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Malignant and Benign Skin Cancer Classification Using Convolutional Neural Network

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Abstract

Skin cancer is one of the deadliest cancers. This cancer ranks third after cervical cancer and breast cancer in Indonesia. In detecting skin cancer, a dermatologist can carry out a biopsy. However, carrying out a biopsy requires a long time and preparation. Innovations to classify and detect skin cancer using artificial neural networks are overgrowing in helping doctors so that prompt and appropriate treatment can be carried out. This project aimed to develop a system to classify skin cancer using Convolutional Neural Networks (CNNs) and the ResNet50 architecture. This research examined the extent of system performance results using accuracy, recall, precision, and f1-score by doing several trials by changing the hyperparameters. The dataset used in this study was obtained online through Kaggle, with two classes, malignant and benign, divided into 80% training data and 20% test data. Based on the testing result, the best hyperparameter system was obtained using the AdaMax optimizer, the learning rate was 0.0001, the batch size was 64, and the epoch was 50. In this research, the performance results were 99% for precision, recall and f1-score. Simulation results show that this method with highly optimized hyperparameters can accurately classify malignant and benign skin cancer.

Keywords: Convolutional Neural Network, ResNet50, Skin Cancer.

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1. Introduction

Skin is the outermost part of the human body, comprised of millions of cells. Skin cells that grow abnormally and divide nonstop lead to skin cancer [1]. In Indonesia, skin cancer has risen significantly in the last ten years, with two to three million cases of non-skin cancer and 132,000 cases of malignant melanoma cancer each year [2]. Skin cancer is in third place after cervical cancer and breast cancer in Indonesia. The number of cases of skin cancer is approximately 5.9% - 7.8% of all types of cancer per year. Basal cell carcinoma (65.5%) is the most common type of skin cancer in Indonesia, followed by squamous cell carcinoma (23%), melanoma malignant (7.9%), and other skin cancers.

Skin cancer classified as the most aggressive is the malignant melanoma skin cancer as it has a high risk of death rate and has kept increasing quickly over the last decade, mainly if this melanoma skin cancer is not detected in advance. Generally, the types of basal cell carcinoma and squamous cell carcinoma are non-melanoma skin cancer. However, in this case, the metastases are less, and only a small percentage leads to death. According to this, early detection and accurate of diagnosis of skin cancer is necessary to help the healing process, proper treatment, and avoid the worst effects of skin cancer [3].

Dermatologists perform a biopsy procedure to get histopathological information from skin samples on the human body, particularly in skin cancer [4]. However, during the biopsy process, it takes one week to read the results of the anatomical histopathology examination and the wound healing time is a little longer. This process is a weakness of the biopsy [5].

Deep Neural Network and Machine Learning have been developed for skin cancer early detection. In the study [6], they used the CNN method to classify skin cancer. It consisted of 7 classes, including actinic fibroma, benign keratosis, melanoma, dermato fibroma, keratosis, vascular lesions, basal cell carcinoma, and melanocytic nevi. This research had an 83.11% accuracy performance with dataset images obtained from

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Human Against Machine with 10000 training images (HAM10000).

Other studies [7] employed two classes, including malignant and benign skin cancer, with dataset images from the International Skin Imaging Collaboration (ISIC). The CNN method was used with ResNet architecture to classify melanoma cancer skin images. They compared several types of ResNet architectures, including 50, 40, 25, 10, and 7. This research obtained the best accuracy performance result by using ResNet50 with an 83.11% value.

The following study [8] compared two methods using the K-Nearest Neighbors (KNN) method and the CNN method. The CNN method showed the best result with 76.56% accuracy, while the KKN only had 75% accuracy. The subsequent study [9] used the CNN method with eight layers of Convolutional 2D architecture, including (16, 16, 32, 32, 64, 64, 128, 128). In the research, the first layer used was (20.20), and the next layer was (5.5 and 3.3) using MaxPooling and AveragePooling and Dropout (0.2). In the research, it obtained a 75% of accuracy performance [9]. In contrast to previous research, the research [10] obtained a dataset from Kaggle with two classes, including malignant and be- nign skin cancer. In this study, two methods, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), were compared for the classification of skin cancer types.When using the SVM method, the accuracy obtained was 69.85%, while the KNN method obtained the best accuracy performance when K-5 with an accuracy of 70.61%.

