

Classification of Koilonychia, Beaus Lines, and Leukonychia based on Nail Image using Transfer Learning VGG-16

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Abstract—Human nail disease is usually ignored since it does not reveal clinical signs that are harmful to one's health. Nail disease, on the other hand, can be an early sign of a health issue. Some types of nail disease can cause infection, injury, or even the loss of the nail itself. It can reduce a person's aesthetics and beauty. Nail disease is very varied, so it is often difficult for clinicians to diagnose because several types have high similarities. Therefore, an automatic nail disease classification method based on nail photos was proposed in this study. The proposed method was based on the VGG-16 neural network architecture with an Adam optimizer. Nail diseases including Koilonychia, Beaus Lines, Leukonychia have been classified in this study. The model in this study is simulated in Python programming. The simulation results show that the highest classification accuracy is 96%, achieved with epoch-10. The transfer learning method based on a neural network simulated in this study is expected to support the clinical diagnosis of nail disease.

Keywords: *nail disease, neural network, transfer learning, VGG-16*

Abstrak—Penyakit kuku manusia biasanya diabaikan karena tidak menunjukkan gejala klinis yang berbahaya bagi kesehatan seseorang. Penyakit kuku, di sisi lain, bisa menjadi tanda awal masalah kesehatan. Beberapa jenis penyakit kuku dapat menyebabkan infeksi, cedera, atau bahkan hilangnya kuku itu sendiri. Hal tersebut dapat mengurangi estetika dan kecantikan seseorang. Penyakit kuku sangat bervariasi, sehingga seringkali sulit bagi klinisi untuk mendiagnosis karena beberapa jenis memiliki kemiripan yang tinggi. Oleh karena itu, metode klasifikasi penyakit kuku otomatis berdasarkan foto kuku diusulkan dalam penelitian ini. Metode yang diusulkan didasarkan pada arsitektur jaringan saraf VGG-16 dengan pengoptimal Adam. Penyakit kuku termasuk *Koilonychia*, *Beaus Lines*, *Leukonychia* telah diklasifikasikan dalam penelitian ini. Model dalam penelitian ini disimulasikan dalam pemrograman Python. Hasil simulasi menunjukkan bahwa akurasi klasifikasi tertinggi adalah 96%, dicapai dengan epoch-10. Metode *transfer learning* berbasis *neural network* yang disimulasikan pada penelitian ini diharapkan dapat mendukung diagnosis klinis penyakit kuku.

Kata kunci: *peripheral arterial disease, ankle brachial index, osilometri*

I. INTRODUCTION

Nail disease in humans is often ignored because it does not directly show clinical symptoms that interfere with human health. However, nail disease can be an early indication of a disorder in the body [1]. In some cases, clinicians identify a disease by observing the patient's nails [2], [3]. Nail disease can be experienced by every-one, regardless of gender and age. Approximately 50% of cases of nail disease are caused by infection [4] If left untreated, it can expand the area of damage and even spread to other nails. Some types of nail disease can cause infection until the nail is damaged and does not grow anymore. This problem will cause new infections in body parts that are not protected by nails. Besides that, it can reduce a person's beauty [5]. Generally, doctors can identify nail disease

through direct observation [6]. It is difficult to distinguish some types of nail disease because it has a high similarity [7], and it depends on the nail shape of each individual. An accurate diagnosis of nail disease is the key to determining therapy so that treatment can be carried out effectively [8].

Recently, nail image processing technology has played an essential role, including biometric application, diagnosis and study of pathological changes. Nail image-based biometric systems have been reported in studies [9], [10]. Meanwhile, the diagnosis of nail disease using an image processing approach has been reported in several studies [11]. The survey by Maniyan and Shivakumar proposed classifying nail disease using its colour, texture, and shape analysis with a support vector machine as a classifier [12]. A similar study by Suguna et al. proposed a nail disease classification method using wavelet analysis and extraction



Figure 1. Sample image of each nail disease

of colour, texture, and shape features [13]. These studies generate a reasonably high accuracy. However, the traditional machine learning method is considered less reliable in implementing large amounts of image data with various backgrounds. The deep learning approach with a convolutional neural network is deemed capable of overcoming the limitations of these traditional methods [14].

