Performance Evaluation of ResNet50 in Skin Cancer Image Classification with Various Optimizers - English (1).docx

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Performance Evaluation of ResNet50 and MobileNetV2 in Skin Cancer Image Classification with Various Optimizers

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Abstract— **Skin cancer is an abnormal growth of skin tissue that can affect some or all layers of the skin. Melanoma is a dangerous form of skin cancer. Early prevention of skin cancer is especially important for high-risk groups. Typically, dermatologists use a biopsy for diagnosis, which involves taking a sample of skin tissue for laboratory examination. However, biopsies are expensive and can cause scarring. Therefore, a computer-based diagnostic alternative is needed to help diagnose skin cancer more quickly and accurately through image analysis. This study evaluates the performance of two deep neural network models, ResNet50 and MobileNet, in detecting skin lesions using three different types of optimizers: SGD, RMSProp, and Adam. This research aims to analyze how the choice of optimizer affects the prediction accuracy and loss value of the two models. Experimental results show that the use of the RMSProp and Adam optimizers generally provides better performance compared to SGD, especially in increasing accuracy and reducing loss values. On the ResNet50 model, the Adam optimizer achieved the highest accuracy of 0.88 with the lowest loss value of 0.4674, while on MobileNet, RMSProp gave the best results with an accuracy of 0.8864 and a loss value of 0.3884. Confusion matrix analysis shows that the model has quite good abilities in detecting malignant and benign cases. This research concludes that choosing the right optimizer greatly influences model performance, and MobileNetV2 shows better generalization ability than ResNet50 in this experiment.**

Keywords— Classification, Optimizer, Skincancer, Melanoma, ResNet50, MobileNetV2

I. INTRODUCTION

Skin cancer is an abnormal growth of skin tissue that can affect some or all layers of the skin [1]. These growths have an irregular structure with cell differentiation at varying levels of chromatin, nucleus, and cytoplasm. This cancer is expansive, infiltrative, and can damage the surrounding tissue, and can spread (metastasize) through blood vessels and/or lymph vessels. The three most common types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and malignant melanoma.

Malignant melanoma is a type of skin cancer that develops in melanocyte cells, which are responsible for producing melanin, the pigment that gives skin its color. Melanoma is a dangerous form of skin cancer. Over the past three decades, the incidence of melanoma has continued to increase. Although most people diagnosed with skin cancer have a high chance of recovery, the survival rate for those diagnosed with melanoma is lower compared to non-melanoma skin cancer [2].

Early prevention of skin cancer is very important for groups at high risk of this disease. Generally, skin doctors (dermatologists) use biopsies to diagnose skin cancer. This process involves taking a small sample of skin tissue for examination in a laboratory. Biopsy is quite expensive and can cause wounds or scratches on the skin [3]. Therefore, a computer-based diagnostic alternative is needed which is expected to help diagnose skin cancer more quickly and accurately through image analysis.

One method that is widely used in medical image classification is the use of convolutional neural networks (Convolutional Neural Networks, CNNs). ResNet50 and MobileNetV2 are two popular CNN architectures used in image classification. ResNet50 is known for its use of residual blocks which allows deeper network training without facing degradation issues. On the other hand, MobileNetV2 is designed for devices with limited computing power by using depthwise separable convolutions which reduces the number of parameters and computational requirements without significantly sacrificing performance.

This research is a continuation of research that has been carried out previously [4] [5]. This research paper proposes the ResNet50 and MobileNetV2 methods for diagnosing skin cancer. This study evaluated the performance of the ResNet50 and MobileNetV2 methods using several optimizers in detecting skin cancer. By applying this approach, it is hoped that an accurate classification will emerge for detecting types of skin diseases in humans so that they receive treatment according to the disease they are suffering from.

II. RELATED WORKS

To increase the accuracy and speed of disease diagnosis, researchers have developed a method for classifying skin cancer.