The research [18] conducted on skin cancer classification indicated that the CNN method along with the ResNet50 architecture is the most reliable method to diagnose the condition. The study developed a system which could classify between malignant and benign skin cancer using the CNN method and ResNet50 architecture. This Research uses Kaggle dataset [11] and it shows that ResNet50 is good for diagnosing skin cancer which has the highest value among other models [18].

2. Materials and Method

In this study, the skin cancer classification system was developed using the CNN method with the ResNet50 architecture. This research examined the extent of system performance results using accuracy, recall, precision, and f1-score by doing several trials by changing parameters such as Optimizer and Learning Rate to get the best results.

Figure 1 is a general system block diagram for classifying malignant and benign skin cancers. In this study, the method used was CNN with ResNet50 architecture. The input image in the system is an RGB image with a total of 3297 skin cancer images with two classes with *jpeg format. Moreover, a pre-processing procedure is necessary to adjust the image size. This involves resizing the image from the original size of 224 x 224 pixels to a smaller size of 128 x 128 pixels to ensure consistency and improve testing metrics and accuracy. Then, the image is trained using the CNN method and ResNet50 architectures with the best hyperparameters that can provide maximum performance in classifying skin cancer according to classes.

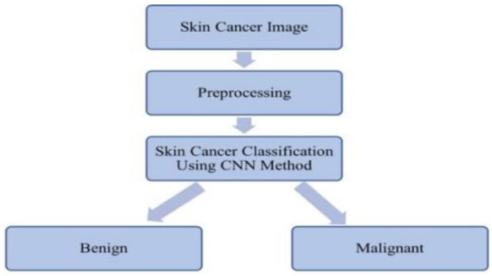
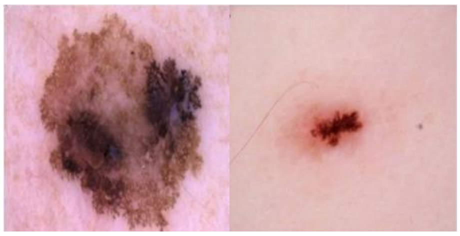


Fig. 1. Skin Cancer Classification Process



(a) (b)

Fig. 2. Skin cancer images. (a) Benign (b) Malignant

2.2. *Dataset*

This study used a secondary dataset for skin cancer with two classes, their images are shown in Fig. 2. This dataset can be accessed online on Kaggle with a total of 3297 RGB images of skin cancer images and an unbalanced number of images between classes, including 1800 images for benign classes and 1497 images for the malignant class [11]. The data were divided into 80% of 2637 images of training data and 20% of 660 images of testing data.

2.3. *Convolutional Neural Network (CNN)*

The Convolutional Neural Network consists of several layers: Convolution Layer for Cancer Classifying, Pooling layer, fully connected layer, Rectified Linear Unit (ReLU) and Sigmoid, as shown in Fig. 3.

The Convolution Layer, which is the basis of the primary process in CNN serves as the first layer in the network architecture. Fig. 4 illustrates the Convolution Layer as input and uses a filter (kernel) to generate a feature map [13]. From Fig 4, the d parameter represents the depth of the layer, while the h parameter represents the height of the layer. The convolution Layer performs convolution output from the previous layer, where the layer is the basis of the primary process of CNN. In im- age processing, the convolution process extracts image input features and produces an inlined transformation output according to the data [14].

In this research, the convolution process was applied to the dataset and the resulting feature maps were processed using batch normalization and ReLu activation to produce non-linear values from the convolution process and improved accuracy and performance for the deep learning model.