Therefore, this study proposes an automatic nail disease classification system using CNN based on the VGG-16 architecture. Nail diseases including Koilonychia, Beau's lines, Leukonychia, are simulated in this study. The evaluation of the proposed model includes accuracy, precision, sensitivity, and F1-score. With the deep learning model in this study, it is hoped that it can be applied to more varied cases of nail disease to help clinicians in the diagnosis and management of nail disease.

II. MATERIAL AND METHODS

A. Nail Image Dataset

The nail disease images used in this study were collected from the Kaggle open dataset [15]. Nail types include Koilonychia, Beau's lines, and Leukonychia in *.png format. Figure 1 shows examples of nail images of each type that were used in this study. A total of 333 images were simulated, consisting of 100 Koilonychia, 131 Beau's lines, and 102 Leukonychia. Image augmentation is also done to increase the training data and balance the data between classes. In the testing phase, 20 images of Koilonychia, 26 images of Beau's lines, and 21 images of Leukonychia were used as test data.

B. Convolutional Neural Network

Convolutional Neural Network (CNN) is an algorithm for feature extraction and classification. CNN is a variation

of the Multilayer Perceptron, which works similarly to a human neural network. CNN was first introduced by Yann Lecun in 1988 [16]. CNN is one of the methods that started the emergence of Deep Learning. In the case of image classification, CNN receives the input image or input, and then it is processed and classified into specific categories (e.g. aeroplane, ship, bird, cat, cow). CNN has a variety of architectures such as VGGNet, Alexnet, DenseNet, ResNet and others. The main components contained in CNN include the input layer, convolutional layer, activation layer, pooling layer, fully connected layer, and output Layer, as presented in Figure 2 [17] [18]. The convolutional layer is used for feature extraction, and the pooling layer generates new filters based on rules. Meanwhile, at the output stage, a fully connected layer consists of many neurons as decision-makers.

The CNN transfer learning model [17] is a general approach in computer vision for building systems in transfer learning. Transfer learning is a solution to the challenge of large-scale data collecting. The collection process does not begin with learning from scratch but relies on previously learned models. In this study, we used transfer learning VGG16 models pre-trained on ImageNet. The testing design aims to see how resilient the suggested model is.

C. Architecture Visual Geometry Group-16 (VGG16)

VGG16 is a CNN architecture commonly used in image recognition or classification [19]. Numerous studies reports that VGG16 can generate high accuracy in some cases of image classification [20], [21]. VGG16 was first introduced in 2014 by Simonyan and Zisserman [22]. As the name implies, this architecture has 16 layers [23]. VGG16 was developed to improve the AlexNet architecture, where the kernel filter was modified to be smaller with a size of 3x3.

The basic architecture of VGG16 is presented in Figure 3. Meanwhile, the model parameters used in this study are shown in Figure 4 and the process of each layer on VGG-16 model are presented in Table 1. During the training phase, the input RGB image measuring 224x224 is carried out by two-dimensional convolution with a kernel size of 3x3. The convolution process is carried out in each layer to generate a feature vector as a parameter in decision making in the classification stage.

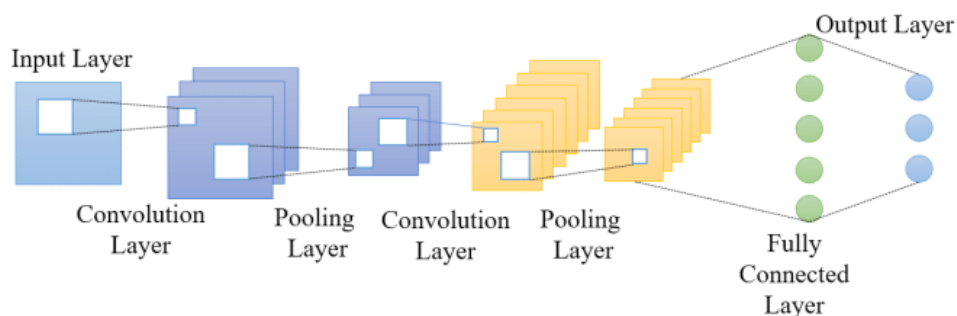


Figure 2. The basic concept of CNN [17]



