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Effect of Learning Rate on VGG19 Model Architecture for Human Skin Disease Classification

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Abstract: The skin is the largest external organ that serves to protect human internal organs and is very sensitive to various diseases, so early detection is very important to reduce the risk and increase the chance of recovery. This study aims to classify skin disease types using CNN algorithm with VGG19 architecture and learning rate adjustment to get a more optimal model, using a dataset from Kaggle consisting of 3,295 images with six classes, including several types of skin diseases and one healthy skin class. The preprocessing process includes dividing the data into training and testing sets, resizing the images to fit the VGG19 architecture, and normalization to scale the pixel values from 0-255 to a range of 0-1. The results show that using a learning rate of 0.00003 produces the best performance with 97.29% accuracy, 97.36% precision, 97.29% recall, and 97.30% F1-score. These findings confirm that the CNN algorithm with VGG19 architecture can classify skin disease types well.

INTRODUCTION

The skin is the largest and outermost organ in the human body and functions as a cover and protector of internal organs from various dangers that come from outside (Hameed et al., 2020), but even though the skin is designed to protective, it is actually a very sensitive organ and is very vulnerable to various diseases, especially if its hygiene is not considered (Goceri, 2021). Skin diseases are currently a very common problem and are frequently found in the global community (Saifan & Jubair, 2022). Skin diseases can affect anyone, regardless of age, gender, or ethnicity.

There are various factors that can cause skin diseases, such as environmental hygiene, changes in climate, physical contact with other sufferers, and allergies. These diseases greatly affect the daily activities of the sufferers, decreasing confidence levels, unbearable itching, until the worst can cause death. The general public's lack of understanding of the various skin diseases and the right way to treat them can result in the disease not going away or getting worse. Early detection is necessary to reduce the risks and increase the chances of recovery (Owda & Owda, 2022). However, currently in many developing countries, skin disease experts are still quite expensive for some people. The rapid development of artificial intelligence (AI) technology can provide a new alternative to perform the task of early detection of the type of skin disease suffered.

AI is a technology that mimics human intelligence to solve a problem (Cellina et al., 2022). Machine Learning (ML) is a branch of AI that allows a computer program to learn patterns from data entered and provide a response based on experience that can automatically increase intelligence over time without human assistance (Möller, 2023). One branch of ML is Deep Learning (DL) which uses a very complex and deep neural network approach (Möller, 2023). Convolutional Neural Network (CNN) is one of the DL algorithms used in image classification tasks. CNN is a development of the classic Artificial Neural Network (ANN) algorithm in which there is a convolution operation (Tugrul et al., 2022). CNN receives input in the form of 2D or 3D images (Le et al., 2021). One of the popular CNN architectures is VGG19 (Simonyan & Zisserman, 2015), which is used due to its depth of 19 layers. The VGG19 architecture captures various details of the image better due to its ability to recognize complex visual patterns gradually, resulting in high accuracy in such classification tasks.

Research on the classification of human skin diseases using the Convolutional Neural Network (CNN) algorithm provides excellent results in diagnosing various types of skin diseases. Research entitled "A machine learning model for skin disease classification using convolutional neural network" (Allugunti, 2022) research that focuses on the classification of skin diseases, especially melanoma. There are three types of classes that are classified, namely malignant lesions, superficial spreading, and nodular melanoma. The results obtained in this study show that the CNN algorithm has the best accuracy rate with 88.83% compared to other classification algorithms. Research entitled "Classification of Skin Disease Using Deep Learning Neural Network with MobileNet V2 and LSTM" (Srinivasu et al., 2021) In a study that classified seven types of skin diseases, the CNN algorithm with MobileNet V2 architecture combined with LSTM obtained the best accuracy compared to other classification algorithms with an accuracy of more than 85%. Another study entitled "Multi-Class Skin Lesion Classification Using a Lightweight Dynamic Kernel Deep-Learning-Based Convolutional Neural Network" (Aldhyani et al., 2022) This research produces a CNN algorithm model that is lighter and more efficient in classifying skin disease types with an accuracy rate of 97.85% and compares the results obtained with several CNN models.