Ari, et al conducted research on skin cancer classification using the EfficientNets method F1 Score = 87% and a Top-1 Accuracy = 87.91% [7]. Arivuselvam et al. conducted research using 1500 images consisting of images of the four types of skin diseases and two types of skin cancer mentioned. The method used is Support Vector Machine [8]. Cengil, et al used 8 algorithms for skin cancer image classification. The algorithm that produces the best accuracy is Alexnet+SVM with an accuracy result of 77% [9]. Rezaoana, et al conducted research with 9 types of skin cancer images. This research uses data augmentation to reproduce images. The accuracy results obtained were 79.45% [10]. Research carried out by [5] used the Random Forest Method with the same images as this research. The accuracy results obtained were 85%. Khasanah and Winnarto [6] has conducted skin cancer classification research using the ResNet50 method, producing an accuracy value of 87%.

The main contributions of this research can be summarized as follows:

1. Use of augmentation techniques to reproduce images and overcome overfitting
2. Additional trials using several optimizers such as Adam and RMSProp to increase accuracy values.
3. Comparison of MobileNetV2 and ResNet50 architectures for skin cancer image classification.

III. Proposed Method

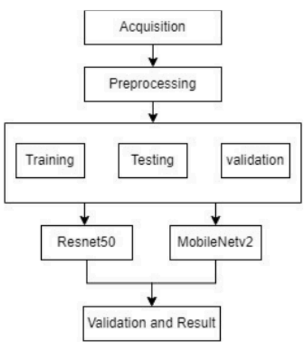


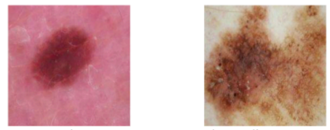
Fig 1. Proposed Method

Data is obtained from public data available on Kaggle. From this data, image preprocessing is carried out, namely the process of image resizing and image augmentation. Next, the image is divided into 3 parts, namely training data with a division of 60%, test data 20% and 20% as validation data. By separating the data, the aim is that the model obtained has the ability to generalize well in the data classification process. Resnet50 and MobileNetV2 architectural models are used for training and validation. Meanwhile, cancer detection is carried out in the data testing process. The performance of architectural models will be selected and then evaluated. In this research, trials were carried out using several optimizers including SGD, RMSProp, and Adam to obtain the best accuracy results.

A. Image Acquisition

Data is obtained from public data available on Kaggle (https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign). The dataset consists of two categories: Benign and Malignant with a total of 3297 images (test data = 660 data, train data = 2637 data).

Images showing skin cancer are shown in Fig. 2.



a. Benign b. Malignant

Fig. 2. Visualisasi Dataset

B. Preprocessing

Image pre-processing is used to speed up computation and expand the dataset for training. In this preprocessing applies data augmentation to reduce model overfitting. The augmentation parameters used in this research were carried out automatically by applying geometric transformations, such as translation, rotation, scale change, shear, vertical and horizontal reversal. The image was resized to 224x224 pixels to reduce the computational pressure of the model. Next, the image is divided into 3 parts, namely training data with a division of 60%, test data 20% and 20% as validation data.

C. ResNet50 Architecture

In the classification process, the algorithm used is deep learning. Deep learning is a part of machine learning that takes inspiration from the way the human brain works by applying multilevel learning [10]. In this context, multilevel refers to the various layers that make up deep learning. The initial layers produce simple features, while the final layers produce more complex features. Deep learning automatically performs feature extraction and classification [11]. The algorithm used for classification is Resnet50. ResNet50 is a 50 layer Residual network and has other variants such as ResNet101 and ResNet152. Using ResNet as a trained model for medical image classification has provided good results. Figure 4 displays the structure of the ResNet50 architecture

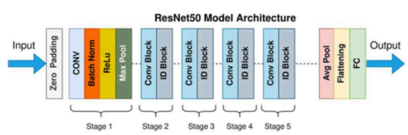


Fig. 3. ResNet50 Architecture

In the process of classifying images using ResNet50, the images will be resized to 224x224 pixels to match the input requirements. Then, the image will be transformed into numerical representations, which will then be fed through the ResNet50 network. Each convolutional layer will extract features from the image, becoming more complex with the depth of the network. Next, these features will pass through residual blocks, where the network learns to combine important information from the input image. This process continues until the image reaches the final layers of the network. In the final layers, the extracted features will be processed through several fully connected layers, ultimately producing a probability distribution over possible classes for the image. The final prediction class for the image is the class with the highest probability in that distribution.