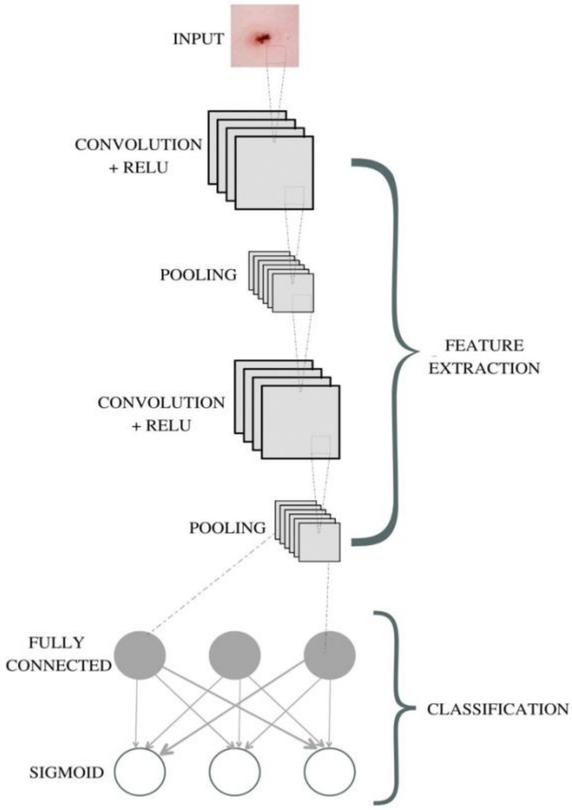


Fig. 3. Convolutional Neural Network for Cancer Classifying

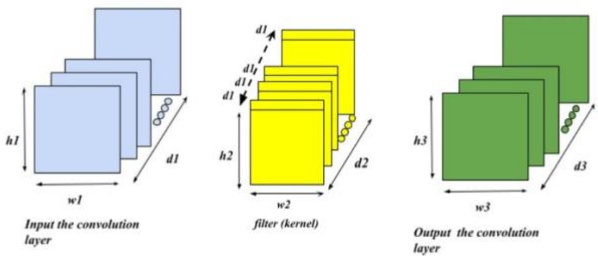


Fig. 4. Convolution Layer

The next layer is the pooling layer. The pooling layer is part of the Convolution Layer to overcome over-fitting. Max pooling is a method used to take the maximum value from the CNN output and create a re- duced image matrix [14]. Average Pooling is a method used to take the average value of each feature map [13]. This research uses average pooling to reduce and classified using the best parameters, resulting in an out- put that can detect objects to be classified according to predetermined classes.

The fully connected layer is applied at the end of the network because each neuron convolution layer requires a process of transforming the matrix data into one-dimensional data before it is entered into the fully connected layer which possibly leads to data information loss and is not reversible [14].

The next layer is Rectified Linear Unit (ReLU), which accelerates and speeds up the convergence process. At this layer, the unsaturated function is applied as presented in Equation 1.

$$f(x) = \max\,(0, x), \tag{1}$$

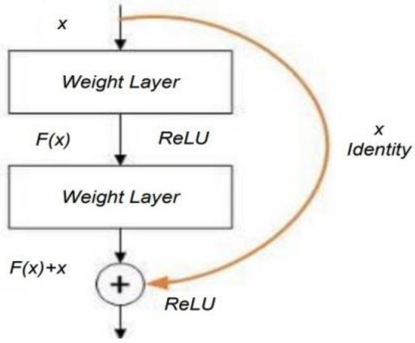


Fig. 5. Resnet Skip Connection Diagram

It shows that if x≤0 so, the value of x=0. If the value of x>0 so, the value of x=x. This is influenced by the receptive field of the Convolutional Layer [14].

The final layer in a Convolutional Neural Network (CNN) is the Sigmoid activation function, which outputs binary values from 0 to 1 [15]. Sigmoid mathematical representation function is presented in Equation 2.

$$y = f(x) = \frac{1}{(1+e^{-x})}, \tag{2}$$

where $y = f\,(x)$ is the sigmoid function and e is Euler's number.

2.4. *ResNet50*

Residual neural network (ResNet) is a largely well-known architecture, this ResNet architecture is state of the art for all categories of object detection classification, and semantic segmentation. The crucial thing in making a CNN model produces a good perm mansion is to have a high depth. ResNet is a solution for deep neural networks, and it is because ResNet can enhance or degrade a network using residual blocks. This block is called a residual block which is a block contained in each CNN layer. This block skips cer- tain layers without destroying the model with the best performance [16]. A residual block is a collection of functions with a skip connection feature, as shown [17].

