Multi-Scale Input dan Multi-Feature Network untuk Dugaan Kanker Payudara," *JOINTECS (Journal Inf. Technol. Comput. Sci.*, vol. 7, no. 2, p. 43, 2022, doi: 10.31328/jointecs.v7i2.3637.

[2] A. Peryanto, A. Yudhana, and R. Umar, "Klasifikasi Citra Menggunakan Convolutional Neural Network dan K Fold Cross Validation," *J. Appl. Informatics Comput.*, vol. 4, no. 1, pp. 45–51, 2020, doi: 10.30871/jaic.v4i1.2017.

[3] A. . Anugrah, "Klasifikasi Tingkat Keganasan Kanker Paru-Paru Pada Computed Tomography (CT) Scan Menggunakan Metode Convolutional Neural Network," *J. Simantec*, vol. 3, no. 2, pp. 45–46, 2018, [Online]. Available: http://arxiv.org/abs/1811.03378

[4] G. Ciocca, P. Napoletano, and R. Schettini, "CNN-based features for retrieval and classification of food images," *Comput. Vis. Image Underst.*, vol. 176–177, pp. 70–77, 2018, doi: 10.1016/j.cviu.2018.09.001.

[5] M. A. Hanin, R. Patmasari, R. Y. N. Fuâ, and others, "Sistem Klasifikasi Penyakit Kulit Menggunakan Convolutional Neural Network (cnn)," *eProceedings Eng.*, vol. 8, no. 1, pp. 273–281, 2021.

[6] M. Raihan, R. Allaam, and A. T. Wibowo, "Klasifikasi Genus Tanaman Anggrek Menggunakan Metode Convolutional Neural Network (CNN)," *e-Prceeding Eng.*, vol. 8, no. 2, pp. 1–1153, 2021.

[7] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 4510–4520, 2018, doi: 10.1109/CVPR.2018.00474.

[8] A. Sirait, "Implementasi CNN Inception-ResNet V2 Untuk Deteksi Covid-19 Melalui CT Scan," p. 20, 2021, [Online]. Available: https://www.scribd.com/document/537752591/Implementasi-CNN-Inception-ResNet-V2-untuk-Deteksi-Covid-19-melalui-CT-Scan

[9] E. G. Winarto, Rahmayati, and A. Lawi, "Implementasi Arsitektur Inception Resnet-V2 untuk Klasifikasi Kualitas Biji Kakao," *Konf. Nas. Ilmu Komput. 2021* , pp. 132–137, 2021.

[10] T. Fatyanosa, "Fine-Tuning Pre-Trained Transformer-based Language Model," 2020, [Online]. Available: https://fatyanosa.medium.com/fine-tuning-pre-trained-transformer-based-language-model-c542af0e7fc1

[11] R. Indraswari, W. Herulambang, and R. Rokhana, "Deteksi Penyakit Mata Pada Citra Fundus Menggunakan Convolutional Neural Network (CNN)," *Techno.Com*, vol. 21, no. 2, pp. 378–389, 2022, doi: 10.33633/tc.v21i2.6162.

[12] D. Gunawan and H. Setiawan, "Convolutional Neural Network dalam Citra Medis," *KONSTELASI Konvergensi Teknol. dan Sist. Inf.*, vol. 2, no. 2, pp. 376–390, 2022, doi: 10.24002/konstelasi.v2i2.5367.

[13] I. W. A. S. Darma, N. Suciati, and D. Siahaan, "Neural Style Transfer and Geometric Transformations for Data Augmentation on Balinese Carving Recognition using MobileNet," *Int. J. Intell. Eng. Syst.*, vol. 13, no. 6, pp. 349–363, 2020, doi: 10.22266/ijies2020.1231.31.

[14] H. Mustafa, S. F. Ali, M. Bilal, and M. S. Hanif, "Multi-Stream Deep Neural Network for

p-ISSN: 2252-3006
e-ISSN: 2685-2411

Diabetic Retinopathy Severity Classification under a Boosting Framework," *IEEE Access*, vol. 10, no. November, pp. 113172–113183, 2022, doi: 10.1109/ACCESS.2022.3217216.

[15] O. Daanouni, B. Cherradi, and A. Tmiri, "NSL-MHA-CNN: A Novel CNN Architecture for Robust Diabetic Retinopathy Prediction Against Adversarial Attacks," *IEEE Access*, vol. 10, no. July, pp. 103987–103999, 2022, doi: 10.1109/ACCESS.2022.3210179.

[16] S. Qummar *et al.*, "A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection," *IEEE Access*, vol. 7, pp. 150530–150539, 2019, doi: 10.1109/ACCESS.2019.2947484.

[17] M. Karatayev, S. Khalyk, S. Adai, M. H. Lee, and M. F. Demirci, "Breast cancer histopathology image classification using CNN," *Proc. - 2021 16th Int. Conf. Electron. Comput. Comput. ICECCO 2021*, 2021, doi: 10.1109/ICECCO53203.2021.9663757.

[18] C. R. Prasad, B. Arun, S. Amulya, P. Abboju, S. Kollem, and S. Yalabaka, "Breast Cancer Classification using CNN with Transfer Learning Models," *2023 Int. Conf. Adv. Technol. ICONAT 2023*, 2023, doi: 10.1109/ICONAT57137.2023.10080148.

[19] B. Bilgic, "Comparison of breast cancer and skin cancer diagnoses using deep learning method," *SIU 2021 - 29th IEEE Conf. Signal Process. Commun. Appl. Proc.*, Jun. 2021, doi: 10.1109/SIU53274.2021.9477992.