Harla Journals

Harla Journal of Engineering and Technology

Journal home page: https://journals.ddu.edu.et/index.php/HJET

Harla journal of Engineering and Technology

Human Skin Fungal Diseases Classification Using Deep Learning Technique

[1*]Tsedenya Debebe, [2]Berihun Molla,

[1] *Information Technology, faculty of computing and Informatics, Jimma Institute of Technology /Jimma University, Jimma, Ethiopia*

[2]*Health Informatics, School of public Health, college of Medicine and Health Science /Arbaminch university , Arbaminch, Ethiopia*

tsedidebebe@gmail.com, berihunmolla44@gmail.com

ABSTRACT

Skin plays a significant role in body temperature regulation. Several risks affect the skin, from the common cause of skin disorders are bacteria, viruses, and fungi. Identifying the disease based on manual feature extractions or the symptoms is time-Consuming and requires extensive knowledge for perfect identification. Previously research was done on Diagnosing, detecting, and classifying skin diseases. However, in the previous work, tinea species and tinea corporates are not identified, especially for black skin color. In this paper, we develop a CNN model to classify skin fungal disease types like tinea pedies, tinea capitis, tinea corporates, and tinea uniguium. Then softmax classifies images as tinea pedies, tinea capitis, tinea corporates, and tinea uniguium. We have collected 407 skin fungal lesion images from patients at Dr. Gerbi's medium clinic of Jimma and JUMC using the smartphone camera (Techno pop two power, Techno Spark4, SamsungA20). After collecting datasets, Image Preprocessing, Image augmentation techniques are applied to increase the performance of the human skin disease classification model. In this study, we have done image preprocessing (image size normalization, RGB to Grayscale conversion, and balancing the intensity of the image). We have normalized the images to three sizes which are 120 x120, 150X150, and 224x224. From the total augmented 1069 images, 80% (727) were for training, 10% (164) for validation, and the remaining 10% (178) for testing. After evaluating the model, we have registered an overall performance accuracy of 83% using our CNN-based HSFDC model. The accuracy achieved 79% and 69% for MobileNetV2 and ResNet 50, respectively. This implies that the developed model is better than the MobileNetV2 and ResNet50 pre-trained CNN Models for our dataset.

Keywords: Skin Disease, Deep Learning, Image processing, MobileNetV2, ResNet 50, CNN

**Corresponding author: Tsedenya Debebe, tsedidebebe@gmail.com,*
DOI:
 Manuscript received October, 2022; revised November, 2022; accepted December, 2022.

1. INTRODUCTION

Human skin is the soft outermost layer of the human body. It contributes to the significant area as it is the largest organ spread throughout the body, occupying 16% of its mass [1]. The human skin plays a significant role in a person's physical appearance. It offers protection against fungal infection, bacteria, allergies, and viruses. It controls the temperature of the body situations that change the skin's texture or damage the skin can produce symptoms like swelling, burning, redness, and itching [2]. The skin is an organ that stores water and fat serves as a barrier between the organism and its environment, and aids in producing vitamin D when exposed to sunlight. The skin surrounds all other parts of the body. Skin thickness varies all over the body, between men, women, and young or old.

The dermis gives skin flexibility and strength. The roles of the dermis include sensing pain and touch, Producing sweat and oils, Growing hair, Bringing blood to the skin, and fighting infection. The deeper subcutaneous tissue is called hypodermis, which is made of fat and connective tissue. It helps to insulate the body from heat and cold. The hypodermis also serves as an energy storage area for fat. This fat provides padding to cushion internal organs as well as muscle and bones and protects the body from injuries [3]. Skin diseases are one of the most common diseases found among humans that harm them, whether it is a small bump, which might lead to bothersome or a vicious structure and then to mortality [4]. There are more than 3000 known skin diseases worldwide [5]. Skin diseases are a huge burden on the world, and there is an alarming need to get them into control at early stages. Skin diseases are becoming the most common health issue among all the countries worldwide [6]. Skin diseases are the most common cause of all human illnesses which affects almost 900 million people in the world at any time [7]. Skin diseases are reported to be the most common disease in humans among all age groups and a significant root of infection in sub-Saharan Africa [8]. An estimated 21–87 % of children in Africa are affected by skin diseases [9]. Skin can be affected by fungal infections, viruses, bacteria, etc… According to the latest WHO data published in 2018 Skin Disease Deaths in Ethiopia reached 2,459 or 0.40% of total deaths [10]. It affects education, relationships, self-esteem, career choices, social, sexual, and leisure activities. Beyond these, skin diseases may cause a sense of depression, frustration, isolation, and even suicidal ideation [11]. The term superficial fungal infections refers to infections produced by pathogenic fungi that affect just the human hair, nails, epidermis, and mucosa. Dermatophytes are

-

the most common cause of superficial fungal infections all over the world, and they are particularly prevalent in developing countries. Tropical and subtropical countries, such as Sub-Saharan Africa, are particularly vulnerable. The most common fungal infections are tinea corpories, Tinea capitis, Tinea Pedis, Tinea cruises, Pityriasis vesicular, etc. [12]. These infections are among the most common diseases in the world, causing serious chronic morbidity. Tinea pedies is a fungus-caused skin disease that primarily affects the leg and foot. It is a fungus that usually starts between the toes. It is most common in people whose feet have become extremely sweaty while being confined within tight-fitting shoes. Athletes' foot commonly starts with a red rash between the toes, typically between the fourth and fifth toe. Tinea Corpories is a type of fungal infection that mostly affects the overall body like hand, leg. It affects mostly children and young adults. Tinea Capitis is a fungal infection that affects the skin around the scalp. Tinea unguium is a fungal skin disease that affects the nail. Onychomycosis is another name for it. The Global Prevalence of onychomycosis is 5.5 % and contributes 50% of all nail diseases [13].Tinea is a geographically widespread group of fungal infections caused by dermatophytes. The organism, its hosts, and local factors all influence type predominance. Infection can occur through contact with infected humans and animals, soil, or inanimate objects. Tinea infections can be difficult to diagnose and treat accurately because of the similarity between different types of fungal morphology. Now, in our research work, we develop a model to classify the most common fungal skin diseases using a convolutional neural network.