Based on previous research, the CNN algorithm has proven successful in classifying the type of skin disease in humans. Therefore, this research is interested in conducting research on human skin disease images using the CNN method. The main difference between this research and the previous one is the type of architecture used in this study using Visual Geometry Group (VGG) 19 architecture for the classification of skin disease types. In addition, this research also adjusts the learning rate to get more optimal model results.

METHOD

The purpose of this research is to measure the performance of machine learning models to classify skin disease types using CNN algorithm with VGG19 as the architecture used. Selection of appropriate learning rate in the training process can produce a more optimal model. To obtain the research results as expected, several stages of the method are carried out which can be seen in Figure 1.

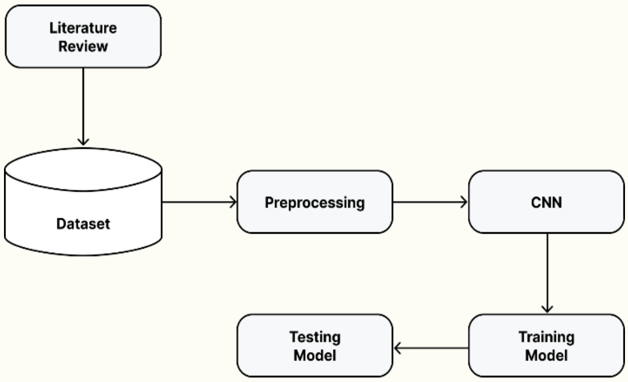


Figure 1. Research method

A. Literature Review

In the early stages of this research, it begins with conducting a literature review with the aim of obtaining new knowledge that is useful to be able to support problem solving in the current research. Literature review serves as a basis for developing knowledge, making guidelines, practices, and if done well can give birth to new ideas (Snyder, 2019).

B. Datasets

The dataset used in this study was obtained from the Kaggle, which is a website that provides open source data resources so that it can be used for free for research purposes. This dataset has 3,295 images of skin diseases spread over five different classes of skin disease types, namely Acne/Rosacae, Chickenpox, Eczema, Ringworm, and Seborrheic Keratoses. In addition to the class of skin disease types, there is also one class which is a type of healthy skin. The details of the dataset can be explained in Table 1.

Table 1. Class and number of images in the datasets

Class	Number of Image
Acne/Rosacae	580
Chickenpox	371
Eczema	877
Ringworm	370
Seborrheic Keratoses	434
Normal/Healthy	663
Total	**3,295**

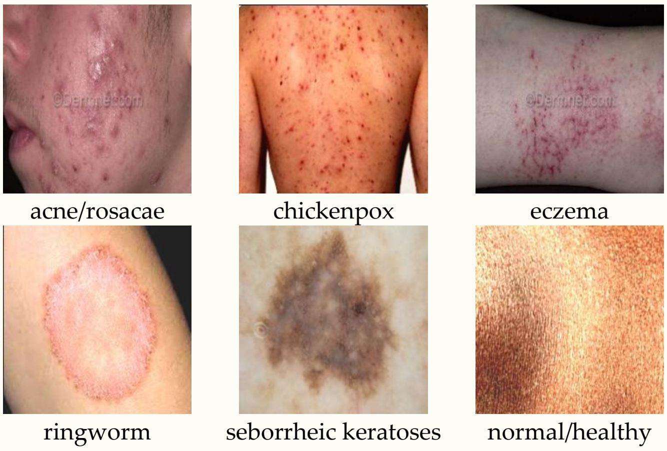


Figure 2. Image of skin disease

C. Preprocessing

Preprocessing is a stage carried out on the dataset that has been obtained previously with the aim of cleaning and preparing the data to be fully used in training Machine Learning models (Ali et al., 2021) (Yunus et al., 2023). This research applies several preprocessing techniques, namely split data, Resize, and Normalization.