In Fig. 5 is a Resnet skip connection diagram, this skip connection represents an identity transformation where input x produces a two-layer output resulting in f(x) so that the overall output is f(x) + x. ResNet has various types of architecture such as 18, 34, 50, 101 to 152 layers [17].

Figure 6 is the ResNet50 architecture. In this ResNet architecture, it is parted into four-layer groups, and each layer has three blocks. Between the blocks of this layer are skip connections and batch normalization. In the skip connection, there are two or three layers containing the ReLU activation function along with Batch normalization and linking between layer blocks [17].

2.5. *System Performance*

This research employed several parameters in calculating: accuracy, recall, precision, and f1-score [14].

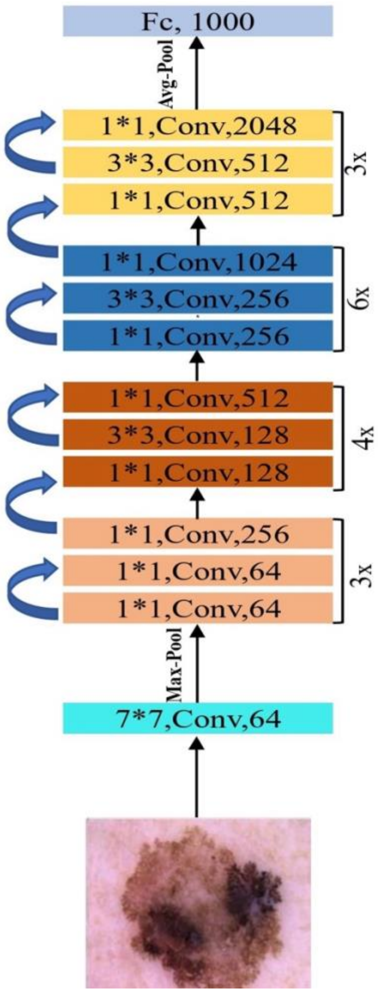


Fig. 6. ResNet50 Architecture

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \times 100\% \,, \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \,, \tag{4}$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \,, \tag{5}$$

where TP (True Positive) is a condition when data is positive and correctly predicted as positive, TN (True Negative) means the data is negative and correctly predicted as negative, FP (False Positive) means data is negative but incorrectly detected as positive, and FN (False Negative) means data is positive but incorrectly detected as negative.

$$f1score = 2 \times \frac{Recall \times \text{Precision}}{Recall + \text{Precision}} \,, \tag{6}$$

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} y_i \,, \tag{7}$$

where N means number of datasets and y^ig is the predicted probabilities of the ground-truth class for sample i.

3. Result and Discussion

Research and analysis of the classification system are carried out. skin cancer using CNN with the ResNet50 model. This research uses RGB images that have been pre-processed by doing resizing to 128×128 pixel from the original image size of 224×224 pixels. Datasets with a total of 3297 images with an unbalanced number of distributions between classes, namely 1800 image for benign skin cancer class and 1497 for malignant skin cancer class. Datasets was used as 80% of the training data, with a total of 2637 images and 20% test data, with a total of 660 images for test data.

In this study, we tested the measurement of system performance results. using accuracy, recall, precision, and the f1-score. by doing some experiments by changing parameters such as the optimizer, learning rate, batch size, and Epoch for the best results. In addition, the hardware was used Asus VivoBook Flip 14 laptop with an AMD Ryzen 5 5500U processor.

3.1. System Testing Results

In this project, testing the system to classify cancer was carried out. benign and malignant skin by using the size of the image that has been preprocessing by re sizing 128×128. To evaluate the system's performance, several scenarios were conducted, including the effect of optimizer type, learning rate, batch size, and epoch.

In the first scenario, various optimizers were used and compared, by using RMSprop, Adam, Nadam, and AdaMax. The random parameters used in the experiment were 0.001 learning rate, 32 batch size, and 50 epochs.