2. LITERATURE REVIEW

In this paper, the authors proposed a method to detect and classify three types of skin diseases namely, herpes, dermatitis, and psoriasis using grey-level co-occurrence matrix (GLCM) for feature extraction and SVM for classification. Their evaluation result was 85% for herpes, 90% for dermatitis, and 95% for psoriasis [14]. They didn’t use a good feature extraction technique. Diseases like Tinea Pedis, Tinea Captis, Tinea Corpories, Tinea unguium.

A support vector machine (SVM) with quadratic kernel has been proposed for the Classification of acne, eczema, psoriasis, benign and malignant melanoma with an accuracy of 83% [15] however, doesn’t consider fungal diseases.

Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network: for classification of melanoma and benign lesions CNN was proposed and they got 81% accuracy [16]. Even though they have used powerful classification algorithm, doesn't consider fungal diseases

Deep learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumor diagnosis: In this paper, the Authors applied a pre-trained Google Net to classify 14 categories of skin tumors with an overall accuracy of 76.5% [17].

The Authors used CNN for feature extraction and they classify three skin diseases namely, Atopic dermatitis, Acne vulgaris, and Scabies with evaluation accuracy of 88%, 85%, and 84.7% respectively and the overall accuracy is 88% [8]. Their model recognizes three skin diseases but does not consider fungal diseases like Tinea Pedis, Tinea Captis, Tinea Corpories, Tinea unguium.

In this authors proposed a mobile-based system that classifies three skin diseases namely melanoma, eczema, and impetigo. They also compared Support Vector Machine (SVM) and Convolutional Neural Networks (CNN). Based on their result CNN performs better classier performance than SVM [18]. Even though their system recognizes skin diseases for what they proposed they did not consider fungal skin diseases like tinea pedies, Tinea Capitis, Tinea Corpories, and Tinea uniguium.

The Authors proposed Smartphone-based skin diseases detection method their system recognized Acne, Eczema, Pityriasis rosea, Psoriasis, Tinea Corporis, Varicella (chickenpox), and Vitiligo. The accuracy achieved was 94% [19]. Even though they include Tinea Corpories, they did not consider other fungal skin diseases like Tinea pedies, Tinea Capitis and Tinea Unguium.

In this research work, the Authors compared five pre-trained deep learning frameworks for the diagnosis of six facial skin conditions from a clinical image and using an InceptionResNet_V2 a precision of 77% was claimed [20].

Using artificial intelligence on dermatology conditions in Uganda: A case for diversity in training data sets for machine learning. The Authors tried to test one AI application, which is developed for skin disease identification for dermatology. They have used a black color image dataset. The accuracy achieved was low i.e.17% [21]. Finally, they conclude that the designed AI application is poor for fungal infections like tinea infections. In all previous works, Tinea capitis, Tinea pedis, and Tinea Unguium are not considered. To fill this gap we develop a model for classifying Tinea Pedis, Tinea Capitis, Tinea Corpories, and Tinea Unguium.

3. STATEMENT OF THE PROBLEM

Any disorder that affects the human skin is referred to as a skin disease. Since skin is the outer covering of our body mostly, it is affected by bacteria, fungus, and viruses. The skin totally protects all of the organs in the human body. As a result, it's critical to pay attention to the skin's overall health. Because any change in its normal, functioning can cause to affect the other parts of the body. Skin diseases are the 4th leading cause of skin burden worldwide [22]. Some of the most common skin illnesses are eczema melanoma, Vitiligo, mycosis, Papillomas, impetigo, scabies, herpes, dermatitis, wart, psoriasis, acne, tinea corpories, tinea pedies, tinea capitis, etc. [23]. Those are very harmful to the skin and can spread throughout if not detected accurately as early as possible. Skin diseases cause significant non-fatal disability worldwide, especially in resource-poor regions [24]. Skin diseases have a psychological effect on humans. It affects people psychologically due to the visible effects of skin diseases on the human body. Based on current epidemiology, human fungal infections can be divided into primary, secondary, and invasive. Fever, pain, and dyspnea are some of the clinical symptoms of skin fungal diseases. Because they are not specific, combined with the complexity of the fungal spore microscopic image itself and the similarity between different types of fungal morphology so that fungal infections Accurate and timely diagnosis and treatment have great difficulties [25]. Early detection and diagnosis of the disease is critical to provide appropriate treatment and prevent further spread. In our country, Ethiopia, blood tests may be used by dermatologists to make a symptom-based diagnosis and further analysis. Common methods for diagnosing skin diseases include history and symptom analysis, skin scraping, visual inspection, dermoscopy, and skin biopsy. However, those diagnosis methods are tedious, time-consuming, requires an extensive understanding of the domain, and are vulnerable to subjective diagnosis. The majority of them necessitate the dermatologist's experience and excellent visual perception. The optic visualization of experts is that the main old-style approach adopted for the popularity and identification of human disease of the skin.

Detection, diagnosis, and classification were done previously by different researchers.in the previous works, researchers used different methodologies and therefore the performance rate of their models are different. However, human skin disorder like tinea pedies, and, tinea corpories are the foremost common disease that wasn't considered within the previous human skin disease classification model. In this thesis, we develop a model to detect and classify tinea corpories, tinea pedies, tinea capitis and, tinea unguium.

4. PROPOSED METHODOLOGY

This study follows an experimental research design. Experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand the causal process. An experimental research design includes dataset preparation, implementation, performance evaluation, designing skin fungal diseases classification model. To detect and classify the fungal skin lesion images, it is important to follow a series of image processing steps. The detail of these steps is shown in fig. 3.1. In this thesis, we follow the image processing concepts to customize the model for skin diseases images detection and classification model. Accordingly, image analysis and understanding are used to classification skin lesion images into four classes Tinea Pedis, Tinea Capitis, Tinea Corpories, and Tinea Unguium.