Figure 3. The architecture of VGG-16

D. Performance Evaluation

The evaluation performance of the model includes accuracy, precision, sensitivity and F1-score. It previously calculated True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN), as presented in Table 2 with the formula for each class offered in Equation 1 to Equation 3.

$$\text{Koilonychia} \begin{cases} TP = Val 1 \\ FN = Val 2 + Val 3 \\ FP = Val 4 + Val 7 \\ TN = Val 5 + Val 6 + Val 8 + Val 9 \end{cases} \quad (1)$$

$$\text{BeausLines} \begin{cases} TP = Val 5 \\ FN = Val 4 + Val 6 \\ FP = Val 2 + Val 8 \\ TN = Val 1 + Val 3 + Val 7 + Val 9 \end{cases} \quad (2)$$

$$\text{Leukonychia} \begin{cases} TP = Val 9 \\ FN = Val 7 + Val 8 \\ FP = Val 3 + Val 6 \\ TN = Val 1 + Val 2 + Val 4 + Val 5 \end{cases} \quad (3)$$

Positive data anticipated to be correct is defined as TP, and negative data predicted to be correct is defined as TN. Meanwhile, FP stands for negative data projected to be positive, and FN stands for positive data that is predicted to be negative. Accuracy is the ratio of correct predictions (positive and negative) to the overall data. Precision is True Positive (TP) with the amount of data predicted to be positive. The sensitivity compares True Positive (TP) with the number of positive data. F1-score is the average of sensitivity and precision. Equation 4 to Equation 7 are the formulas for precision, sensitivity, F1-score and accuracy [20].

Table 1. Process details of each layer on VGG-16 model

Layer	Step
1	Conv. 64 filters
2	Conv. 64 filters + Max pooling
3	Conv. 128 filters
4	Conv. 128 filters + Max pooling
5	Conv. 256 filters
6	Conv. 256 filters
7	Conv. 256 filters + Max pooling
8	Conv. 512 filters
9	Conv. 512 filters
10	Conv. 512 filters+Max pooling
11	Conv. 512 filters
12	Conv. 512 filters
13	Conv. 512 filters+Max pooling
14	Fully connected with 4096 nodes
15	Fully connected with 4096 nodes
16	Output layer with Softmax activation with 1000 nodes.

Table 2. the evaluation performance between predicted class and actual class

Actual	Predicted		
	Koilonychia	Beaus Lines	Leukonychia
Koilonychia	Val 1	Val 2	Val 3
Beaus Lines	Val 4	Val 5	Val 6
Leukonychia	Val 7	Val 8	Val 9

III. RESULTS AND DISCUSSION

In this study, a total of 333 nail disease images dataset were used for the training and testing process. The dataset

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1 - score} = \frac{2 * \text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (6)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

consists of 100 koilonychia class images, 131 Beau's lines class images, and 102 Leukonychia images. The test was carried out with trans-fer learning parameters Batch size of 20 and epoch variations. The VGG-16 modelling architecture used is shown in Figure 4. The Loss and accuracy during training of the proposed model to classify the nail disease image into Koilonychia, Beau's lines, and Leukonychia at epoch=10, for example, are shown in Figure 5.

Based on the proposed model, it can be found that the highest accuracy value of 96% for classifying nail disease into Koilonychia, Beau's lines, and Leukonychia at epoch=10, as shown in Table 3.

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=====VGG16 summary=====
Model: "vgg16"

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Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0

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Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

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Figure 4. The total parameters of proposed VGG-16 model

As for visualization, a comparison of precision, sensitivity, and F1-scores for each class are presented in Fig.6. We can see that Leukonychia nail disease achieves the highest performance among the others. Based on the sample image in Figure 6, Leukonychia has a bold white-line marker, making it more distinct from the Koilonychia and Beau lines.

A comparative study was also carried out with some previous studies which are shown in Table 4. The proposed method of classifying nail disease in this study outperforms previous studies in the case of three classes of classification.

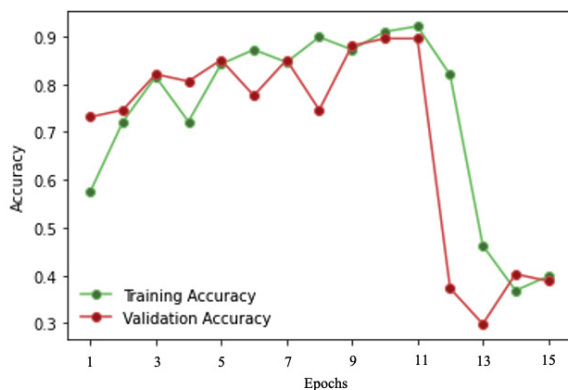


Table 3. The testing results of nail disease classification into koilonychia, beau's lines, and leukonychia using VGG-16.

