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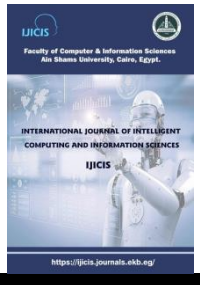

CLASSIFICATION OF DERMATOLOGIC MANIFESTATIONS OF CARDIOVASCULAR DISEASE USING EFFICIENTNETV2 CNN MODEL

Abraham E Evwiekpaefe*

Department of Computer Science,
Faculty Of Military Science And Interdisciplinary Studies,
Nigerian Defence Academy,
Kaduna, Nigeria.
aeevwiekpaefe@nda.edu.ng

Oghenegueke F Amrevuawho

Department of Computer Science,
Faculty Of Military Science And Interdisciplinary Studies,
Nigerian Defence Academy,
Kaduna, Nigeria.
ogheneguekeamrevuawho@nda.edu.ng

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Abstract: *The skin is one of the organs of the human body where various internal health problems including cardiovascular diseases tend to show some notable signs and symptoms. The dermatologist may be one of the first clinician to recognize that someone does have cardiovascular disease because warning signs can develop on the skin. The aim of this research is to use the efficientNetV2 model for the classification of dermatologic manifestations of cardiovascular disease based on transfer learning. The EfficientNetV2 model was modified and trained as a classifier for the selected images of dermatologic manifestations of cardiovascular disease. A total of 2665 images consisting of 430 for Cyanosis, 480 for Liverdo reticularis, 780 for Xanthoma, 430 for Stasis dermatitis, 540 for fingernails clubbing, and other 1100 images of both normal skin and general objects were used in the training of the model. Data augmentation was also used to increase the amount of training images and finetuning was employed on the model. Google Collaboratory was used as the platform to train the model. The trained model with fine-tuning was able to obtain a considerable accuracy of 96.04%. The EfficientNetV2 convolutional neural network (CNN) model performed exceptionally well in the image classification.*

Keywords: *Deep Neural Network, Images, Model, Skin Disease, Transfer Learning*

1. Introduction

The largest and one of the most vital organs in the human body is the skin. The skin's surface area ranges from 1.2m2 to 2.2m2, weighing between 4kg and 5kg. It carries out a variety of tasks but its primary functions include protecting the body, maintaining body temperature, and sensing, among others. The three layers that make up the skin are subcutaneous, dermis, and epidermis layers [1].

*__Corresponding Author__: Abraham E Evwiekpaefe

Computer Science Department, Faculty Of Military Science And Interdisciplinary Studies, Nigerian Defence Academy, Kaduna, Nigeria

Email address: aeevwiekpaefe@nda.edu.ng

Dermatological disorders also referred to as skin diseases or disorders are pathologic ailments that affect the body's surface, which includes the skin, hair, nails, and related glands. They can affect all layers of the skin and have a variety of causes, including infections, tumors, inflammation etc. They are the most common diseases (disorders) in the world as people of all ages are affected by it. This is as a result of changing lifestyles and the environment [2,3]. According to the latest WHO data published in 2020 Skin Disease Deaths in Nigeria reached 1,468 or 0.10% of total deaths [4].

A variety of illnesses that affect the cardiovascular system are referred to as cardiovascular diseases (CVDs). The terms heart disease and CVDs are sometimes used interchangeably. CVDs are characterized by restricted or obstructed blood arteries, which can result in a heart attack, a stroke, or chest pain (angina) [5].

The skin is one of the organs of the human body where various internal health problems tend to show some notable signs and symptoms and this constitutes these skin diseases (disorders). There are a variety of etiologies for the cutaneous signs of CVDs. An underlying disease can cause them directly, such as cyanosis caused by a congenital heart defect or edema caused by congestive heart failure [6]. Dermatologist may be the first clinician to recognize that you do have cardiovascular disease because warning signs can develop on your skin [7]. These cutaneous symptoms are frequently utilized to aid in the diagnosis of underlying CVDs [8]. In certain cases, dermatologic signs are part of a larger systemic or vascular illness that also includes cardiovascular system problems [9]. Numerous dermatological disorders have been connected to CVDs, and recognizing signs and symptoms that could be used to diagnose cardiovascular disease is one of the most important areas in clinical data analysis [10].