-

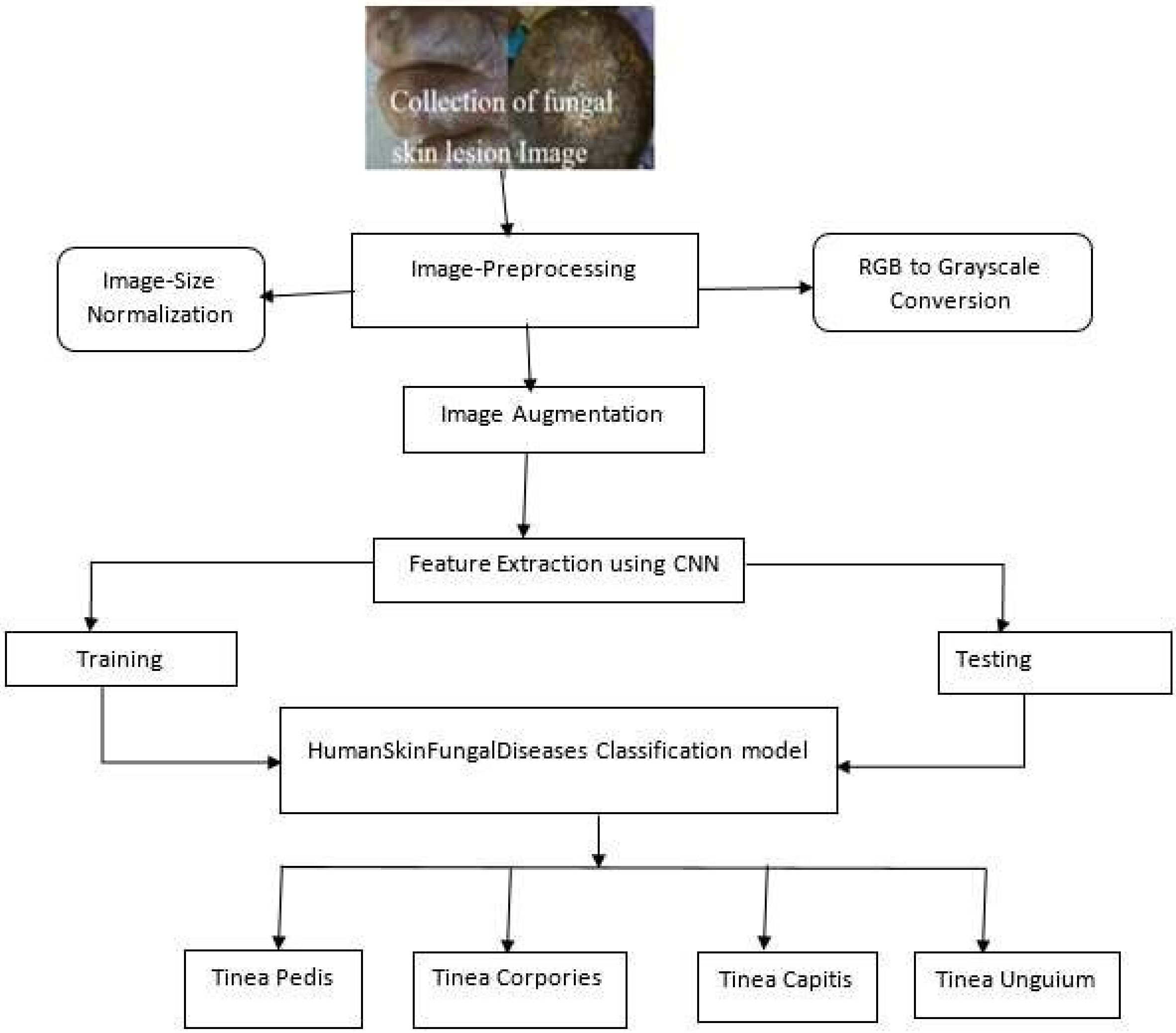


Fig. 1. Research design Block diagram

5.1 Image pre-processing

Image processing is a technique of improving the quality of an image after removing irrelevant image data from an image in various applications and domains. Medical images contain a lot of irrelevant and unwanted parts in the actual format of the scanned images. To remove such annoying parts in an image, it is required some of the image preprocessing techniques for better visualization of the images before finding the diseases in particular [26]. Image pre-processing is an essential step because enhancing the quality of the original image enhances the detection of the lesion region. For example, in our data set hair is a noise to be removed. Image preprocessing is a term used to describe operations on images at the most basic level of abstraction, in which both the input and output are intensity images, which are commonly represented by a matrix of image function values.

To increase the quality of acquired images, image-preprocessing techniques are used. CNN's use little pre-processing when compared to traditional classification algorithms which use filters that are hand-engineered. The independence of human intervention in learning filters is a good advantage of CNN. It is a supervised deep learning approach that requires large labeled data for training on the network. After training the model will learn the weights and the accuracy of the classifier is improved [27]. Normalization, image color conversation, and image resize were the image preprocessing techniques employed in this investigation.

5.1.1 Image Resize

Initially, the image was not uniform in size therefore, to facilitate image preprocessing techniques all images have a uniform size to enlarge and reduce the given image size in pixel format. This step is necessary when you need to increase or decrease the total pixel for the standardization of the image. Moreover, resizing the image reduces processing time and computational cost. The collected images have different sizes. Image resize is the basic step in image preprocess because the data set must have a similar size that is preferable for the proposed method and the large pixel's size consumes too much computational cost and time. We compare three types of image size by resizing the dataset into 120X120, 150X150, and 224X224 pixels.

5.1.2 Image brightness normalization

As part of skin lesion preprocessing, we resized each skin lesion image, convert the image to Grayscale and balance the image intensity using histogram equalization. Histogram Equalization is an image processing technique that adjusts the contrast of an image by using its histogram. To enhance the image's contrast, it spreads out the most frequent pixel intensity values or stretches out the intensity range of the image.