1) Split Data, is a technique that aims to divide the dataset into three large groups, namely 80% for training, 10% for validation, and 10% for testing. Training data is used for the ML model, the validation data helps adjust the model parameters, and the testing data is utilized to assess the performance of the ML model (Muis et al., 2023).
2) Resizing, is a preprocessing technique that aims to homogenize the dimensions of images that were previously different to be the same by changing all image dimensions to 224x224 pixels (Khairandish et al., 2022).
3) Normalization, is initially the image before ML processing will be converted into a matrix where each row and column will symbolize the pixel value. Each pixel has a value range of 0-255, the normalization process will multiply each pixel value by 1/255 with the aim that the ML model can learn efficiently (Anand et al., 2022).

D. CNN

Convolutional Neural Network (CNN) is an advanced from of DL algorithm integrated with Artificial Neural Network. CNN is composed of three primary components, which are input layer, hidden layer, and output layer (Tian, 2020). This study using CNN architecture, namely VGG19. VGG19 is one of the CNN architectures developed by Visual Geometry Group, consisting of 19 layers, namely 16 convolutional layers and 3 fully connected layers. The main advantage of VGG19 lies in the depth and number of layers, allowing the model to capture different levels of detail in the data. The structure of this architecture can be seen in Figure 3, which shows how each layer plays a role in the step-by-step image recognition and classification process, from simple feature extraction to final decision-making. With its depth and complexity, VGG19 proves capable of achieving high levels of accuracy on various image classification datasets.

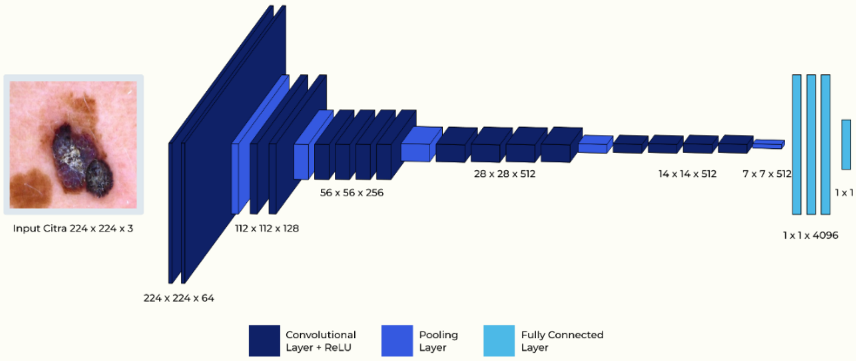


Figure 3. VGG19 architecture

1) Convolutional Layer, is the most important layer in the hidden layer CNN the main function of this layer is to obtain important information from the input image. The convolution layer is a structure in which there are a number of filters, each of which has a weight and bias (Sarıgül et al., 2019). The training process is done by performing the dotproduct function between the input image and the filter to generate feature maps.

2) Rectified Linear Unit (ReLU), is a non-linear activation function that serves to eliminate negative values from the results of the convolution operation and replace them with zero (Tian, 2020).

3) Pooling Layer, is a layer that aims to reduce the dimensional size of feature maps (Mustaqeem & Kwon, 2019) without losing the main features. There are two most commonly used pooling methods, namely maximum pooling and average pooling. This research uses the maximum pooling method.

4) Fully Connected Layer, is the last layer in the CNN algorithm that serves as a classifier. Each neuron from the previous layer is connected to the next layer and each resulting value will be a reference for how much a value matches a certain class (Khan et al., 2020). Before the classification process is carried out the previous convolution matrix will be converted into a 1x1 vector where this process is known as flatten (Ng et al., 2019).

E. Training Model

Model training is a stage where training will be carried out on the CNN model. The model will be given training data with the aim of learning existing patterns or relationships. At this training stage, the selection of settings for the learning rate value is carried out to get a more optimal model. The model parameter configuration used in the training process can be seen in Table 2.