D. MobileNetV2 Architecture

MobileNet is a CNN architecture that is used to overcome the need for computing large amounts of data. The main difference between the MobileNet architecture and CNN architectures in general is the use of a convolution layer with a filter thickness that is the same as the thickness of the input image. MobileNet has 2 convolution layers, namely depthwise convolution and pointwise convolution [12]. The main advantage of using the MobileNet architecture is that the model requires relatively less computational effort than conventional CNN models so it can work with lower computational capabilities [13].

The MobileNetV2 architecture is shown in Figure 3:

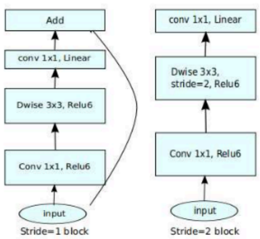


Fig 4. MobileNetV2 Architecture

IV. RESULTS AND DISCUSION

To find the best accuracy in the ResNet50 model, several parameter calculations are required. Comparing several optimizers will be carried out in this research which is a step in the ResNet50 model learning process, where the number of epochs that will be determined can influence the size of the learning process and will stop at the time and value determined through iteration. Based on previous research, the number of epochs is influenced by several factors, namely the amount of data, learning rate and optimizer. But the more you add, the more often the network weights are updated. So it can be assumed that the measure of time will be linear with the number of data sets. A difference in numbers that is too small will usually produce accuracy results that are not much different. So the epochs that will be used in this research are 20 epochs with three optimizers, namely SGD, RMSporp, and Adam. This classification process was carried out with 3297 data which was divided into training, testing and validation data, then 32 batch sizes were used. The next step is to carry out training on skin cancer images that have been divided into fit models.

A. Results from Optimizers Comparison

Optimizer selection requires considerations related to the model and data being used. Experimentation and evaluation are often necessary to determine the best optimizer for a particular task. Below are the results of a comparison of the SGD, RMSporp, and Adam optimizers.

TABLE I. ACCURACY AND LOSS OPTIMIZERS

Model + optimizers	Accuracy	Loss
RezNet50 + SGD	0.53	0.7390
RezNet50 + RMSProp	0.85	0.5743
RezNet50 + Adam	0.88	0.4674
MobileNet + SGD	0.75	0.5151
MobileNet + RMSProp	0.88	0.3884
MobileNet + Adam	0.87	0.5151

Table 1 presents the experimental results of testing the accuracy and loss of two deep neural network models, namely ResNet50 and MobileNetV2, using three different optimizers: SGD, RMSProp, and Adam. The use of different optimizers can affect model performance in terms of prediction accuracy and loss values.

ResNet50:

a. With the SGD optimizer, the model achieved an accuracy of 0.53 with a loss value of 0.7390.
b. Using the RMSProp optimizer, the model's accuracy significantly increased to 0.85 with a loss value of 0.5743.
c. The Adam optimizer provided the highest accuracy of 0.88 and the lowest loss value of 0.4674.

MobileNet:

a. When using the SGD optimizer, the model achieved an accuracy of 0.75 with a loss value of 0.5151.
b. With the RMSProp optimizer, the model showed an improved accuracy of 0.88 and a reduced loss value of 0.3884.
c. The Adam optimizer resulted in an accuracy of 0.87 with the same loss value as SGD, which is 0.5151.

From the table, it is evident that the RMSProp and Adam optimizers generally yield better accuracy and loss results compared to SGD, especially in the ResNet50 model. For MobileNetV2, RMSProp delivers the best performance in terms of accuracy and loss, indicating that the choice of optimizer has a significant impact on model performance.

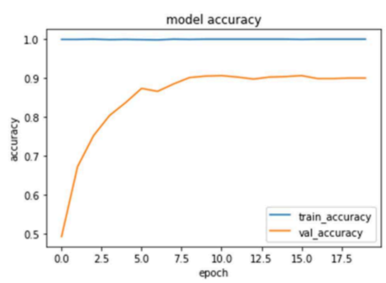


Fig 5. ResNet50 Accuracy Graph

The blue line in Figure 3, which is nearly flat and at a high value, indicates that the model has very high accuracy on the training data. This suggests that the model is very effective at classifying the training data correctly. The orange line shows that the accuracy on the validation data initially increases rapidly but then levels off. This indicates that the model learns from the data early in training, but after a few epochs, the model does not significantly improve its accuracy on the validation data. This could suggest that the model is reaching its maximum capacity in terms of generalization.