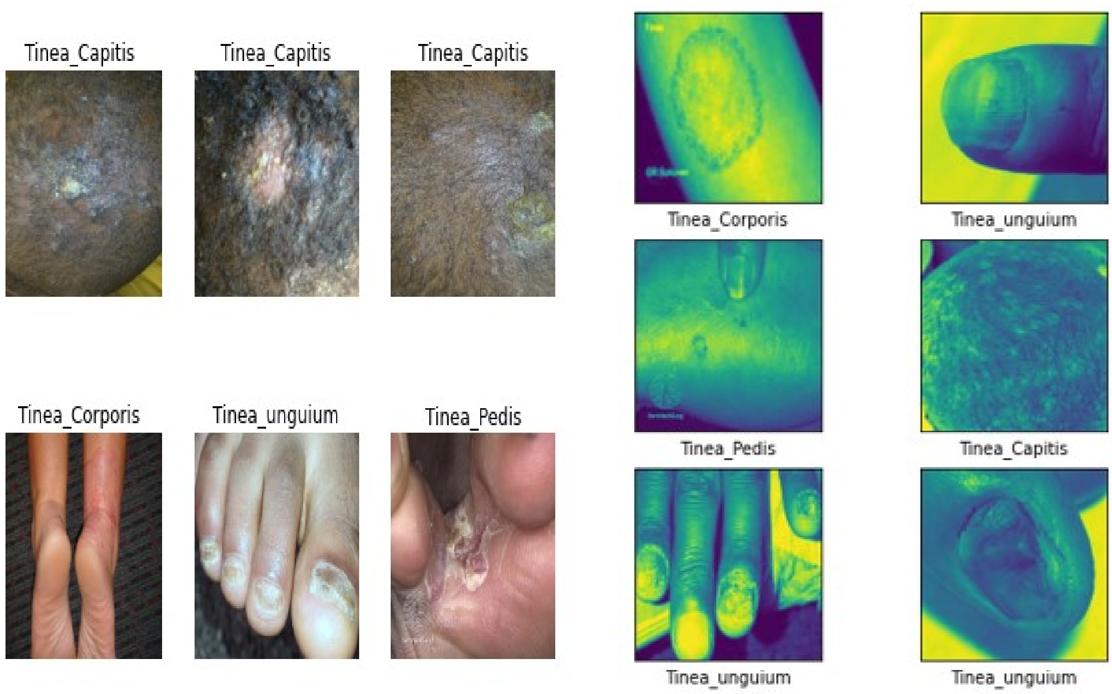
-

A) B)

Fig. 2. Original image (A) and adjusted histogram (B)

5.1.3 Image Color Conversion

In this study, after the size of all acquired images becomes uniform, the color is converted from RGB to grayscale. Here is the visualization of color conversion.



A) B)

Fig.3. RGB color mode and Gray scale color mode

-

5.1.4 Feature Extraction

Feature extraction is a technique that changes the original feature of data to a new smaller feature that is more informative than the previous. This smaller set of informative features is important for recognition to discriminate among different labels. It is the process of retrieving meaningful information from an image that is used for the classification of images into different categories. It is the process to represent a raw image in a reduced form to facilitate decision-making such as pattern detection, classification, or recognition.

Finding and extracting reliable and discriminative features is always a crucial step to complete the task of image recognition and computer vision. To extract the descriptive feature from skin lesions images. Generally, extracted features are descriptive and commonly texture features, color feature size or shape feature, etc. CNN's represent an interesting method for adaptive image processing. This study employed the CNN feature extraction model. This is because the CNN model is the current state of the art in image detection and classification tasks. To extract deep features CNN is better. The powerful learning ability of deep CNN is primarily due to the use of multiple feature extraction stages that can automatically learn representations from the data [28].

5.1.5 Data Augmentation

Deep learning usually requires a large amount of data to train. A small amount of data often causes over-fitting. But in reality, a large number of labeled medical fungal images are expensive and difficult to obtain, so we need to create data. Data augmentation is one of the regularization methods to prevent machine learning models from overfitting. Data Augmentation is a technique used to artificially increase or expand the size of the training dataset. It is important because sometimes there is a very limited-sized training data set is available for most of the real-life complex problems (e.g. medical datasets) and the fact is that more training data samples can result in a more skillful CNN model [29]. There are several data augmentation operations are available such as cropping, rotations, flipping, translations, contrast adjustment, scaling, etc. In this thesis, we augment the total acquired images which are 407 images labeled into four classes namely, Tinea Capitis, Tinea Corpories, Tinea Pedis, and Tinea Unguium, and after augmentation, we have the total data set of 1069 images.

-

Table 1. Total collected Dataset

No	Diseases type	No of images before augmentation	No of images after augmentation
1	Tinea Capitis	120	304
2	Tinea Pedis	96	264
3	Tinea Corpories	71	229
4	Tinea Unguium	120	272
Total number of images collected		407	1069

6 MODEL EVALUATION

In our study, the performance of the proposed model is evaluated based on the counts of test records that are correctly and incorrectly predicted by the model. Based on this, the performance of the classifier can be evaluated by using evaluation measures such as accuracy and error rate. Correctly and incorrectly classified counts of the test model are tabulated in a table known as a confusion matrix. The commonly used measurement metrics such as precision, recall, f1 score, and support are used to compute the accuracy of the system which is defined as follows.

The recall is the ratio of many correctly predicted over the total number of samples used.

$$\text{Recall} = \frac{\text{Correctly predicted}}{\text{Total number of samples}} \qquad \frac{(TP)}{(TP+TN)} \tag{1}$$

$$\text{Precision} = \frac{\text{Correctly predicted}}{\text{Total No of positive count}} \qquad \frac{(TP)}{(TP+FP)} \tag{2}$$

The f1score can be interpreted as a weighted harmonic mean of the precision and recall and is defined as

-

$$\text{F1- score} = \frac{2\times(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

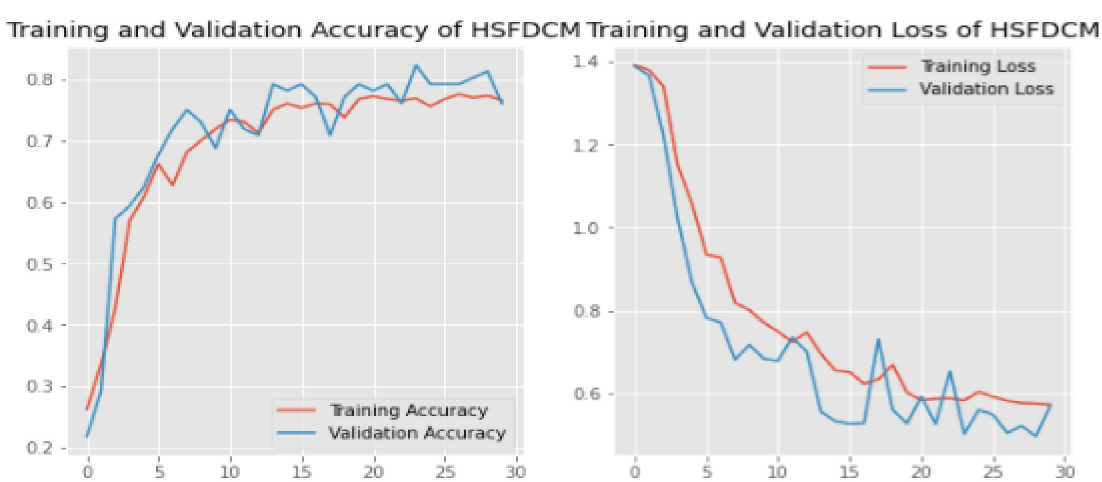
7 EXPERIMENTATION

7.1 Experimenting to find appropriate Image sizes to achieve maximum accuracy

When you need to raise or decrease the total pixel for image standards, this image resizing is needed. Furthermore, shrinking the image greatly reduces processing time and costs. The collected images have different sizes. Image resize is the basic step in image preprocess because the data set must have a similar size the large pixel's size consumes too much computational cost and time. The collected images have different sizes. We resized to the image size of 120X120, 150X150, and 224X224. In this experiment, 224X224 registered the highest accuracy. As the size of the image increases it needs much computational time. The result is as follows

