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Dilated Convolutional Neural Network for Skin Cancer Classification Based on Image Data

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ABSTRACT

Skin cancer is a disorder of cell growth in the skin. Skin cancer has a big impact, causing physical disabilities that can be seen directly and high treatment costs. In addition, skin cancer also causes death if nor treated properly. Generally, dermatologists diagnose the presence of skin cancer in the human body by using the Biopsy process. In this study, the Dilated Convolutional Neural Network method was used to classify skin cancer image data. Dilated Convolutional Neural Network method is a development method of the Convolutional Neural Network method by modifying the dilation factors. The Dilated Convolutional Neural Network method is divided into two stages, including feature extraction and fully connected layer. The data used in this study is HAM1000 dataset. The data are dermoscopic image datasets which consists of 10015 images data from 7 types of skin cancer. This study conducted several experimental scenarios of changes in the value of d, which are 2, 4, 6, and 8 to get the optimal results. The parameters used in this study are epoch = 100, minibatch size = 8, learning rate = 0.1, and dropout = 0.5. The best results in this study were obtained with value of $d = 2$ with the value of accuracy is 85.67% and the sensitivity is 65.48%.

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A. INTRODUCTION

Skin cancer is a disorder of cell growth in the skin (Council, 2020). Skin Cancer has a big impact, causing physical disabilities that can be seen directly and high treatment costs. There are several types of skin cancer including *Benign Keratosis-like Lesions* (BKL), *Melanocytic Nevi* (NV), *Vascular Lesion* (VASC), *Dermatofibroma* (DF), *Melanoma* (MEL), *Actinic Keratoses* dan *intraepithelial Carcinoma* (AKIEC), *Basal Cell Carcinoma* (BCC)(Tschandl et al., 2018). Generally, dermatologists diagnose the presence of skin cancer in the human body by using the Biopsy process. This biopsy process is too expensive and injures the human body, specifically on the skin.

Along with the development of technology, there are many modern technologies that can detect objects, faces, and so on. This can be done using image data. Image data is a two-dimensional image that contains pixels with certain values which are the result of an analogue image. Image data can be used as a parameter in the classification process (Caraka et al., 2017)(Xu et al., 2020)(Wang et al., 2018). Classification of image data has been widely studied in this modern era, one of method than can be used is by using Deep Learning. Classification of image data using Deep Learning is more precise than Machine Learning because Deep Learning is able to handle image data with accuracy and smooth margins (Demir et al., 2021).

One of the methods included in Deep Learning is the Convolutional Neural Network (CNN) Method (Nugroho et al., 2020). The Convolutional Neural Network (CNN) method was inspired by the visual cortex research conducted by Hubel and Wiesel on the cat's sense of vision (Aprianto, 2021). This method has become the most popular because it is able to study and generalize a problem like the human brain (Indolia et al., 2018). In recent years, the Convolutional Neural Network (CNN) method has achieved success in the field of image classification because it has good results (Lei et al., 2019)(Maulana & Rochmawati, 2019).

Research related to image data classification using the Convolutional Neural Network method has been widely carried out. A research by (Q. Li et al., 2014), performed automatic classification of High Resolution Computed Tomography (HRCT) lung images of interstitial lung disease patterns with good accuracy results. In another study (Pratt et al., 2016) obtained 95% for the sensitivity and 75% for the accuracy in the classification of diabetic retinopathy image data. Then, another research that related to Convolutional Neural Network is classifying breast cancer image data and get accuracy 73.6% (Ragab et al., 2019). Another research is classifying dermoscopic image data on skin cancer Fu'adah et al., (2020) with the best accuracy is 99%. Due to its improved capabilities, this method is suitable to be used to solve complex problems or problems that use large-scale data. As a result, the computational process using the Convolutional Neural Network method will take a long time (Putra et al., 2020)(Krizhevsky et al., 2007)(Qotrunnada & Utomo, 2022). To overcome this, in this study the Dilated Convolutional Neural Network method will be used because according to research conducted by (Lei et al., 2019) the Dilated Convolutional Neural Network method gets better results and a shorter time in the image classification process compared to Convolutional Neural Network method.

