Modification of Convolutional Neural Network GoogLeNet Architecture with Dull Razor Filtering for Classifying Skin Cancer

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***Abstract*—Skin is the widest external organ covering the human body. Due to a high intensity exposure to the environment, the skin can experience various health problems, one of which is skin cancer. Early detection is needed so that further medication for patients can be done immediately. In this regard, the use of artificial intelligence (AI)-based solutions in detecting skin cancer images can be used to detect skin cancer potentials. In this study, the classification of benign and malignant skin cancer types was carried out by utilizing GoogLeNet Convolutional Neural Network (CNN) method. The GoogLeNet architecture has the advantage of having an inception module, allowing the convolution and pooling processes to run in parallel terms that can reduce computing time and speed up the classification process without lowering the system accuracy. This study consisted of several stages, starting from the data acquisition of 600 skin cancer images from Kaggle.com to the uniformity of the input size that allows the system to work faster. There was also a utilization of dull razor filtering to reduce input image noise due to hair growing along the epidermis. After the preprocessing process was complete, GoogLeNet architecture processed the image input before categorizing the input into benign or malignant skin cancer. The system's performance was then evaluated using performance parameters such as accuracy, precision, recall, and F-1 score, and it was compared to other methods. The system managed to obtain satisfactory results, including the accuracy of 97.73% and the loss of 1.7063. As for precision, recall, and F-1 score parameters, each received an average value of 0.98. The system performance proposed by the authors successfully have better accuracy compared to the previous study with much less use of datasets. The test results show that CNN method is able to detect and classify skin cancer accurately, so it is expected that this method could help medical workers in diagnosing the community.**

***Keywords*—Accuracy, CNN, F1-Score, GoogLeNet, Skin Cancer, Loss, Precision, Recall.**

I. INTRODUCTION

Skin is the widest organ covering the human body [1]. The skin acts as a guard of the body's defense against pathogens or substances that can harm the organs inside. As a result of its outermost location, the skin often experiences health problems, one of which is skin cancer. Skin cancer is a lump or overgrowth of skin tissue irregularly which damages the surrounding tissue [2]. In Indonesia, skin cancer ranks third after uterine cancer and breast cancer as the most common cancers [2]. Skin cancer is divided into benign and malignant skin cancer. After all, 7.9% of total skin cancer cases in Indonesia are classified as malignant (malignant melanoma) due to invasive cancer cells, causing it to have a high mortality rate. Although cases of skin cancer especially in malignant cancer are relatively low, early detection of skin cancer remains needed to keep patients under control; hence, patients can immediately get an appropriate medical treatment. Artificial intelligence (AI)-based solutions, through deep learning in the image, can be a solution to help medical workers in conducting examinations and classifying cancer types since this model can accurately recognize patterns through the owned image features. In addition, the accuracy obtained when using this model is relatively high, so that the potential of skin cancer in patients can be immediately known and further treatment of skin cancer diagnosed can be immediately given to prevent worsening of the patient's condition.

Several studies on the classification of AI-based for skin cancer classification have been conducted. Reference [3] was conducted skin cancer detection using the convolutional neural network (CNN) by checking on the imagery using a method called asymmetry, border, color, diameter, and evolution (ABCDE). In this method, input images were divided into benign and malignant classes with output in the form of class 1 or 0. Class 1 meant the image contained malignant cancer cells and 0 meant the image did not contain cancer cells. The best accuracy obtained was 89.5%. In [4], skin cancer detection was conducted in deep learning-based dermal cells, using Deep Learning Studio as an architectural platform. Reference [5] conducted research to detect and classify skin cancer using transfer learning combining the architectures of VGG19, Inception V3, SqueezeNet and ResNet50 to improve the accuracy score. In [6], skin cancer detection and classification were conducted using support vector machine (SVM) through the SVM kernel method and radial function base to detect data and divide them into classes of benign or malignant cancers. The best accuracy result was 92.10%. Subsequently, [7] used the two dropout layers-CNN model, a deep learning, and machine learning method to distinguish objects, including types of cancer, whether malignant or benign. The best accuracy obtained was 88.40%. Reference [8] utilized computer-aided diagnosis (CAD) to detect skin cancer based on ABCD rules, the best accuracy yield obtained was 92.00%. Reference [9] used differential evolution based artificial neural network (DE-ANN) and automatic segmentation using fuzzy c-means