The results from the ResNet50 model graph indicate a possible overfitting issue with this model. The main indicator is the large discrepancy between the very high training accuracy and the stagnant validation accuracy, as well as the very low training loss compared to the validation loss, which does not decrease further. The model seems to be very good at memorizing the training data but not as effective on unseen data (validation data).

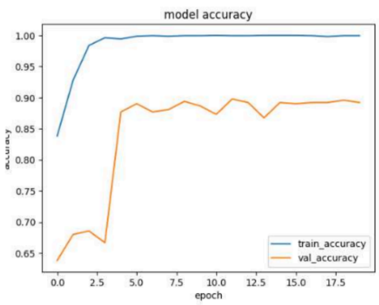


Fig 6. MobileNetV2 Accuracy Graph

The blue line in Figure 4 represents the training accuracy, which increases sharply during the first few epochs and approaches its maximum value (around 1.0) after about 5 epochs. After this point, the training accuracy stabilizes and remains high throughout the rest of the training. The orange line represents the validation accuracy, which shows significant improvement during the early epochs, reaching around 0.90. After this peak, the validation accuracy fluctuates slightly but remains fairly high and stable throughout the remainder of the training.

The results from the MobileNetV2 model graph indicate that the model performs well, with both high and stable training accuracy and validation accuracy after the initial few epochs. The model successfully learns the training data and generalizes well to the validation data, suggesting that it has matured sufficiently in learning patterns from the given dataset.

Comparing the two models, MobileNetV2 demonstrates better generalization ability than ResNet50 in this experiment. Although ResNet50 has high training accuracy, it requires additional strategies to address overfitting and improve performance on validation data. In contrast, MobileNetV2 appears well-balanced in learning both training and validation data, indicating that it is better suited for use with unseen data.

Table II. Confussion Matrix

	Malignant	Benign
Pred. Malignant	327	33
Pred. Benign	42	256

Predicted Malignant:

a. Malignant (True Positives, TP): The model successfully identified 327 samples that are truly malignant correctly.

b. Benign (False Positives, FP): The model incorrectly predicted 33 benign samples as malignant.

Predicted Benign:

a. Malignant (False Negatives, FN): The model incorrectly predicted 42 malignant samples as benign.

b. Benign (True Negatives, TN): The model successfully identified 256 samples that are truly benign correctly.

Analysis from Table 1:

a. True Positives (TP): A total of 327 malignant cases were correctly classified, indicating that the model is quite effective at detecting malignant cases.

b. False Positives (FP): There were 33 benign cases incorrectly classified as malignant. This could lead to unnecessary discomfort or anxiety for patients who are actually benign.

c. False Negatives (FN): A total of 42 malignant cases were missed (classified as benign), which is a serious error as malignant cases were overlooked and could result in greater health risks.

d. True Negatives (TN): A total of 256 benign cases were correctly classified, showing that the model also has good ability in identifying benign cases.

This confusion matrix indicates that the model has relatively good performance but still has room for improvement, particularly in reducing the number of False Negatives. Reducing False Negatives is crucial to ensure that malignant cases are not missed, which is especially important in the context of detecting serious diseases like cancer. Further optimizing the model with techniques such as data balancing, feature enhancement, or adjusting classification thresholds may be necessary to improve classification accuracy.

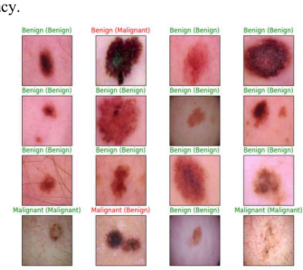


Fig 7. MobileNetV2 Prediction Results

The model generated from the classification results is used for image prediction. The images are of Malignant and Benign class. The image shows that images that were correctly predicted are green, and images that were incorrectly predicted are red.