Epochs	Nail Disease Classes	Precision	Sensitivity	F1-score	Accuracy
5	Koilonychia	94%	85%	89%	94%
	Beaus Lines	93%	96%	94%	
	Leukonychia	95%	100%	98%	
10	Koilonychia	95%	90%	92%	96%
	Beaus Lines	93%	96%	94%	
	Leukonychia	100%	100%	100%	
15	Koilonychia	94%	96%	95%	89%
	Beaus Lines	88%	86%	87%	
	Leukonychia	81%	81%	81%	

Table 4. Comparison with previous studies

Study	Method	Classification case	Accuracy (%)
Abdulhadi et. al [24]	Alexnet	4	92.5
Indi and Gunge [6]	RGB analysis	5	65
Nijhawan et. al [25]	hybrid of Convolutional Neural Network (CNNs1)	11	84.58
This study	VGG-16	3	96

IV. CONCLUSION

Nail disease in humans is often ignored because it does not directly show clinical symptoms that interfere with human health. However, nail disease can be an early indication of a disorder in the body. In this research, we proposed a transfer learning method VGG-16 with an Adam optimizer to classify the nail disease into three class namely Koilonychia, Beau's lines, and Leukonychia. In this study, a total of 333 nail disease images dataset were used for the training and testing process. The dataset consists of 100 koilonychia class images, 131 Beau's lines class images, and 102 Leukonychia images. The test was carried out with transfer learning parameters batch_

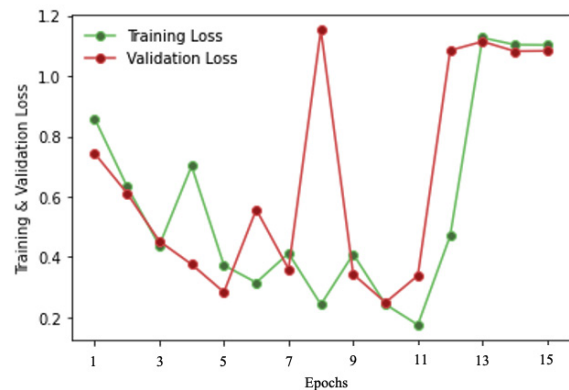


Figure 5. Nail disease classification performance during the training process

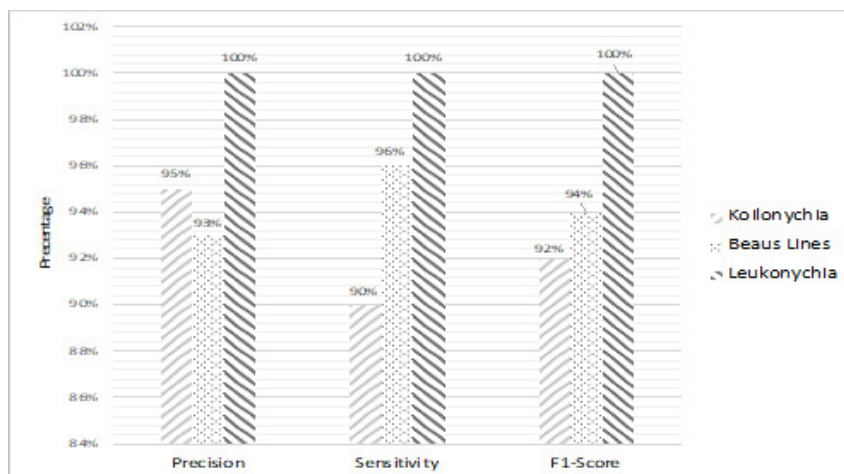


Figure 6. The performance evaluation result of nail disease classification.

size=20 and epoch variations. The simulation results show that the highest classification accuracy was 96%, achieved with epoch-10. The transfer learning method based on a neural network simulated in this study was expected to support the clinical diagnosis of nail disease.

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