From the results in Figure 7, shows the comparison optimizer on testing the influence of the optimizer RMSprop, Adam, Nadam, and AdaMax. In this study, the lowest accuracy value was observed when employing the RMSprop optimizer, resulting in a performance of 81%. Additionally, the precision value, recall value, and f1-score value all stand at 81%.While the highest accuracy performance is achieved when utilizing the AdaMax optimizer, yielding an outstanding 98% accuracy, the precision value, recall value, and f1-score also reach a remarkable 98% each. The second scenario involved changing the learn- ing rate, with values of 0.1, 0.01, 0.001, and 0.0001 tested using AdaMax optimizer, 32 batch size, and 50 epochs.

From the results in Figure 8, it shows that in testing the effect of learning rates of 0.1, 0.01, 0.001, and 0.0001. In this study, the lowest accuracy performance is obtained when using a learning rate of 0.1. with a yield of 75%. The precision value is 79%, the recall value is 75%, and the f1-score value is 74%. While the highest accuracy performance is obtained when using a learning rate of 0.0001 with a yield of 98%. The precision value is 98%, the recall value is 98%, and the f1-score value is 98%.

The third scenario tested the effect of batch size, with batch sizes of 8, 16, 32, and 64 tested using AdaMax optimizer, 0.0001 learning rate, and 50 epochs.

Figure 9 shows that in testing the effect of batch sizes 8, 16, 32 and 64, The lowest accuracy performance is attained when utilizing a batch size of 8, yielding an accuracy of 89%. Furthermore, the precision value, recall value, and f1-score value are all recorded at 89%.