7.1.1 Image Size 120 by 120 experiment

In this experiment, the model is trained using an image size of 120X120. From this, we have achieved 77%,76% for training and validation accuracy respectively. The plot diagram shows accuracy and loss result in figure below.



-

Fig. 4. Accuracies and Loss confusion metric's for 120 X 120 image size

7.1.2 Image size 150 by 150 experiment

In this experiment, the model is trained using an image size of 150X150. From this, we have achieved 79%,78% for training and validation accuracy respectively. This result shows that image 150X150 achieves better performance than image size 224X224 but it requires more time to train. The plot diagram shows the accuracy and loss result in figure below.

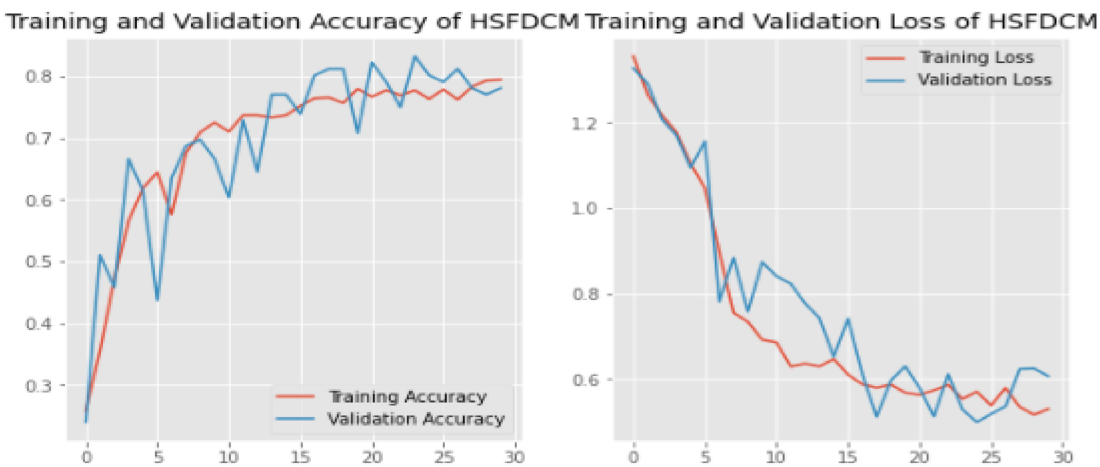


Fig. 5. Accuracies and Loss confusion matrix for 150X150 image size for HSFDC Model

7.1.3 Image size 224 by 224 experiment

The model is trained with an image size of 224X224 in this experiment. We were able to attain 83 %, 80 %, and 80 % accuracy for training and validation, respectively. This result shows that image 224X224 achieves better performance than image sizes 120X120 and 150X150 but it requires more time to train. The plot diagram shows the accuracy and loss result in figure below.

-

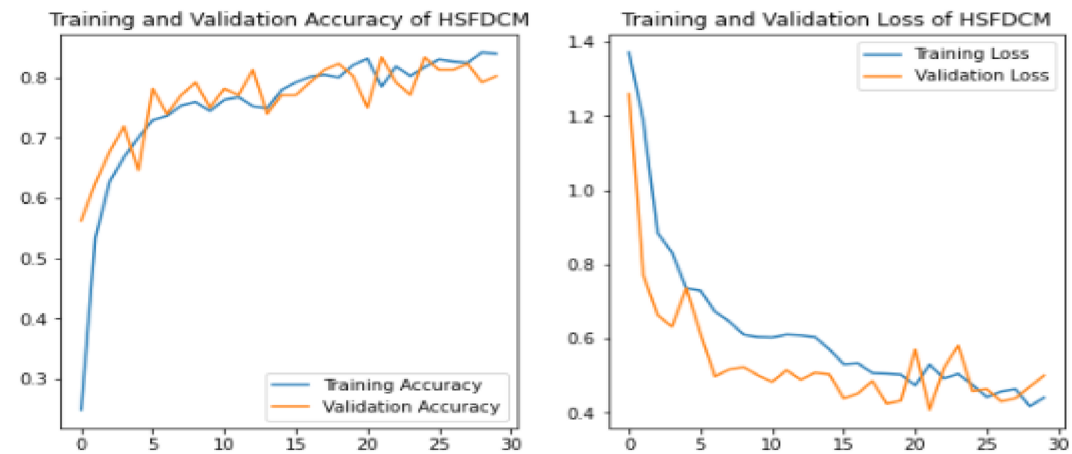


Fig. 6. Accuracy (A) and Loss (B) for 224 X 224 image size

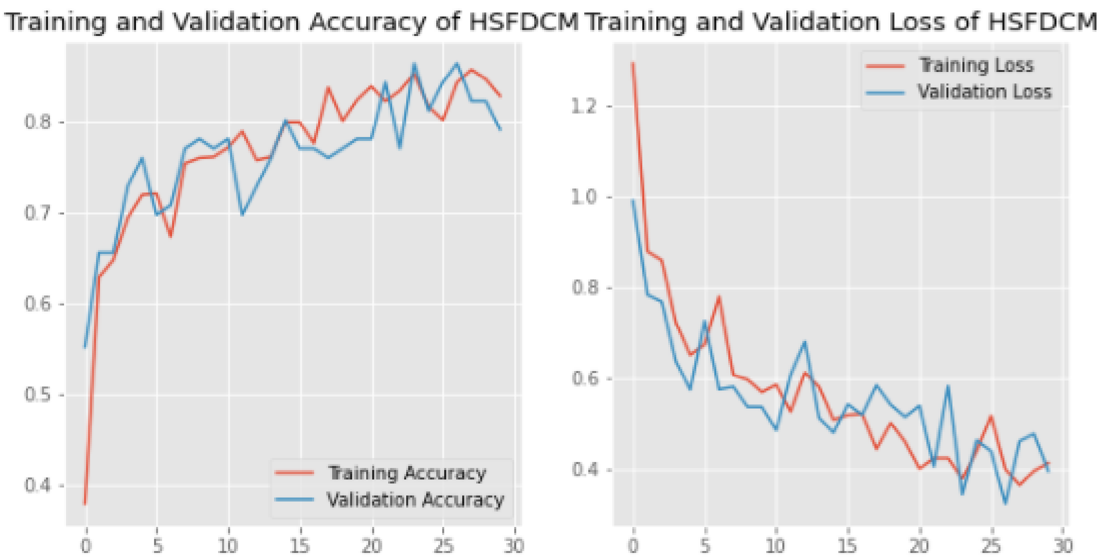
7.2 Experimenting to find appropriate Activation function to achieve maximum accuracy