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clustering, with the best accuracy of 97.40%. In [10], the deep convolutional neural network (DCNN) was utilized for data contrast and classification of skin cancer, the best accuracy obtained was 95.41%. In [11], a skin cancer diagnosis was made using CNN a modified GoogLeNet architecture by adding transposed convolutional layers (deconvolution) after the last convolution. The accuracy value obtained was 93.09%.

CNN is a classification method that can be used in digital image classification, especially on skin cancer imagery. This method is expected to help doctors more accurately diagnose skin cancer disease in the epidermis layer so that the appropriate treatment can be determined [12], [13]. Based on [11], the authors wish to utilize CNN GoogLeNet architecture with less images input compared, as well as provide additional methods with the use of dull razor filtering to reduce noise in the image input caused by fine hair and unify the image size as input. Hence, this method can improve the accuracy obtained when it is compared to previous research.

II. THE PROPOSED METHOD

A. Convolutional Neural Network

Convolutional Neural Network (CNN) is one of the deep neural network methods that has good accuracy in image recognition. CNN is an image processing method, the development of a multilayer perceptron (MLP) in which data are propagated in the neurons in two dimensions [14]. CNN is a neural network feed forward operation implemented based on the workings of the human visual cortex, using several elements that work in parallel by processing grid-patterned data. CNN consists of several layers, namely convolution layer, pooling layer, and fully connected layer that works hierarchically, so that the output at the previous layer will be the input at the next layer [15]. CNN is a deep learning method consisting of many mathematical operations, one of the advantages of the CNN method is that it does not require certain characteristic extraction methods, so the stages for the image classification process can be faster. However, CNN requires a much more amount of data for the training process, so the computational load becomes greater and expensive graphics processing units are needed for system training.

B. GoogLeNet Architecture

GoogLeNet architecture is a modification of the CNN architecture managed to become the best model on ILLSVRC14. This architecture works by detecting images with 5 to 22 layers, yet still has high accuracy. The concept of architectural work is based on activation values on deep networks that is not entirely important since there is a value of zero due to previous correlations, so activation values that are not fully connected are required [16]. To meet these conditions, GoogLeNet has a layer inception module inspired by the human visual cortex model, which optimizes sparse structure to support computing. In the inception module layer found in GoogLeNet architecture, a 1 × 1 matrix convolution is performed prior to convolution with 3 × 3 and 5 × 5 matrices. This method is used to reduce the dimensions of modules that contribute to increasing the depth of analysis and network expansion while maintaining system performance. In general, in the GoogLeNet architecture, convolution and pooling layer serve to extract data, inception modules serve to reduce computational load and increase data depth, and fully connected layers serve to accommodate the results of the pooling layer process at the end of the GoogLeNet architecture. The system's output will be replaced with simple global average pooling, which helps to reduce the total size of parameters without sacrificing accuracy.

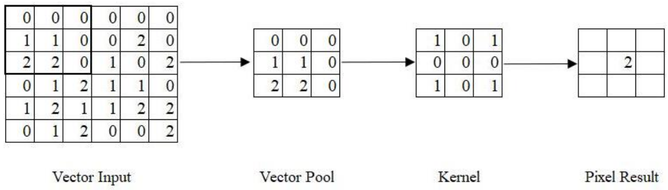

Fig. 1 Convolution process.

