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Enhancing Skin Cancer Classification Using Optimized InceptionV3 Model

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A B S T R A C T

Skin cancer is a disease that starts in skin cells characterized by uncontrolled growth that can attack skin tissue. Although it has a high cure rate if treated in a timely manner, a delay in diagnosis can have serious consequences. The use of computer technology, especially Artificial Intelligence (AI), has played an important role in improving health services, including in the context of skin cancer. New innovations in the classification and detection of skin cancer using artificial neural networks have led to significant improvements in diagnosis and treatment. One promising approach is using the InceptionV3 algorithm, which has high accuracy and is capable of processing high-resolution images. This study aims to implement InceptionV3 to classify two types of skin cancer, namely malignant and benign, with an emphasis on improving accuracy performance. With the pre-processing process, namely augmentation and the addition of several features, this study aims to provide accurate and efficient results in skin cancer classification. The results of this study can have a positive impact in increasing the accuracy of early detection of skin cancer, especially by future researchers.

1. Introduction

Skin cancer is a type of cancer that starts in skin cells and is characterized when skin cells grow uncontrollably and have the potential to attack surrounding tissues or all layers of the skin [1]. Even though it can be detected at an early stage and has a high cure rate if treated on time, a late or inaccurate diagnosis can have a serious impact on the patient [2], [3].

The use of computer technology to improve health service standards has been widely applied, one of which is the application of artificial intelligence (AI) which has a number of important roles in the health context, especially in the context of cancer. AI is used for various functions such as disease diagnosis, prognostic prediction, classification of cancer types, and analysis of various pathologies [4].

This can be a solution to overcome problems faced in the health sector, including accelerating the classification of cancer images so that they are more efficient [5]. New innovations in the classification and detection of skin cancer using neural networks have opened the door for significant improvements in the diagnosis and treatment of skin cancer. Artificial intelligence technologies, such as artificial neural networks, have brought great benefits in the fields of medicine and dermatology, especially when it comes to medical image analysis [6].

One promising approach is the use of neural networks algorithms such as InceptionV3 for classifying dermatological images and detecting types of skin cancer [3]. The InceptionV3 algorithm is a neural network architecture capable of classifying images with a high degree of accuracy and processing images with high resolution [7], [8]. The use of deep learning algorithms such as InceptionV3 has been successfully applied by many researchers for image classification [3], [8], [9], [10], [11]. One of them was carried out by N. Dong, et al in 2020 by carrying out a cell classification that combines Inception v3 and artificial features, which effectively improves the accuracy of cervical cell recognition and achieves accurate and effective cervical cell image classification based on Herlev Data set [12].

This study aims to implement the InceptionV3 algorithm for the classification of two types of skin cancer with a focus on increasing accuracy. There are two types of skin cancer used, namely malignant and the second type of skin cancer is benign. By carrying out pre-processing processes such as image augmentation, split data and adding several additional features to the InceptionV3 algorithm, it is hoped that it will be able to provide the best accuracy performance results and efficiency in classifying skin cancer types.

2. Research Method

The following are the stages of research conducted by researchers presented in Figure 1.

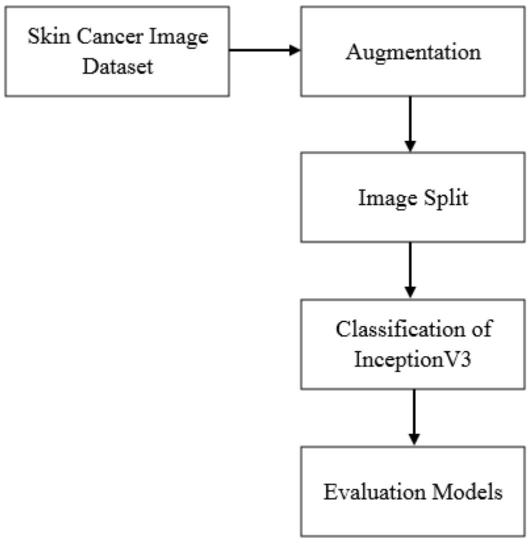

Figure 1. Research Method

2.1. Skin Cancer Image Dataset

The dataset used in this study was taken from the internet site, namely kaggle which contains a dataset of skin cancer images for the process of classifying skin cancer types. Kaggle provides image types of skin cancer with 2 classes, namely malignant and benign. The total data is 2,637 images, with 1,440 benign class images and 1,197 malignant class images [13].