Based on the introduction, this study proposes using Dilated Convolutional Neural Network method to classifying the skin cancer based on image data. Contribution on this study is by using the development method of the Convolutional Neural Network method by modifying the dilation factor. This study is expected to providing progress in technology, especially in the basic knowledge and applied sciences and to be able for applying mathematics computation to the health technology.

B. METHODS

The data that used in this study is the HAM1000 dataset (Codella et al., 2019). The data is a dermoscopic image dataset consisting of 10015 data with a size of 600×450 pixels. The amount of data that used on this study can be seen in Table 1.

Table 1. The HAM1000 Dataset of Skin Cancer (Codella et al., 2019)

Diagnose	Origin Dataset
Benign Keratosis-like Lesions (BKL)	1099
Melanocytic Nevi (NV)	6705
Vascular Lesion (VASC)	142
Dermatofibroma (DF)	115
Melanoma (MEL)	1113
Actinic Keratoses dan intraepithelial Carcinoma (AKIEC)	327
Basal Cell Carcinoma (BCC)	514

In this study, the original dataset on the Table 1 divide into two categories. Those are training dataset and testing dataset. It can be seen on Table 2, for each category on the data has been divided into two categories, as shown in Table 2 and Figure 1.

Table 2. Details of The Data Used

Diagnose	Training Dataset	Testing Dataset
Benign Keratosis-like Lesions (BKL)	824	275
Melanocytic Nevi (NV)	5028	1677
Vascular Lesion (VASC)	106	36
Dermatofibroma (DF)	86	29
Melanoma (MEL)	834	279
Actinic Keratoses dan intraepithelial Carcinoma (AKIEC)	245	82
Basal Cell Carcinoma (BCC)	385	129