1) Convolution Layer: Convolution layer is a layer that performs mathematical functions by applying the kernel iteratively. This layer employs an array of numbers called kernels. Kernels are applied to inputs known as tensors, which are also arrays of numbers used to extract input images producing output values that are referred to as linear transformations containing spatial information. This procedure undergoes an iteration process, so there are several repetitive fields [15], [17]. The convolution process can be seen in Fig. 1.

2) Stride: Stride is the part that controls the filter set to perform the convolution function on the image input [15]. If stride's value is 1, the kernel will shift by 1 pixel horizontally and vertically. The smaller the stride value used, the more detailed the information obtained from the convolution process. It will increase the computing time; however, it does not necessarily mean that the system's performance will be improved.

3) Padding: Padding is the addition of pixel sizes with a certain value to fill the gap in convolution results from the beginning to the end [15]. The value that is usually used is 0, so it is called zero padding. It serves to match the results of convolution output so that there are no significant dimensional differences with input dimensions. This will allow the extraction results to contain more and more detailed information.

4) Activation Function: The activation function is the stage that is performed after the convolution process is complete. This operation has various types of usable equations, one of which is the linear rectification unit (ReLU), performing non-linear functions and enhancing the model representation. The result of the ReLU activation function will be an output with a value of 0 if the input is negative. The output value will be equal to the input value if the input value is positive. The ReLU function can be seen in (1).

$$f(x) = \begin{cases} 0, & x \le 0 \\ x, & x > 0 \end{cases} \tag{1}$$

5) Inception Module: Inception modules are layers that allow all filters (1 × 1, 3 × 3 and 5 × 5) to operate on the same

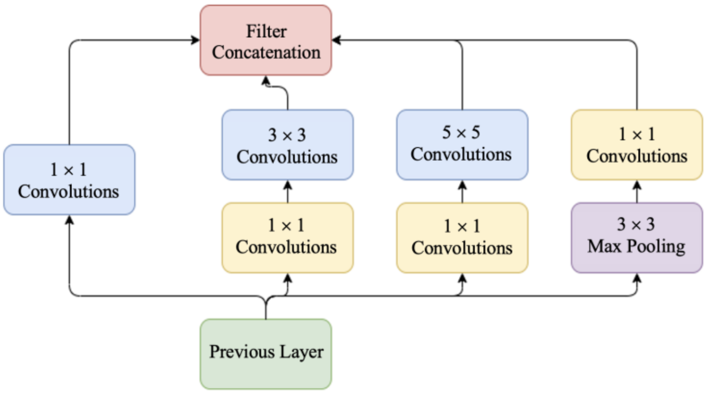

Fig. 2 Representation of inception module.

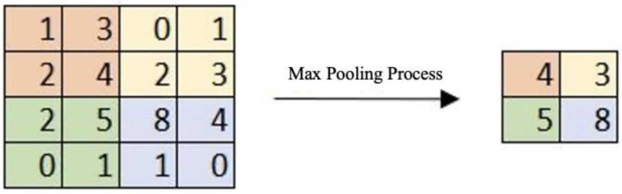

Fig. 3 Max pooling operation.

Fig. 4 System in general.

TABLE I
CONFUSION MATRIX

		Prediction Class		
		True	***False***	**Total**
Actual Class	***True***	TP	FN	P
	False	FP	TN	N
	Total	P’	N’	P + N

image section and then string the convolution results into a single output with outputs resulting from pooling layers. Inception modules allow convolution functions and pooling processes to work in parallel whose result will be one output. In the inception process, a 1 × 1 filter is used before passing through other convolution layers and max pooling to ease the computational load; hence, it will not overload the work of the device [18]. How inception modules work is in Fig. 2.

6) Pooling layer: Pooling layer is a down-sampling or sub-sampling method in spatial dimensions to reduce the number of features extracted in an image [19], [20]. Pooling layer uses the kernel in the process of reducing the pixels of an image. If the input image has smaller size than that of the kernel used, then the input image will be given zero padding first [19]. Subsequently, the kernel will be shifted throughout the image using the convolution process. There are two types of operations used in the pooling layer, namely max pooling and average pooling. Max pooling takes the highest value from each kernel shift, whereas average pooling takes the average value of each kernel shift stage. Max pooling is one of the most widely used operations. The illustration of max pooling operation can be seen on Fig. 3.