Figure 2 is an example of each image used in this study, where Figure 2(a) is a type of malignant skin cancer and Figure 2(b) is a type of benign skin cancer.

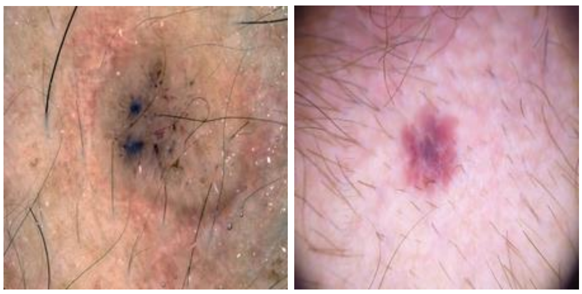

Figure 2. Skin cancer image used for research

2.2. Augmentation

The image augmentation process is a technique for increasing the number of image data variations available in the training dataset so that the image becomes larger than the original number [14]. The goal is to improve the performance of machine learning models. The augmentation processes carried out at this stage are rescale, image rotation, shift, and also horizontal flip.

2.3. Image Split (Training Data and Testing Data)

Separation of images into training data and testing data is an important step in the development of image recognition or classification models. The goal of this split is to train the model on data not used in the test, so as to gauge how well the model generalizes to data it has never seen before[15].

2.4. Classification of Inceptionv3

The classification process using the InceptionV3 method was carried out on 2 types of skin cancer images, namely malignant and benign images. In this study, the method involves the use of the InceptionV3 architecture, which has two main stages, namely the feature learning stage and the classification stage [16].

At this hold, the image resizing automation process is also carried out before classification is carried out. The image resizing process changes the physical size of the image. The main purpose of this process is to change the image resolution, the number of pixels or details contained in the image [17]. The resize process automatically resizes the image to be equal to 224x224 in size.

In this study, a classification process was carried out, where after going through the feature learning stage, the InceptionV3 model issued a classification in the form of a probability distribution of classes that might exist in the dataset. The class with the highest probability is considered as the final classification of the model.

2.5. Evaluation Models

The testing and evaluation stage is an important stage in scientific research, especially in the context of developing models or experiments [18]. At this stage, the validation process is carried out on the InceptionV3 model that has been built using training data. Then evaluate the accuracy of the model using the confusion matrix. Figure 3 below is a confusion matrix with 4 different combinations of predicted values and actual. values.

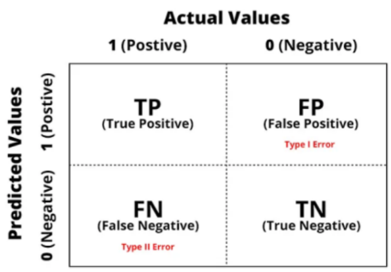

Figure 3. Confusion Matrix

The confusion matrix helps in understanding the extent to which the model predicts correctly or incorrectly for each class. Usually, in the case of two classes (positive and negative) with four elements namely True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN) [19].

3. Result and Discussion

3.1. Classification of Inceptionv3

The process of implementing the InceptionV3 algorithm to create a model is done by first changing all image dimensions to 224x224 as shown in Figure 4 below.

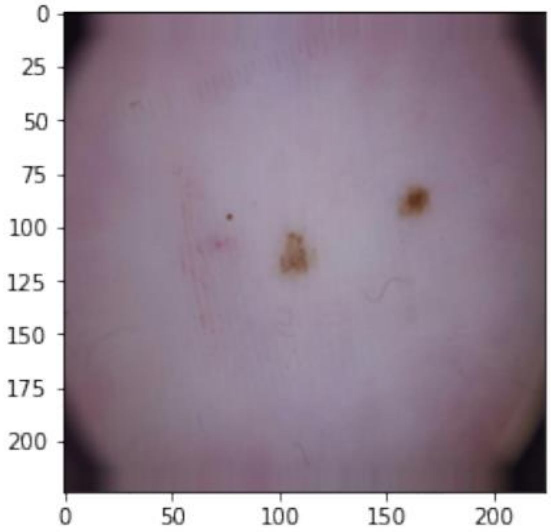

Figure 4. Image after resizing process

The InceptionV3 training model is given a pre-trained weight, namely imagenet with additional features such as learning_rate, optimizer, epochs to improve classification accuracy performance.

The results of the 10 epoch training model obtained a loss value of 0.2762, and an accuracy value of 0.8665. the loss and accuracy values can be said to be good for training data.

3.2. Evaluation Models

At this stage an evaluation process is carried out on the training model. Evaluation is described in the form of a confusion matrix as shown in Figure 5.