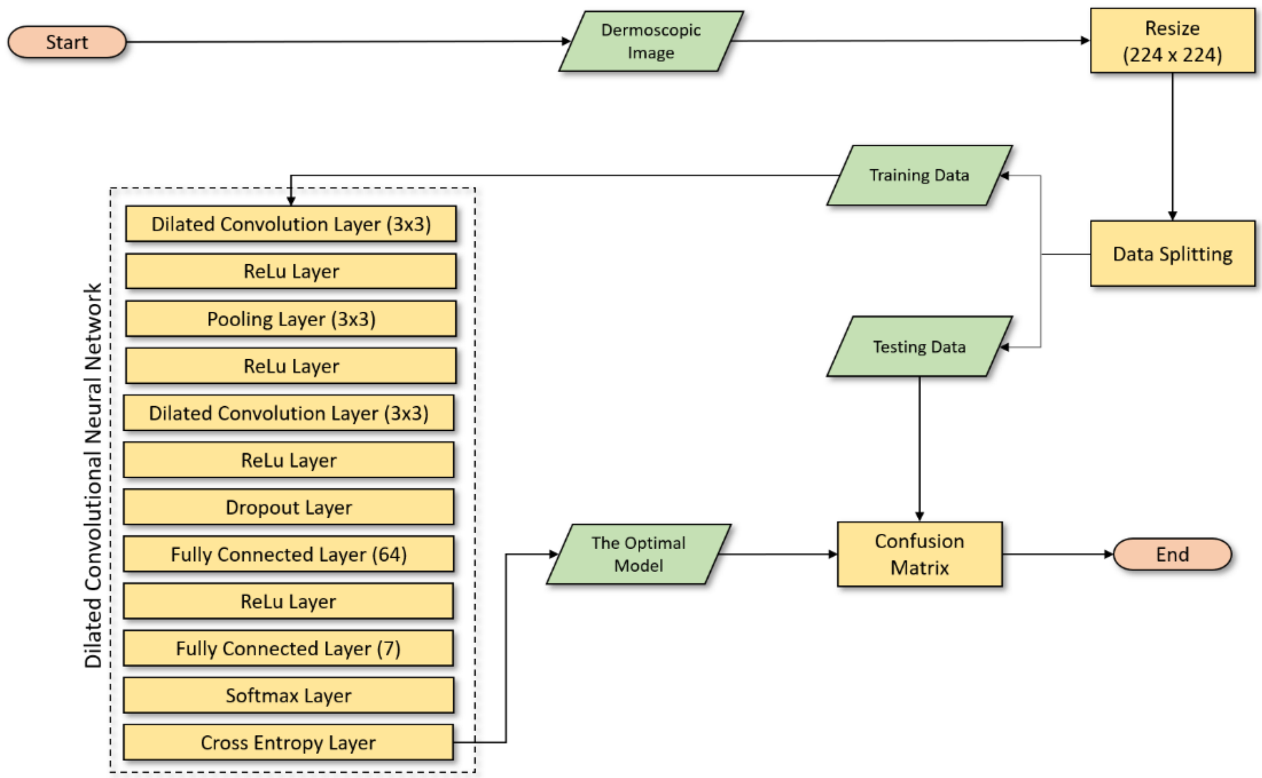

Figure 1. Experiment Flowchart for Dilated Convolutional Neural Network

The research flowchart can be seen in Figure 1. Based on Figure 1, First step on this study is resizing the image data to 224×224. That size is used because several popular methods such as GoogleNet architecture, resnet50 architecture, resnet101 architecture, Alexnet architecture, etc. all use 224×224 to the image data. The detail of the data can be seen on Table 1.

The next step is dividing the data into two categories, those are training data and testing data. The next step is building the architecture that will be used in the extraction stage of Dilated Convolutional Neural Network. The architecture used consists of 8 layers consisting of an input layer, 2 dilated convolution layers, 1 average pooling layer, 3 ReLu layers, and a dropout layer. This architecture was chosen because according to research conducted by (Khalifa et al., 2020), this architecture gets better results than the other architectures.

The next step is processing the training data into the Dilated Convolutional Neural Network Method to looking for the best weight on each convolution layer obtained randomly. The weight will be used to extracting image that will be used in the next process. The Dilated Convolutional Neural Network method is divided into two stages, including feature extraction (ReLu layer, Pooling Layer, Dilated Convolution Layer, Dropout Layer) and fully connected layer (classification process). After getting the best result, it will be checking by the confusion matrix.

1. Pre-processing

At this stage, the dataset is prepared and then the image is resized to fit to the input size, which is 224×224. Next step on this process is divided the data by using k-fold method. K-fold method is a technique used to measure the performance of a model built by taking a random sample to be used dataset of testing process (Marcot & Hanea, 2021).

2. Feature Extraction

a. Dilated Convolution Layer

The basic principle of the Dilated Convolutional Neural Network is to provide a hole/space between the points with each other in the process of multiplying the input matrix with the kernel. The Convolutional Neural Network method uses value $d = 1$, then the Dilated Convolutional Neural Network method uses value $d > 1$ (Lin et al., 2018). The calculation of the Dilated Convolutional Neural Network method can use Equation (1) but with a value $d > 1$. The difference between dilated convolution and convolution can be seen in Figure 2.

$$z_{(m,n)} = \sum_{a=0}^{f-1}\sum_{b=0}^{f-1} w_{(a,b)} i_{(m+da,n+db)} \quad , d > 1 \tag{1}$$