7) Simple Global Average Pooling: Simple global average pooling is one type of pooling layer that uses average functions. The simple global average pooling layer takes the average value of all feature map results, which has an impact on reducing the size of the output parameter [16]. Simple global average pooling bears similarities to the structure of convolution by performing coordination operations between feature maps and categories, thus increasing the classification process. It also eases the computational burden. In addition to facilitating classification, in simple global average pooling, there are no parameters for optimization, so overfitting can be avoided [21].

8) Dropout: Dropouts are used by randomly removing several neurons in the training process. Each neuron has the same probability weight [22]. This process aims to reduce the burden of computing to improve network performance.

9) Confusion Matrix: The confusion matrix is a matrix used to measure the classification models’ performance by comparing class information with the classification results [23]. There are four elements of the confusion matrix. The first element is true positive (TP), which means that the current state of the actual class is true and the output also shows the correct result. The second element is true negative (TN), in which the actual class’s current condition is false and the prediction results are also incorrect. The third element is false positive

TABLE II
GOOGLENET ARCHITECTURE MODEL

Layer	Layer Description	Output Shape
1	Input Layer	None, 64, 64, 3
2	Conv2D	None, 64, 64, 64
3	Max Pooling	None, 32, 32, 64
4	Conv2D	None, 32, 32, 64
5	Conv2D	None, 32, 32, 192
6	Max Pooling	None, 16, 16, 192
7	Inception (3a)	None, 16, 16, 256
8	Inception (3b)	None, 16, 16, 480
9	Max Pool	None, 8, 8, 480
10	Inception (4a)	None, 8, 8, 512
11	Inception (4b)	None, 8, 8, 512
12	Inception (4c)	None, 8, 8, 512
13	Inception (4d)	None, 8, 8, 528
14	Inception (4e)	None, 8, 8, 832
15	Max Pool	None, 4, 4, 832
16	Inception (5a)	None, 4, 4, 832
17	Inception (5b)	None, 4, 4, 1024
18	Average Pool	None, 1, 1, 1024
19	Dropout	None, 1, 1, 1024
20	Flatten	None, 1024
21	Dense	None, 2
22	Sigmoid	None, 2

(FP), which occurs when the class is incorrect, but the prediction results are correct. The final element is false negative (FN), which occurs when the class is actually true, but the prediction result is incorrect [23]. Table I shows the representation of the confusion matrix.

10) System Design: In this study, several stages were carried out in detecting types of skin cancer whether it is malignant or benign skin cancer. The stages conducted in the study are illustrated in Fig. 4. From Fig. 4, the first stage of this study is data acquisition. The data used in this study was the secondary data consisting of benign and malignant skin cancer images that were obtained from *www.kaggle.com*. The total data used was 600 skin cancer image data, consisting of 132 test data images and 528 training data images.

The next stage is preprocessing, in which resizing is conducted to uniformize the image size. After that, the fur pixel on the skin cancer image was removed by using dull razor filtering.

The final stage is the main process using CNN method, where the process of extracting features and classification was carried out to determine the type of skin cancer image, whether malignant or benign. In the main process, the training and testing stage was carried out.

The training stage was done to find the pixel value used as a database reference. The method used for training was the CNN GoogLeNet architecture since it has the ability to classify an image processed across layers with varying levels of depth. In the training process, the total iteration was carried out as many as 125 iterations (epoch value 125) with batch size 32.

Following that is the testing phase of the designed system. The testing process began with testing the size of the image. In addition, testing of the type of optimizer was carried out. The third stage was testing the best learning rate, while the last was epoch value testing. Furthermore, from several test stages, the best system performance parameter value was obtained.