In this experiment, the model is trained using an image size of 224X224, RGB color mode to check the appropriate activation function for HSFDCModel. We conduct this experiment using Relu and ELU separately. The result is as follows.

7.2.1 HSFDCModel using 224X224 image size and ELU Activation Function

In this experiment, the model was trained using 224X224 image size RGB color mode and with Elu as an activation function. From this, we have achieved 82%, 79% for training and validation accuracy respectively. This result shows that the Elu activation function registered less performance than Relu. The plot diagram shows this accuracy and loss result in figure.

-



A) B)

Fig. 7. Training (A) and validation accuracy loss (B) of HSFDCModel result using Elu

7.2.2 HSFDCModel using 224X224 image size and Relu Activation Function

In this experiment, the model was trained using 224X224 image size, RGB color images, and with Relu as an activation function. From this, we have achieved 83, and 80% for training and validation accuracy respectively. This result shows that the Relu activation function enhances the performance of Elu. Experimenting to find an appropriate color mode to achieve maximum accuracy

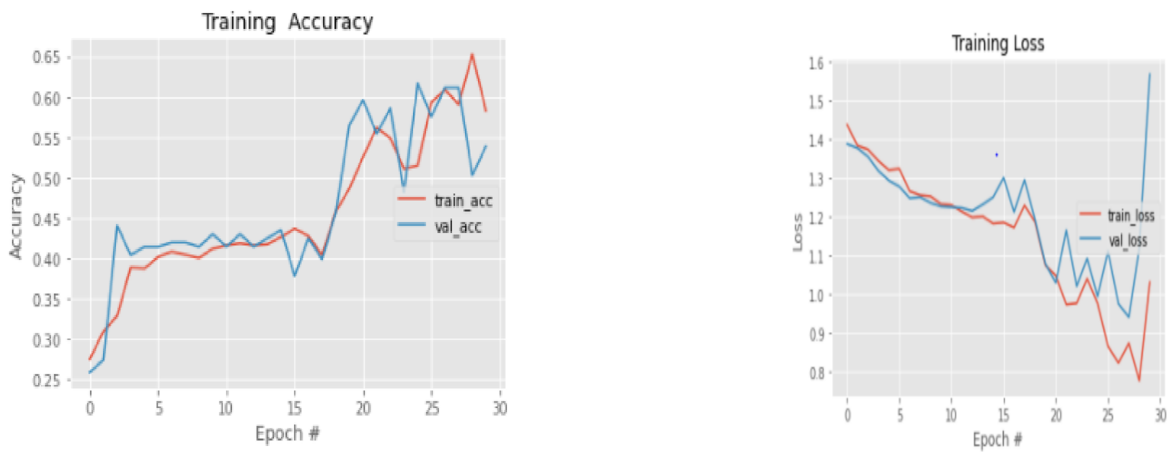
In this experiment, the appropriate color mode for Skin fungal diseases classification is identified. We have done two experiments using RGB and Grayscale color mode with an image size of 224X224. The result shows that the classification accuracy using RGB color is better than using grayscale color mode.

7.2.3 Experimenting HSFDCModel using RGB color mode

In this experiment, we have used RGB color mode to identify which color mode achieves better results and as *a result using RGB color mode for HSFDCModel achieves the highest accuracy.*

7.2.4 Experimenting HSFDCModel using Grayscale color mode

Two-color modes we have examined the performance of the RGB color and Grayscale separately. We have compared RGB and Grayscale color mode using HSFDCModel by using an image size of 224X224. The results suggest that utilizing RGB color mode enhances classification accuracy over using grayscale color mode. The result is as follows.



A) B)

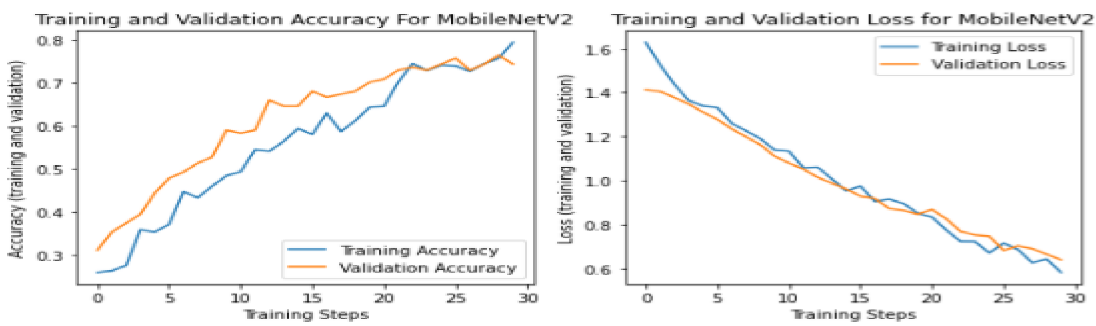
Fig. 8. Training accuracy and training loss using Gray color

7.3 Identification of suitable algorithm for skin disease image classification model

Comparison is done with deep neural networks using the same dataset and parameter with architectural differences in the model. As we described in the methodology section 3.3.4, there are different types of deep neural network models such as AlexNet, ResNet, MobileNet, VGG16, VGG19, and GoogleNet. From these models, we select MobileNet V2 and ResNet 50 to evaluate our model. The reason selects this model is related to hardware dependency, since, this architecture runs on the CPU.