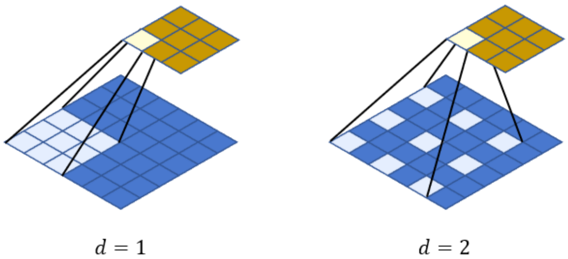

Figure 2. Convolutional Neural Network; Dilated Convolutional Neural Network (Lei et al., 2019)

In the convolution layer, the result of multiplying the input value with the filter is the output value (Naranjo-Torres et al., 2020). The two-dimensional convolution operation is expressed by input $\boldsymbol{I}_{(\boldsymbol{m},\boldsymbol{n})}$ with filter $\boldsymbol{W}_{(\boldsymbol{a},\boldsymbol{b})}$.

Definition 1 (Dilated Convolutional) (Chakraborty et al., 2019)
Given an input $x : N \rightarrow \mathrm{R}^n$ and a kernel $w : \{0, \dots, k-1\} \rightarrow \mathrm{R}$, the dilated convolutional function $(x_{*d}w)$: $\mathrm{N} \rightarrow \mathrm{R}^n$ is:

$$(x_{*d}w)(s) = \sum_{i=0}^{k-1} w(i) \times (s - id) \tag{2}$$

Where N is the set of natural numbers, k is the size of kernel, and d is the dilation factor.

b. Average Pooling Layer
Average pooling layer is one of method that can reduce the size of matrix. Illustration of the average pooling process can be seen in Figure 3.

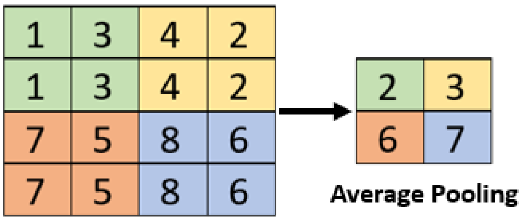

Figure 3. Average Pooling (Putra et al., 2020)

Based on Figure 3, average pooling layer can be calculated by:

$$\frac{1+3+1+3}{4} = 2$$

c. Rectified Linear Unit (ReLu) Layer
ReLu layer is one of the activation functions that aims to anticipate negative values in the previous process. The Mathematical equation of the function can be seen in Equation (3) (Rumelhart et al., 1986) .

$$\begin{gathered} y = \max(x, 0) \\ \frac{\partial y}{\partial x} = \begin{cases} 0 & , x \leq 0 \\ 1 & , x > 0 \end{cases} \end{gathered} \tag{3}$$

d. Dropout Layer
Dropout layer is a technique used to avoid overfitting. During the iteration process in training, several neurons will be randomly removed from the network with a probability p value, the p value used is generally 0.5 (Labach et al., 2019). The illustration can be seen in Figure 4.

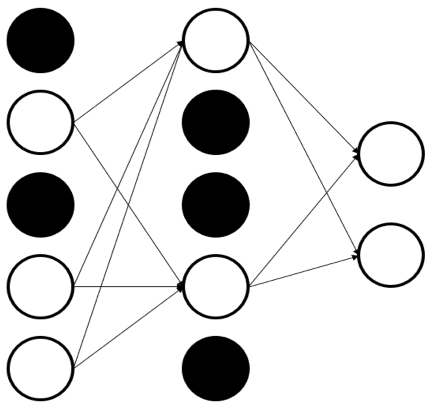

Figure 4. Dropout Layer

Based on Figure 4, Dropout Layer is a process that nullifies the contribution of some neurons towards the next layer and leaves unmodified all others.