11) CNN Model Configuration: In this study, a system was designed to detect types of skin cancer cells, whether they belong to malignant or benign types. The system was designed with GoogLeNet's CNN architecture method. The concept of the GoogLeNet architecture can be seen from the inception module, which is the convolution process on GoogLeNet that differs from other architectures in that it uses 1 × 1, 3 × 3, 5 × 5, and max pooling convolution that is done in parallel at the same time. Table II shows the GoogLeNet architectural model used in the study.

In Table II, image input data in the form of skin cancer cell imagery is included in the CNN model of GoogLeNet architecture. In this study the convolution and max pooling process carried out simultaneously were combined into one in concatenation. Then, it proceeds to the classification stage, which begins with flatten functions to change the data arrangement to one dimension. Dropout is used to limit incoming neurons, whereas sigmoid is used to classify images of skin cancer cells as malignant or benign.

To see the success of the designed model, measurements were taken on several parameters, including accuracy, loss, precision, recall, and F1-score. After that, these parameters can be determined by using the confusion matrix.

III. RESULTS AND DISCUSSIONS

The testing stage was carried out after the training process completed. The test image data used in this study were 132 data consisting of 61 images of benign skin cancer and 71 images of malignant skin cancer. After going through several stages of testing, then some of the best parameters were generated. The results of the study showed that the most optimal parameters that produce the best performance included the image size 64 × 64, SGD Optimizer, learning rate 0.001, and cross categorical entropy loss model. The results of accuracy and loss using the proposed CNN model in this study are shown in Fig. 5 and Fig. 6.

Fig. 5 shows accuracy for each iteration of the training and testing process. According to Fig. 5, the study results do not show the occurrence of overfitting. It implies that the difference in accuracy values during the training and testing processes is not overly significant. Similarly, in Fig. 6, the loss value generated during the training and testing processes does not produce a significant difference. Fig. 6 shows that the value of loss decreases during the training and testing process. The best results in this study were an accuracy of 97.73 percent and a loss of 1.7063.

Meanwhile, Fig. 7 depicts the results of confusion matrix system testing. From this figure, it can be seen that the majority of the test data out of 132 test data can be properly classified according to the existing class of skin cancer types. In addition, Table III shows other performance parameters, namely F1-score, recall, and precision with the average value generated for

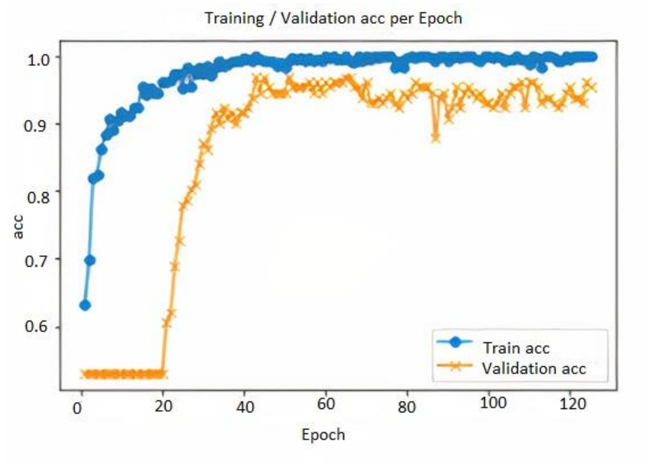

Fig. 5 Accuracy graph on training and testing process.

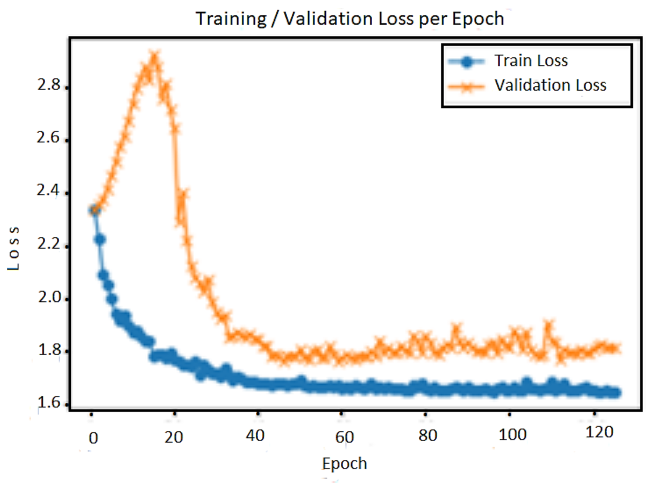

Fig. 6 Loss graph on training and testing process.