V. Conclusion

This research is a development of previous studies which focused on skin cancer image classification. This research uses the ResNet50 and MobileNetV2 neural network models with various optimizers (SGD, RMSProp, and Adam). RMSProp and Adam generally provide better results compared to SGD in terms of accuracy and loss in both models. On ResNet50, the Adam optimizer provides the highest accuracy and lowest loss, while on MobileNetV2, RMSProp provides the best performance. This shows that the choice of optimizer greatly influences model performance, and RMSProp and Adam are more effective than SGD in this experiment.

In terms of algorithm comparison, MobileNetV2 shows better generalization capabilities compared to ResNet50, with more consistent accuracy across optimizers and lower loss values. ResNet50 although achieving high training accuracy, appears to be more prone to overfitting and may require additional strategies to improve performance on validation data.

Overall, the model used in this research shows quite good performance, there is still room for improvement, especially in terms of minimizing critical errors such as False Negatives. Choosing the right optimizer and making further adjustments to the model will be important steps forward.

References

[1] H. M. Balaha and A. E.-S. Hassan, "Skin cancer diagnosis based on deep transfer learning and sparrow search algorithm," *Neural Comput. Appl.*, vol. 35, no. 1, pp. 815–853, Jan. 2023, doi: 10.1007/s00521-022-07762-9.

[2] "IJERPH | Free Full-Text | Skin Cancer Detection: A Review Using Deep Learning Techniques." Accessed: Jun. 02, 2024. [Online]. Available: https://www.mdpi.com/1660-4601/18/10/5479

[3] Y. S. Pathania, Z. Apalla, G. Salerni, A. Patil, S. Grabbe, and M. Goldust, "Non-invasive diagnostic techniques in pigmentary skin disorders and skin cancer," *J. Cosmet. Dermatol.*, vol. 21, no. 2, pp. 444–450, 2022, doi: 10.1111/jocd.14547.

[4] N. Khasanah, R. Komarudin, N. Afni, Y. I. Maulana, and A. Salim, "Skin Cancer Classification Using Random Forest Algorithm," *SISFOTENIKA*, vol. 11, no. 2, p. 137, May 2021, doi: 10.30700/jst.v11i2.1122.

[5] N. Khasanah and M. N. Winnarto, "Application of Deep Learning with ResNet50 for Early Detection of Melanoma Skin Cancer," *J. Med. Inform. Technol.*, pp. 16–20, Mar. 2024, doi: 10.37034/medinftech.v2i1.31.

[6] "Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer".

[7] B. Arivuselvam and E. Al, "Skin Cancer Detection And Classification Using Svm Classifier," *Turk. J. Comput. Math. Educ. TURCOMAT*, vol. 12, no. 13, Art. no. 13, Jun. 2021, doi: 10.17762/turcomat.v12i13.8838.

[8] E. CengiL, A. Çinar, and M. Yildirim, "Hybrid Convolutional Neural Network Architectures for Skin Cancer Classification," *Eur. J. Sci. Technol.*, Oct. 2021, doi: 10.31590/ejosat.1010266.

[9] N. Rezaoana, M. S. Hossain, and K. Andersson, "Detection and Classification of Skin Cancer by Using a Parallel CNN Model," in *2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*, Bhubaneswar, India: IEEE, Dec. 2020, pp. 380–386. doi: 10.1109/WIECON-ECE52138.2020.9397987.

[10] W. Zhang, X. Gu, L. Tang, Y. Yin, D. Liu, and Y. Zhang, "Application of machine learning, deep learning and optimization algorithms in geoengineering and geoscience: Comprehensive review and future challenge," Gondwana Research, vol. 109, pp. 1–17, Sep. 2022, doi: 10.1016/j.gr.2022.03.015.

[11] A. W. Shandi Noris, "Implementasi deep learning untuk klasifikasi tanaman hias beracun menggunakan algoritma convolutional neural network (cnn),"vol. 6, no. 1, pp. 39–46, 2023

[12] Hendriyana and Y. H. Maulana, "Identifikasi Jenis Kayu menggunakan Convolutional Neural Network dengan Arsitektur Mobilenet," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 4, no. 1, pp. 70–76, 2020.

[13] P. N. Srinivasu, J. G. Sivasai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNetV2 and LSTM," *sensors*, pp. 1–27, 2021.

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