Table 2. Hyperparameter configuration

Hyperparameter	Value
Batch Size	32
Optimizer	Adam
Learning Rate	0.00001, 0.00003, 0.00005
Epoch	10

F. Testing Model

Testing the model is a stage that aims to test the performance of the model that has previously been trained. In this study, testing used a confusion matrix. Confusion matrix can measure the performance of a model by labeling the prediction results and the actual label which will be displayed on the x-axis and y-axis respectively (Baranwal et al., 2020). Accuracy, Precision, Recall, and F1-Score of a model can be obtained with the following equation (Putra et al., 2023).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1-Score} = 2 \text{ X } \frac{Precision \text{ X } Recall}{Precision+Recall} \tag{4}$$

with:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

RESULTS AND DISCUSSIONS

Evaluating the CNN algorithm model with VGG19 architecture and adjusting the learning rate parameter settings used to classify skin disease types. Figure 4 illustrates a performance comparison of the CNN model using various learning rate values. It can be seen that the learning rate with a value of 0.00003 obtained the best results with accuracy reaching 0.00003: 97.29%, Precision: 97.36%, Recall: 97.29%, and F1 Score: 97.30%. The selection of a learning rate of 0.00003 as the optimal value reflects a balance between convergence speed and model training stability. This learning rate is low enough to ensure smoother weight updates, thus reducing the risk of overshooting or unstable convergence, while remaining high enough to achieve effective results. As such, this learning rate allows the model to effectively capture complex patterns and features in skin disease data, contributing to the accuracy and reliability of the resulting diagnosis.

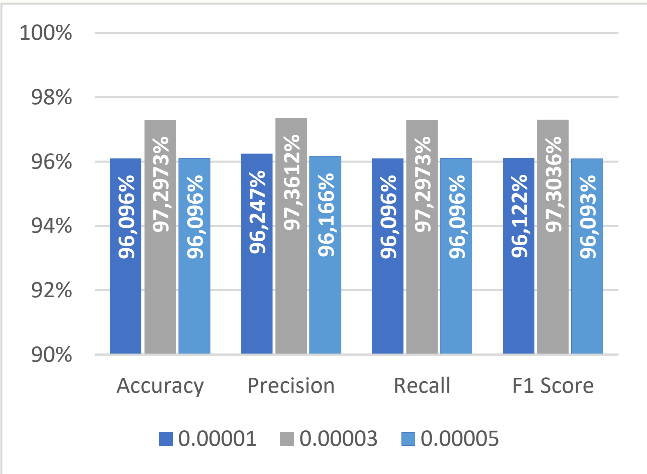


Figure 4. CNN performance comparison

Figure 5 shows the confusion matrix from testing the machine learning model with a learning rate of 0.00003. The confusion matrix clearly shows each correct and incorrect prediction, with rows and columns labeled with the existing class names. The lighter the color in each column of the confusion matrix signifies higher accuracy achieved by the model for classification. Overall, the machine learning model with a learning rate of 0.00003 demonstrates good performance in classifying skin disease conditions. This model can classify eczema conditions well, this can be seen with a more dominant color, while in other conditions the resulting color is more faded. This can be caused because the amount of test data in the eczema class is higher than other classes.

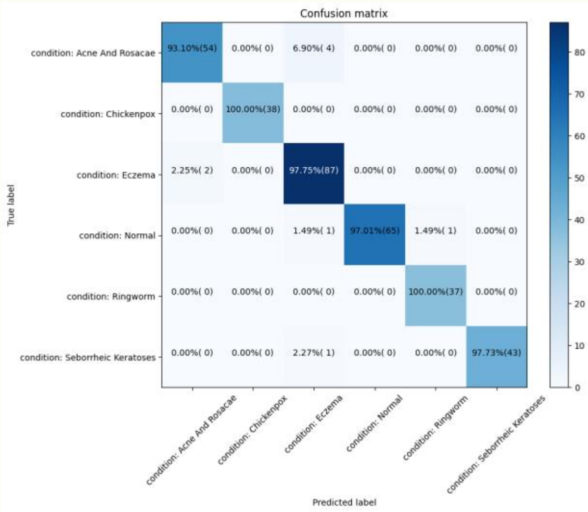


Figure 5. Confusion matrix

Figure 6 presents the training and validation graphs for accuracy and loss, depicting their progression across different epochs. The graph illustrate the percentage of accuracy and loss against the number of epochs. As the number of epochs increases, the accuracy of training and validation shows an increase and conversely the loss of training and validation decreases. The best results were obtained at epoch 9 with accuracy and loss of 0.966 and 0.094 respectively.