3. Classification

At this stage consists of several layers in which several nodes/neurons are fully connected to the previous layer, namely the forward method and the backward method (Rumelhart et al., 1986). The mathematical equation of the forward method can be seen in Equation (4).

$$z_i = b_i + \sum_{j=1}^{c} x_j w_{ij} \tag{4}$$

Where x is the input, x is the output, b is the bias, c is the vector length of the input, and v is the weight that will be used. While, the mathematical equation of the backward method can be seen in Equation (5) and Equation (6). From the output to the hidden layer

$$\frac{\partial J}{\partial z_i} = \frac{\partial J}{\partial y_i} . \frac{\partial y_i}{\partial y_{net}} . \frac{\partial y_{net}}{\partial z_i} \tag{5}$$

From the hidden layer to the input

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial z_i} . \frac{\partial z_i}{\partial z_{net}} . \frac{\partial z_{net}}{\partial x} \tag{6}$$

4. Confusion Matrix

The information of the actual results and the prediction results from the classification system obtained on the confusion matrix. The results of the system performance can be evaluated by using the data in the matrix by calculating several, which are:

True Positive (TP) : is a positive class from the data identified as positive class,
True Negative (TN) : is a negative class from the data identified as negative class,
False Positive (FP) : is a negative class from the data identified as positive class,
False Negative (FN) : is a positive class from the data identified as negative class.

		Predict	
		No	**Yes**
Actual	**No**	TN	FP
	Yes	FN	TP

Figure 5. Confusion Matrix

From the Figure 5, it can produce statistical calculations of the accuracy and sensitivity values (X. Li et al., 2021). From the result of the accuracy and sensitivity, it can determine the good or bad performance of the built classification system. Accuracy is a result that represents the amount of data classified with actual data. Thus, the greater the value of accuracy, the more data that is classified correctly. The mathematical equation of accuracy can be seen in Equation (7).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{7}$$

Sensitivity is a result that represents the number of correct data classified in the positive class. Thus, the greater the sensitivity value, the greater the classification system can classify positive classes well. The mathematical equation of sensitivity can be seen in Equation (8).

$$Sensitivity = \frac{TP}{TP + FN} \tag{8}$$

Precision is a result that represents the number of instances that are relevant, out of the total instances the model retrieved. The mathematical equation of precision can be seen in Equation (9).

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

Recall is a result that represents the number of instances which the model correctly identified as relevant out of the total relevant instances. The mathematical equation of recall can be seen in Equation (10).

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

F1-score is simply the harmonic mean of Precision and Recall. The mathematical equation of sensitivity can be seen in Equation (11).

$$f1 - score = 2 \times \frac{Precision \times recall}{precision + recall} \tag{11}$$

C. RESULT AND DISCUSSION

In this study, the classification process of skin cancer was carried out using the Dilated Convolutional Neural Network (DCNN) method. This method uses several experiments to change the d value of 2, 4, 6, and 8 to be carried out in the classification process to obtain optimal results. Several types of skin cancer classified in this study include Benign Keratosis-like Lesions (BKL) on Figure 6, Melanocytic Nevi (NV) on Figure 7, Vascular Lesion (VASC) on Figure 8, Dermatofibroma (DF) on Figure 9, Melanoma (MEL) on Figure 10, Actinic Keratoses and Intraepithelial Carcinoma (AKIEC) on Figure 11, Basal Cell Carcinoma (BCC) on Figure 12.

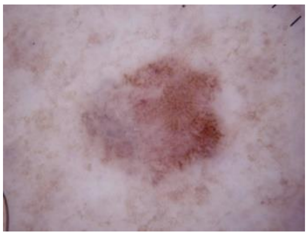

Figure 6. Benign Keratosis-like Lesions (BKL)

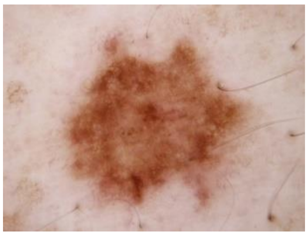

Figure 7. Melanocytic Nevi (NV)

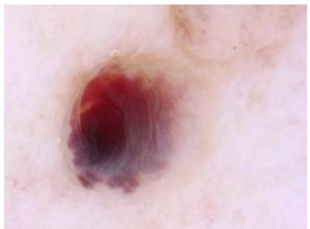

Figure 8. Vascular Lesion (VASC)