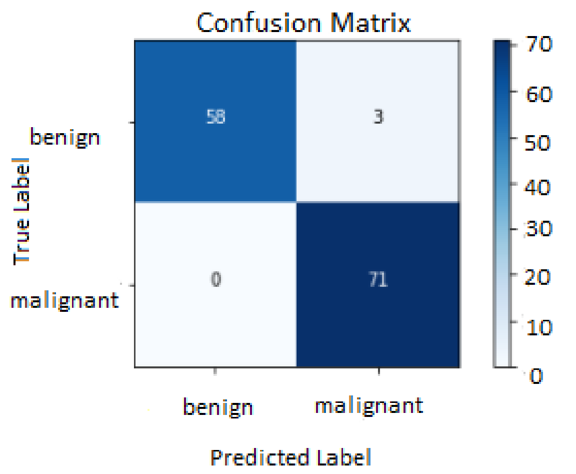

Fig. 7 Confusion matrix of skin cancer classification system.

each parameter is 0.98. It suggests that the CNN model of the proposed GoogLeNet architecture in this study has a fairly high accuracy in classifying two types of skin cancer: benign skin cancer and malignant skin cancer.

The system performance parameters generated in this study are presented in Table III. Besides accuracy and loss, precision,

TABLE III
SYSTEM PERFORMANCE PARAMETERS OF THE PROPOSED CNN MODEL

Class	Precision	Recall	F-1 Score	Amount of Data
Benign	1.00	0.95	0.97	61
Malignant	0.96	1.00	0.98	71
Average	0.98	0.98	0.98	132

recall and F-1 scores were measured for each class type. The average value generated from the three parameters was 0.98.

When compared to [11], there are several things being the focus. First, from the dataset used, this study only used the original dataset, whereas [11] used augmentation data. In the preprocessing stage, [11] only performed the resizing process; however, in this study, preprocessing stage consisted of resizing and removing the feather pixels with dull razor filtering. In terms of system performance, the best accuracy in [11] was 93.09%, while in this study the best accuracy produced was 97.73%. It is due to the fact that the object detected in this study is seen more clearly after manually removing fine hair pixels with dull razor filtering.

IV. CONCLUSION

The study designed a system to classify benign and malignant skin cancer. The skin cancer image data used is the secondary data obtained from *www.kaggle.com*. The 660 data used in the study were divided into 132 test data and 528 training data. By using the CNN method with GoogLeNet architecture, it can be concluded that the system designed is able to classify two types of skin cancer. The results obtained in this study were the accuracy of 97.73% and the loss of 1.7063. Other parameters such as F-1 score, recall, and precision obtained an average value of 0.98. It is suggested that other deep learning methods can be used in future research to improve accuracy in distinguishing between benign and malignant skin cancers. Furthermore, implementation in the form of applications can be done so that skin cancer types can be detected in real-time.

CONFLICT OF INTEREST

The Author's team declare that the article entitled "Modification of Convolutional Neural Network GoogLeNet Architecture with Dull Razor Filtering for Classifying Skin Cancer" is free from conflicts of interest.

AUTHOR CONTRIBUTION

Conceptualization, Sofia Saidah and Efri Suhartono; methodology, I Putu Yowan Nugraha Suparta; writing—original drafting, Sofia Saidah; review and editing, Sofia Saidah, Efri Suhartono and I Putu Yowan Nugraha Suparta.

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