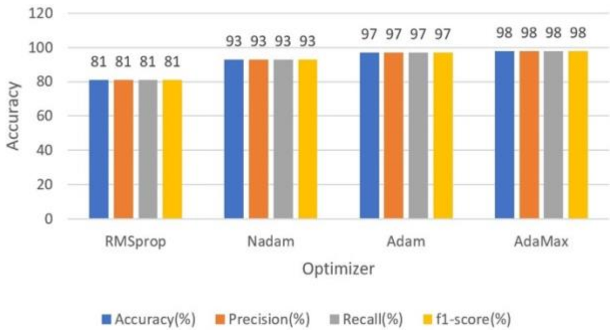


Fig. 7. Effect of Optimizer Type

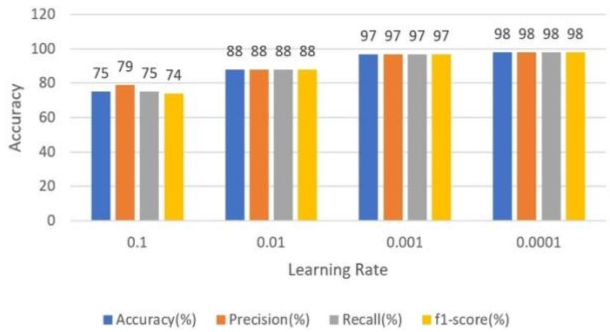


Fig. 8. Effect of Learning Rate

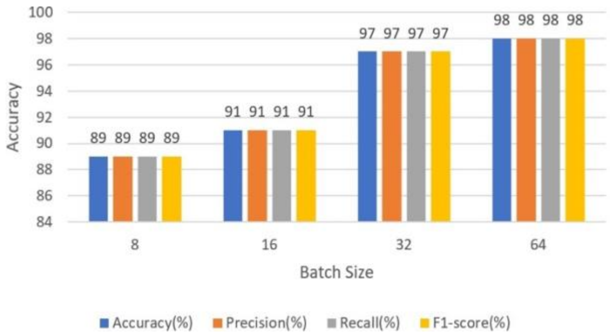


Fig. 9. Effect of Batch Size

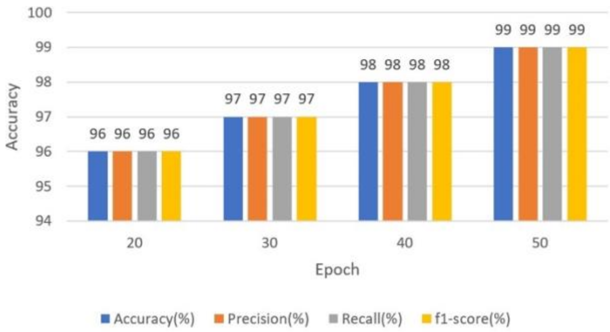


Fig. 10. Effect of Epoch

The highest accuracy performance is achieved when utilizing a batch size of 64, yielding an impressive 99% accuracy, the precision value, recall value, and f1-score value also reach an impressive 99% each.

The fourth and final scenario involved changing the epoch value, with 20, 30, 40, and 50 epochs tested using random parameters with AdaMax optimizer, 0.0001 learning rate, and 50 epochs.

The results in Figure 10 shows that in testing the influence of epochs 20, 30, 40, and 50. In In this study, the lowest performance accuracy value was obtained when using epoch 20, yielding a precision value, recall value, and f1-score value of 96% each. On the other hand, the highest accuracy performance was achieved when using epoch 50, resulting in a precision value, recall value, and f1-score value of 99% each.

The results of these experiments were analyzed to determine the optimal system configuration for accurately classifying skin cancer. It was concluded that using the AdaMax optimizer resulted in the highest accuracy value. AdaMax is designed to speed up the optimization process and produce better results in some cases. Therefore, the next experiment will use the AdaMax optimizer as a fixed optimizer.

Moreover, it was found that using a smaller learning rate increased the network accuracy level in the classification training process, resulting in better detailed and performance results. Therefore, 0.0001 will be used as a fixed learning rate in the next experiment. Additionally, using a bigger batch size also increased the network accuracy level in the classification training process. As a result, 64 will be used as a fixed batch size in the next experiment.

It was also found that the highest accuracy performance was achieved with epoch 50, resulting in a precision value of 99%, recall value of 99%, and an f1 score value of 99%.

3.2. *Test Scenario Optimization Analysis*

This research examined the measurement of system performance results using accuracy, recall, precision, and f1 score. By doing some experiments by changing parameters such as Optimizer and Learning Rate to get the best results with RGB images that had been pre-processed by resizing the image.

Based on the result shown in Table 1 and Table 2 can be concluded that the AdaMax optimizer gets the highest accuracy value because the AdaMax opti- mizer is an extension optimizer from Adam which is designed to speed up the optimization process so that it can produce the best results in some cases. And the lower learning rate can result in a greater level of net- work accuracy in conducting the classification training process so that the resulting performance can be better.

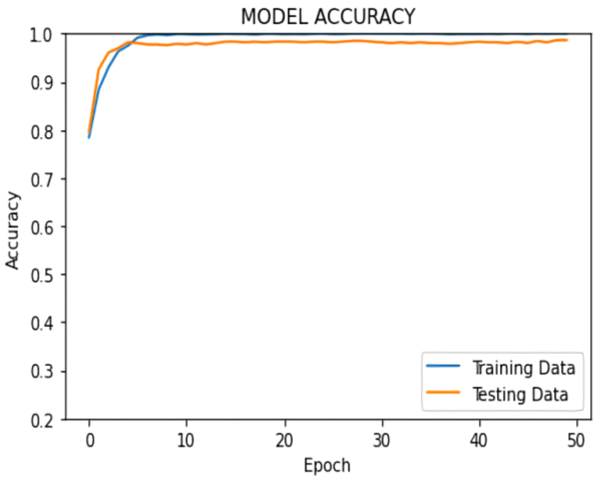
Figure 11 shows the graph of the accuracy and loss model using the best hyperparameters to classify skin cancers with a validation accuracy of 98.64% and loss validation of 0.0475 carried out by 50 epochs. While the value of training accuracy was 99.96% and loss was 0.0012.