7.3.1 Experimentation Result for MobileNetV2 model

In this experiment, the MobileNetV2 model was trained using 224X224 image size, RGB color channel, and Relu activation function because our model (HSFDCM) achieves better results in 224X224 image size, RGB color images, and Relu activation function as shown in the above three experiments. We got 79%, 74% training, and validation accuracy respectively. This shows HSFDCModel achieves better (83%) than the performance of MobileNetV2. As shown in figure 4.11 the training and validation accuracy, training, and validation loss are plotted.

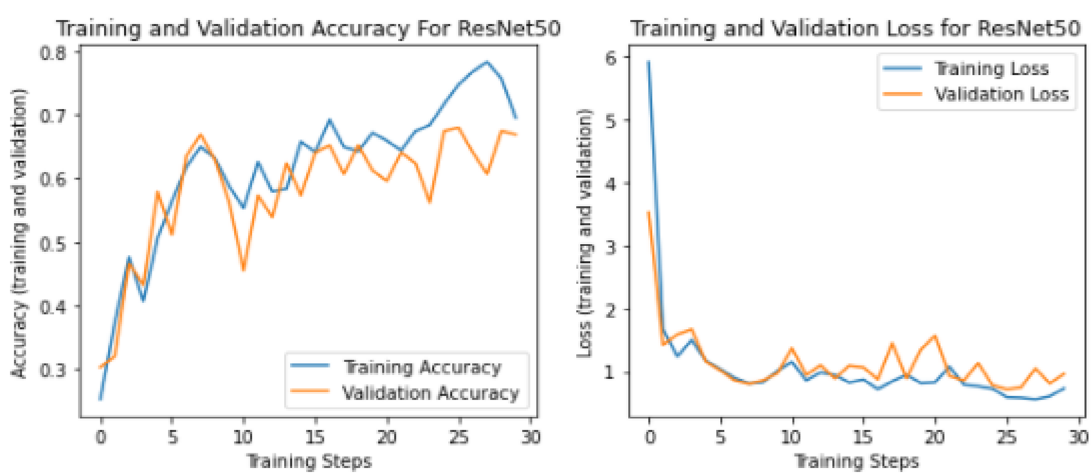


A) B)

Fig.9. MobileNetV2 model accuracy (A) and loss (B) result

7.3.2 Experimentation Result for ResNet 50 Model

In this experiment, the ResNet50 model was trained using 224X224 image size, RGB color channel, and Relu activation function because our model (HSFDCM) achieves better results in 224X224 image size, RGB color images, and Relu activation function as shown in the above three experiments. We got 69%, 66% training, and validation accuracy respectively. This shows HSFDCModel achieves better (83%) than the performance of ResNet50. As shown in figure 4.12 the training and validation accuracy, training, and validation loss are plotted.



-

Fig. 10. ResNet50 model result

8. RESULT

Based on the above training result we evaluate our model using deep learning evaluation techniques. The classification report is described based on the experiment result. The overall prediction of the model is measured by accuracy. Because our prepared dataset is balanced in each class distribution.

Model used	Image size	Activation function	Color Channel	Training Accuracy	Validation Accuracy
HSFDCM	120X120	Relu	RGB	77%	76%
HSFDCM	150X150	Relu	RGB	79%	78%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Elu	RGB	82%	79%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Relu	Gray	58%	53%
HSFDCM	224X224	Relu	RGB	83%	80%
MobileNetV2	224X224	Relu	RGB	79%	74%
ResNet50	224X224	Relu	RGB	69%	66%

Table 2. Summary of experiments result

-

9. CONCLUSION

In this study, we used a pre-trained CNN model to classify fungal skin disease types that are common in developing countries. This is unending research, and future work includes more than increasing and cleaning the dataset by continuing to collect. Feature extraction of the skin lesion images and use the extracted features in the advanced deep learning algorithms in convolutional neural networks and see how the result compares with the result of this study. Developing the skin diseases classification model supports the health sector experts (Dermatologists) in classifying skin lesion images. Using a smartphone camera, the datasets were collected from patients at Dr. Gerbi's medium clinic of Jimma and JUMC. Finally, the model is developed, and this model is used to identify and classify the four common fungal skin lesion types. The classification occurs after the convolutional neural network extracts the features of the images. Softmax classifiers classify based on the image features, which CNN extracts before displaying the result as tinea capitis, tinea pedis, tinea corporates, and tinea unguium. We register an overall performance accuracy of 83%.

-

REFERENCES

[1] S. J. ,. A.-O. a. T. S. John D'Orazio, "UV radiation and the skin," *International Journal of Molecular Sciences,* vol. 14, p. 12222–12248, 2013.

[2] N. V. K. N. a. U. S. Yadav, "Skin diseases detection models using image processing: A survey.," *International journal of computer applications ,* vol. 12 , no. 137, pp. 34-39, 2016.

[3] K. A. Zimmermann, "live science," 22 October 2018. [Online]. Available: https://www.livescience.com/27115-skin-facts-diseases-conditions.html. [Accessed 12 11 2021].

[4] B. R. Gulati S, " Serving the dermatologists: skin diseases detection.," *In Information and Communication Technology for Sustainable Development,* pp. 799-822, 2020.

[5] M. .. S. F. S. T. B. A. B. a. A. Z. L. Tizek, "Skin diseases are more common than we think : screening results of an unreferred population at the Munich Oktoberfest," *Journal of the European Academy of Dermatology and Venereology,* no. DOI: 10.1111/jdv.15494, pp. 1-8, 2019.

[6] R. S. b. R. A. c. T. Shanthi a, "Automatic diagnosis of skin diseases using convolution neural network," *Microprocessors and Microsystems,* vol. 76, pp. 1-7, 2020.

[7] D. D. A. Dagne, "Recognizing neglected skin diseases: WHO publishes pictorial training guide," World Health Organization Global, 8 Jun 2018. [Online]. Available: Available:https://www.who.int/neglected_diseases/news/WHO-publishes-pictorial-training-guide-onneglected-. [Accessed 12 11 2021].

[8] A. A. P. Y. C. N. K. N. Samuel Akyeramfo-Sam, "A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks," *International Journal of Information Technology and Computer Science ,* vol. 11, pp. 54-60, 2019.

[9] A. O. P. R. A. B. E. W. L. a. D. B. Kelbore, "Pattern of skin diseases in children attending a dermatology clinic in a referral hospital in Wolaita Sodo, southern Ethiopia," *BMC dermatology 19,* p. 1_8, 2019.