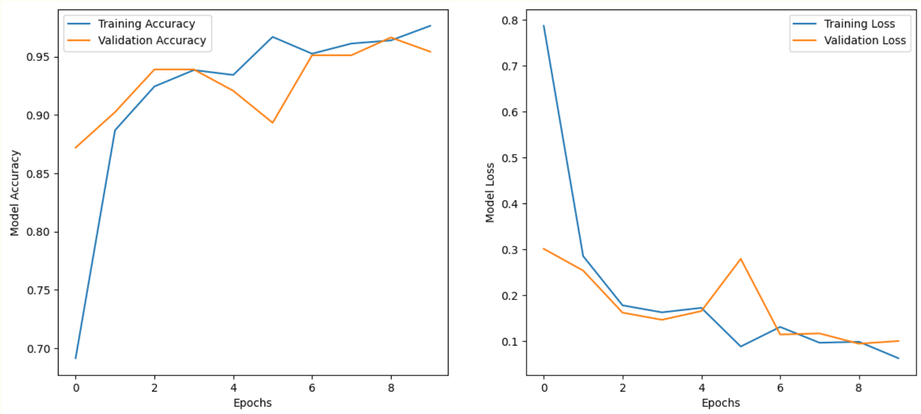
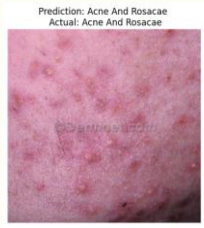
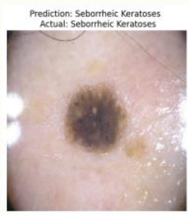
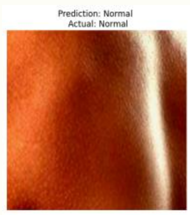
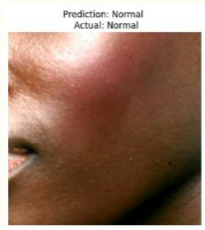


Figure 6. Line graph of training and validation results

Table 3 illustrate the results of testing the model with a new image that has not been seen by the model during the training process. The results obtained from show that the model can recognize various classes of skin disease types and healthy skin types.

Table 3. Example of prediction results

Class	**Prediction Result**	
Acne/Rosacae		
Chickenpox		
Eczema		
Ringworm		
Seborrheic Keratoses		
Normal/Healthy		

The evaluation results of the CNN model optimized by the use of appropriate learning rate values were able to provide accurate diagnosis results for various types of skin diseases. With a high level of accuracy, the model is able to recognize and differentiate various skin lesions, thereby increasing confidence in the diagnosis. In addition, the high precision value indicates that when the model identifies a lesion as positive, it is likely that the identification is accurate, which is important to avoid misdiagnosis and inappropriate treatment. The well-balanced recall also indicates that the model can detect most cases of skin diseases, which is crucial in early detection.

CONCLUSIONS

This study was conducted with the aim of measuring the performance of CNN algorithm with VGG19 architecture and learning rate parameter adjustment in classifying human skin disease images. This research shows that the model that uses a learning rate of 0.00003 gets the best performance with an accuracy of 97.29%, Precision: 97.36%, Recall: 97.29%, and F1 Score: 97.30%. Based on this, it shows that the CNN algorithm with VGG19 architecture can classify types of skin diseases in humans and can be an alternative to diagnose the type of skin disease suffered. For future research, increasing the number of skin disease classes is recommended so that it can perform more diverse skin disease classification tasks. In addition, the use of data augmentation techniques can increase the diversity of the dataset, as well as the application of the model to dermatological images taken in various lighting conditions and viewing angles. Implementation of the model in a web-based or mobile application can be done so that it can be used by the wider community.

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