Figure 9. Dermatofibroma (DF)

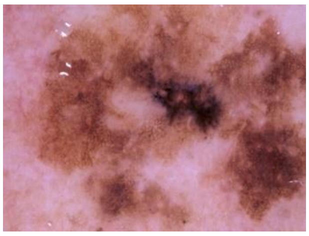

Figure 10. Melanoma (MEL)

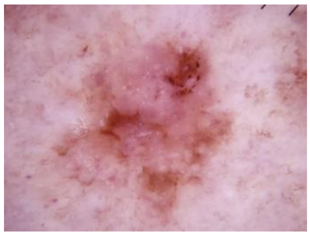

Figure 11. Actinic Keratoses dan intraepithelial Carcinoma (AKIEC)

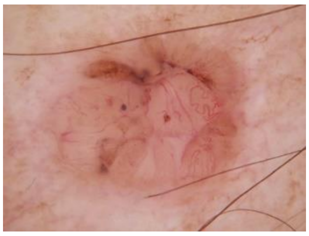

Figure 12. Basal Cell Carcinoma (BCC)

The Dilated Convolutional Neural Network architecture used in this study can be seen in Figure 1. The architecture on this study based on the research (Khalifa et al., 2020). On that research, the architecture that used is able to get good results without using too many layers. The parameters used in this study are epoch = 100, minibatch size = 8, learning rate = 0.1, and dropout = 0.5. The comparison of the accuracy carried out in this study can be seen in Table 3.

Based on Table 3 it can be seen that in this study used several experiments, those are $d = 2, d = 4, d = 6$ and $d = 8$. Each dilation factor was tested by using k-fold method with $k = 1, k = 2, k = 3$ and $k = 4$. The accuracy can be calculated by Equation (7). Based on Table 3, for the dilation factor is $d = 2$, four accuracy values are obtained for each k, $k = 1$ is 84.49%, $k = 2$ is 85.67%, $k = 3$ is 81.79%, and $k = 4$ is 83.58%. The best accuracy for $d = 2$ is 85.67%, that best result on $k = 2$. While for the dilation factor is $d = 4$, four accuracy values are obtained for each k, $k = 1$ is 74.88%, $k = 2$ is 74.60%, $k = 3$ is 75.08%, and $k = 4$ is 74.67%. The best accuracy for $d = 4$ is 74.88%, that best result on $k = 1$. The other results for the dilation factor is $d = 6$, four accuracy values are obtained for each k, $k = 1$ is 73.96%, $k = 2$ is 74.68%, $k = 3$ is 75.40%, and $k = 4$ is 75.55%. The best accuracy for $d = 6$ is 75.55%, that best result on $k = 4$. The last dilation factor is $d = 8$, four accuracy values are obtained too for each k, $k = 1$ is 68.97%%, $k = 2$ is 68.17%, $k = 3$ is 71.33%, and $k = 4$ is 72.71%. The best accuracy for $d = 4$ is 72.71%, that best result on $k = 4$. The best accuracy for this study is on $d = 2$ with $k = 2$ and the accuracy is 85.67%, as shown in Table 3 and Figure 13.

Table 3. Comparison of The Accuracy by Using Dilated Convolutional Neural Network

k	Accuracy			
	d = 2	**d = 4**	**d = 6**	**d = 8**
1	84.49%	74.88%	73.96%	68.97%
2	85.67%	74.60%	74.68%	68.17%
3	81.79%	75.08%	75.40%	71.33%
4	83.58%	74.67%	75.55%	72.71%
Average	83.88%	74.81%	74.90%	70.29%