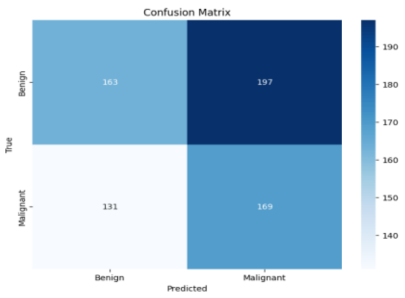

Figure 5. Confusion matrix from validation data results

Figure 5 shows that the model correctly classifies 163 images with the Benign class, and 169 images with the Malignant class are classified correctly. then there were 131 images classified incorrectly as the Malignant class, then as many as 197 images incorrectly classified in the Benign class.

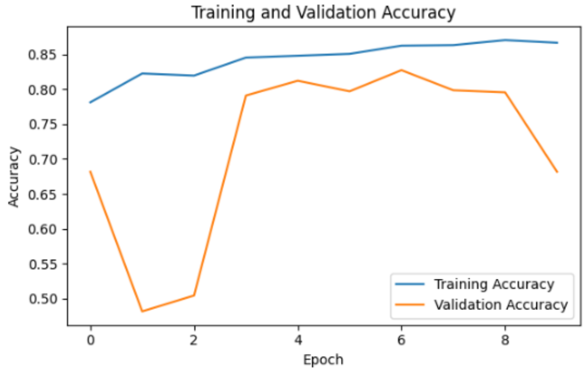

Figure 6. The results of accuracy

The results of the accuracy of the training data show an increase when given a higher epoch, but conversely the results of the accuracy of the validation data show a decrease when the epoch is higher. The results of the accuracy comparison can be seen in Figure 6.

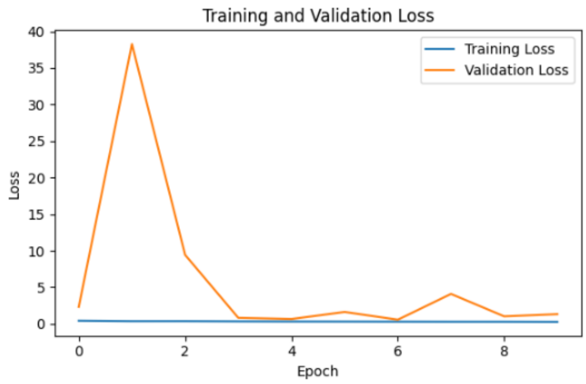

Figure 7. The results of loss

Figure 7 shows the results of loss or misclassification values for training data and validation data. The results show that the loss value for the validation data decreases when the epoch value is added, and the loss value for the training data shows that there is no change when the epoch is higher. This happens because when building the model, it is given a pre-trained weight, namely imagenet.

Picture. 8 is the result of evaluating the classification process using the InceptionV3 model which is shown in the confusion matrix in Figure 8..

			Predicted	
	precision	recall	f1-score	support
Benign	0.55	0.45	0.50	360
Malignant	0.46	0.56	0.51	300
accuracy			0.50	660
macro avg	0.51	0.51	0.50	660
weighted avg	0.51	0.50	0.50	660

Figure 8. Confusion matrix of image classification results

It can be seen that the precision generated for each class is 0.55 for the Benign class and 0.46 for the Malignant class. Precision measures the degree to which a model actually correctly predicts positives. Then the recall results generated for each class are 0.45 for the Benign class and 0.56 for the Malignant class. Recall shows how far the model can detect all true positive cases. The f1-score result for the Benign class is 0.50 and for the Malignant class is 0.51 which means that the closer to the value 0 the result is said to be less good.

4. Conclusion

In this study, we have trained and evaluated a classification model to recognize skin cancer using a dataset containing images of skin cancer categorized as benign and malignant. The model's ability to recognize skin cancer with an accuracy of 50.30% indicates that the model has not reached an optimal level of performance. The precision of 46.17% indicates the model's ability to correctly identify the malignant class (positive) but has a fairly high rate of false positives. Recall of 56.33% shows the ability of the model to find most of the actual malignant classes. F1-Score of 50.75% describes the balance between precision and recall. Nonetheless, these results indicate that the model can contribute to automatic identification of skin cancer. However, there is room for improvement in improving model performance, such as applying data augmentation techniques, exploring more complex model architectures, or improving hyperparameter tuning parameters. This study recognizes that skin cancer classification is a complex task and often requires more and more high-quality data and further research to achieve better performance.

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