Table 1. Optimizer Test

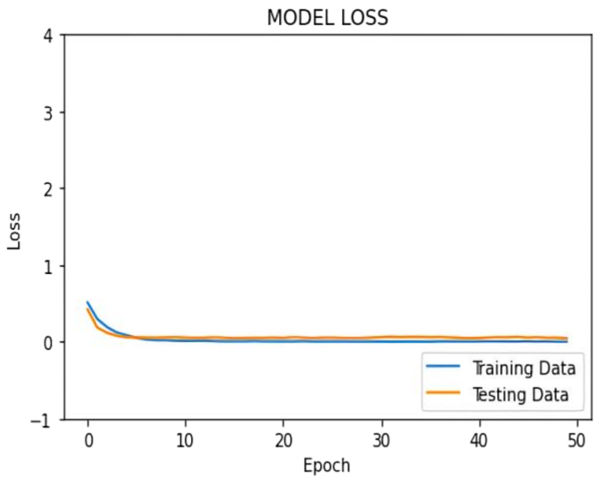
Optimizer	Accuracy	Precision	Recall	F1-Score
RMSprop	81	81	81	81
Nadam	93	93	93	93
Adam	97	97	97	97
Adamax	98	98	98	98

Table 2. Learning Rate Test

Learning Rate	Accuracy	Precision	Recall	F1-Score
0.1	75	79	75	74
0.01	88	88	88	88
0.001	97	97	97	97
0.0001	99	99	99	99



(a) Accuracy



(b) Loss

Fig. 11. Scenario Performance Results

Based on Table 3 shows that the 660 images separated into two classes of benign skin cancer (benign) as many as 300 images, and malignant skin cancer (malignant) 360 images were used as test data confusion matrix and gained 99% of accuracy. The Confusion Matrix can be seen on Figure 12. In the benign skin cancer class, the precision value was 98%, the recall value was 99%, and the f1-score value was 98%. While in the malignant skin cancer class, the precision value was 99%, the recall value was 99%, and the f1-score was 99%.

If it compared with the previous research [18] which used the same dataset [11] was also divided into 2 classes, including benign and malignant skin cancer. This research [18] was performed on multiple models and got the highest model by using resnet50 with an accuracy of 86.571%, precision of 86.48%, recall of 86%, and f1-score of 86.239% with the highest model, ResNet50.

Table 3. Epoch Test

Class	Precision	Recall	F1-Score	Total
Benign	98	99	99	303
Malignant	99	99	99	357
Total	98.5	99	99	660

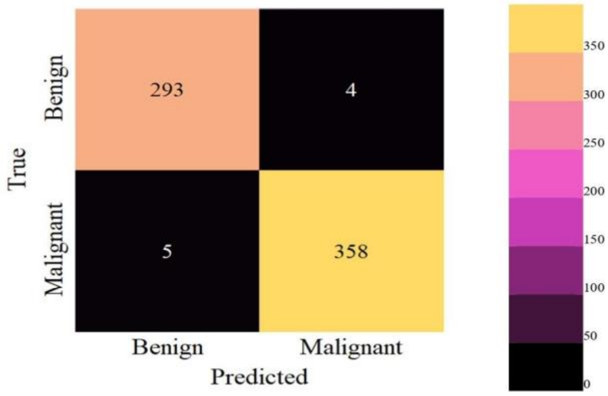


Fig. 12. Confusion Matrix

This research, however, had an advantage over the previous one, as it used a larger training dataset (660 compared to 350) and different image sizes (128x128 px compared to 176 x 176 px). Additionally, the optimizer used was different (AdaMax compared to Adam).

It can be concluded that this research is better than the previous one [18], as it uses different parameters such as the type of optimizer, number of epochs, and so on. Furthermore, this research focuses on the comparison of testing systems, such as types of optimizers, learning rates, batch sizes, and epochs, to obtain optimal parameters with better accuracy, precision, recall, and f1-score results than the previous research.

4. Conclusion

In this study, a substitute system was designed to classify malignant and benign skin cancer using the CNN method with the ResNet50 architecture. It took 30 minutes to do the training. In this research, the validation performance value was 99% for precission, recall and f1-score with the best parameters using the AdaMax optimizer, the Learning rate of 0.0001, batch size of 64 and epoch of 50.

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