PREDICTION CLASS

ACTUAL CLASS

Class	AKIEC	BCC	BKL	DF	MEL	NV	VASC
AKIEC	64	1	3	0	5	9	0
BCC	10	93	2	0	3	21	0
BKL	9	1	145	1	18	101	0
DF	5	7	1	3	0	12	1
MEL	6	0	3	0	170	98	1
NV	3	3	7	0	21	1641	2
VASC	0	0	0	0	2	3	31

Figure 13. Confusion Matrix of The Best Result

Confusion matrix of the best result in this study can be seen on Figure 13. Based on Figure 13, the Dermatofibroma (DF) class tends to be predictable to the Melanocytic Nevi (NV) class. This is most likely due to the fact that the number of datasets used is not balanced with the amount of data for the Melanocytic Nevi (NV) class. Based on Table 1, it can be seen that the number of Melanocytic Nevi (NV) dataset used is about 67% of the total data. This trend can also be seen in other classes that are predictable in the Melanocytic Nevi (NV) class. Based on the confusion matrix, the sensitivity can be calculated by using Equation (8). The value of sensitivity is 0.65.

From the results obtained the Dilated Convolutional Neural Network method is able to classify skin cancer well. Contribution on this study is by using the development method of the Convolutional Neural Network method. This study conducted several experimental scenarios of changes in the value of d, which are 2, 4, 6, and 8 to get the optimal results. The result of this study is also able to provide a better accuracy of 85.67%, as shown in Table 4.

Table 4. Comparison of Performanced Evaluation

	Convolutional Neural Network Method (Raja Subramanian et al., 2021)	**Convolutional Neural Network (VGG-19)-SVM Method (Yohannes & al Rivan, 2022)**	**Proposed Dilated Convolutional Neural Network Method**
Training Accuracy	83.11%	-	91.92%
Testing Accuracy	83.04%	65.33%	85.67%
Precision	0.81864	0.6851	0.81837
Recall	0.80509	0.6533	0.65475
F1-Score	0.82797	0.6577	0.72748

Based on Table 4, the proposed Dilated Convolutional Neural Network can be compared with the standard Convolutional Neural Network method by (Raja Subramanian et al., 2021) and the Convolutional Neural Network-SVM method by (Yohannes & al Rivan, 2022) using the same dataset, that is HAM10000 dataset. It can be seen that proposed Dilated Convolutional Neural Network method is better than the standard Convolutional Neural Network Method and Convolutional Neural Network-SVM method. I can be seen by the testing accuracy, the proposed Dilated Convolutional Neural Network method has accuracy 85.67% while the accuracy of Convolutional Neural Network by (Raja Subramanian et al., 2021) is 83.04% and the accuracy of Convolutional Neural Network-SVM is 65.33%. It can be seen on Table 4 that the proposed Dilated Convolutional Neural Network is capable of classifying with an average accuracy is more than 80% by using the HAM10000 dataset better than CNN method ang CNN-SVM method.

D. CONCLUSION AND SUGGESTIONS

Based on the results obtained, it can be concluded that the Dilated Convolutional Neural Network method is capable of classifying with an average accuracy is more than 80% by using the HAM10000 dataset well. Contribution on this study is by using the development method of the Convolutional Neural Network method by modifying the dilation factors. This study conducted several experimental scenarios of changes in the value of d, which are 2, 4, 6, and 8 to get the optimal results. It’s proven by the result of this study is able to provide a better accuracy of 85.67%. It can be compared to the Convolutional Neural Network method with an accuracy of 83.04% (Raja Subramanian et al., 2021) and the Convolutional Neural Network-SVM method with an accuracy of 65.33% (Yohannes & al Rivan, 2022) using the same dataset, that is HAM10000 dataset. It can be seen that the Dilated Convolutional Neural Network is better than the standard Convolutional Neural Network Method and Convolutional Neural Network-Support Vector Machine. However, this method is still unable to overcome the data imbalance which in this case the data is dominated by the NV class. It is hoped that further research will be able to use balance data or oversampling technique for the imbalanced data.

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