[10] WORLDHEALTHRANKINGS, WORLD HEALTH ORGANIZATION , 2018. [Online]. Available: https://www.worldlifeexpectancy.com/ethiopia-skin-disease. [Accessed 20 07 2021].

[11] A. Bewley, "The neglected psychological aspects of skin disease," vol. 3208, 2017.

[12] B. P. ". f. i. Kelly, "Superficial Fungal Infections. skin disorders," *Pediatrics in review,* vol. 4, pp. 1-19, 2012.

[13] A. K. R. R. M. S. G. V. B. M. P. A. T. A. S. M. B. e. a. Gupta, "Global perspectives for the management of onychomycosis," *International journal of dermatology,* vol. 10, p. 1118–1129, 2019.

[14] Q. G. a. T. J. Li-sheng Wei, "Skin Disease Recognition Method Based on Image Color and Texture Features," *Computational and Mathematical Methods in Medicine,* 2018.

[15] A. S. a. M. A. H. N. Hameed, "A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning," *In2018 10th Computer Science and Electronic Engineering (CEEC) ,* pp. 186-191, 2018.

[16] E. N.-E. e. al, "Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network," *in Annu Int Conf IEEE Eng Med Biol Soc,* pp. 1-4, 2016.

-

[17] Y. F. e. al, "Deep learning-based, computer -aided classifier developed with a small datasetof clinical images surpasses board-certified dermatologists in skin tumor diagnosis," *" Br. J. Dermatol,* pp. 0-3, 2018.

[18] A. B. H. A. N. K. Mrs. Jayashree Hajgude, "Skin Disease Detection Using Image Processing with Data Mining and Deep Learning," *International Research Journal of Engineering and Technology (IRJET),* vol. 06, no. 04 , pp. 4363-4366, 2019.

[19] C. P. J. W. A. J. A. J. S. C. M. G. B. J. M. L. T. A. T.-a. R. J. J. Jessica Velasco, "A Smartphone-Based Skin Disease Classification Using MobileNet CNN," *International Journal of Advanced Trends in Computer Science and Engineering,* vol. 8, pp. 2632-2637, 2019.

[20] Z. H. E. W. e. al, "Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images," *IEEE Access,* vol. 7, pp. 66505-66511, 2019.

[21] L. H. M. O. J. M. B. D. M. W. L. D. R. F. N. a. A. B. Kamulegeya, "Using artificial intelligence on dermatology conditions in Uganda: A case for diversity intraining data sets for machine learning," pp. 1-30, 2019.

[22] N. A. S. a. M. A. H. Hameed, "A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning," *Computer Science and Electronic Engineering (CEEC),* pp. 185-191, 2018.

[23] R. B. S. E. C. S. E. R. A. H. M. T. &. M. Hay, "Skin Diseases.," 2016. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK11733/. [Accessed 12 11 2021].

[24] D. S. &. K. C. &. D. B. &. E. E. Freeman, "Global Burden of Skin Disease: Inequities and Innovations," *EPIDEMIOLOGY (R DELLAVALLE, SECTION EDITOR),* vol. 6, no. 3, pp. 204-210, 7 aug 2017.

[25] Y. F. a. H. Z. Yuan Zhou, "Human Fungal Infection Image Classification Based on Convolutional Neural Network," in *In Chinese Conference on Image and Graphics Technologies Springer*, Singapore, 2019.

[26] S. a. T.Velmurugan, "Preprocessing by Contrast Enhancement," *International Journal of Pure and Applied Mathematics,* vol. 118, pp. 3681-3688, 2018.

[27] M. R. M. A. S. Hariharan, "Image Classification using Convolutional Neural Networks," *International Journal of Pure and Applied Mathematics,* vol. 119, no. 17, pp. 1307-1319, 2018.

[28] 2. A. S. 2. U. Z. a. A. S. Q. Asifullah Khan1, "A Survey of the Recent Architectures of Deep Convolutional Neural Networks," *Published in Artificial Intelligence Review,* 2018.

[29] A. Ghosh.et.al, "Fundamental Concepts of convolutional Neural Network," *In Recent Trends and Advances in Artificial Intelligence and Internet of Thing springer,* pp. 519-567, 2020.

[30] K. R. S. B. Ms.Siva S Sinthura, "Advanced Skin Diseases Diagnosis Leveraging Image Processing," in *Proceedings of the International Conference on Electronics and Sustainable Communication Systems*, 2020.

[31] J. S. Lee JG1, "Deep Learning in Medical Imaging: General Overview," *Korean J Radiol,* vol. 17, no. 4, pp. 570-584, 2017.

-

Appendix : Developed model summary

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_1 (Sequential)    (None, 224, 224, 3)       0
_________________________________________________________________
conv2d_62 (Conv2D)           (32, 222, 222, 64)        1792
_________________________________________________________________
max_pooling2d_62 (MaxPooling (32, 111, 111, 64)        0
_________________________________________________________________
conv2d_63 (Conv2D)           (32, 109, 109, 64)        36928
_________________________________________________________________
max_pooling2d_63 (MaxPooling (32, 54, 54, 64)          0
_________________________________________________________________
conv2d_64 (Conv2D)           (32, 52, 52, 64)          36928
_________________________________________________________________
max_pooling2d_64 (MaxPooling (32, 26, 26, 64)          0
_________________________________________________________________
conv2d_65 (Conv2D)           (32, 24, 24, 64)          36928
_________________________________________________________________
max_pooling2d_65 (MaxPooling (32, 12, 12, 64)          0
_________________________________________________________________
conv2d_66 (Conv2D)           (32, 10, 10, 64)          36928
_________________________________________________________________
max_pooling2d_66 (MaxPooling (32, 5, 5, 64)            0
_________________________________________________________________
conv2d_67 (Conv2D)           (32, 3, 3, 64)            36928
_________________________________________________________________
max_pooling2d_67 (MaxPooling (32, 1, 1, 64)            0
_________________________________________________________________
flatten_10 (Flatten)         (32, 64)                  0
_________________________________________________________________
dense_24 (Dense)             (32, 64)                  4160
_________________________________________________________________
dense_25 (Dense)             (32, 4)                   260
=================================================================
Total params: 190,852
Trainable params: 190,852
Non-trainable params: 0
_________________________________________________________________
```