Diagnosing skin disorders traditionally requires a great deal of experience [1]. Various illness diagnosing classification algorithms have been created in order to predict disease with high accuracy [11]. As a result, computer-based disease diagnosis comes into play because it may produce result in a shorter amount of time and sometimes with greater accuracy than human analysis utilizing laboratory techniques. The purpose of this paper is to use the efficientNetV2 to classify dermatologic manifestations of cardiovascular disease based on transfer learning. This model should be of great assistance to both dermatologist and cardiologist in the diagnosis and classification of dermatological signs related to CVDs.

2. Review of related literature

Cardiovascular diseases are frequently linked to a wide range of dermatological symptoms. These cutaneous symptoms are frequently utilized to aid in the identification of the underlying cardiovascular disease. This section focuses on literatures on dermatologic signs of cardiovascular disease.

Chan [12] established that the skin has been known over the years as a fast and accurate specimen for complementing diagnosis of certain cardiovascular disease but didn’t propose any reliable technique that can be employed using the skin for diagnosing of cardiovascular disease for their findings to be adopted.

McDonnell [10] provided a detailed discussion of different skin disorders that are connected with cardiac disease in a study on cardiac disease and the skin. They established that Cyanosis, flushing, erythema, and digital clubbing are usual indicators identified in cardiac patients, according to the research.

Dwivedi Shridhar [13] presented an overview on the topic of cutaneous markers related with atherosclerosis, as well as the markers' strengths and flaws in detecting early coronary atherosclerosis.

Clinical markers like xanthelasma, xanthoma, arcus juvenilis, acanthosis nigricans, skin tags, ear lobe crease, nicotine stains, premature graying in smokers, hyperpigmented hands in betel quid sellers, central obesity, and signs of peripheral vascular disease were found to be signs for identifying asymptomatic CAD in high-risk individuals.

O'Neill et al. [7] described primary cutaneous disorders with concomitant cardiac pathology, which include congenital syndromes, inherited cutaneous disorders associated with later cardiovascular disease, and syndromes associated with early cardiovascular pathology in a study on Cardiac manifestations of cutaneous disorders. Their findings established that there are a variety of cutaneous symptoms for both early and advanced cardiovascular disease.

Toh et al. [14] investigated the links between diet, plasma, and skin carotenoids and CVD risk markers, as well as the role of plasma carotenoids as a mediator in the association between skin carotenoids status (SCS) and CVD risk. Multiple linear regression and binary logistic regression models were used to evaluate the relationships between carotenoids status, traditional CVD risk factors and composite CVD risk indicators. Carotenoids' bioavailability may be important for cardiovascular protection. SCS, which is triggered by plasma carotenoids, has the potential to be a noninvasive surrogate test for evaluating CVD risk in middle-aged and older people. The results of this study back up the use of skin carotenoids status evaluated by Resonance Raman spectroscopy as a developing alternative biomarker for plasma carotenoids that can be used to determine the risk of cardiovascular disease in middle-aged and older people.

To predict new cardiovascular disease and mortality in people with type 2 diabetes, Boersma et al. [15] found that assessing skin autofluorescence (SAF) can assist predict the onset of cardiovascular disease (CVD) and mortality in those with type 2 diabetes (T2D). SAF was found to have a stronger connection than cholesterol or blood pressure to future CVD events and mortality. The SAF was measured using an Advanced Glycation End Products (AGE) reader, and the reading was subsequently evaluated using several statistical methods.

In a paper on automated skin disease identification using deep learning algorithm, Sourav et al. [11] suggested a way to employ several computer vision-based approaches to automatically predict skin disorders. The system accurately predicts skin disorders based on maximum votes from three publicly accessible image recognition architectures which are InceptionV3, InceptionResnetV2, and MobileNet with modifications for skin disease application. The feature extraction phase, the training phase, and the testing/validation phase were the three phases of the system. To train itself with the numerous skin photos, the system used deep learning model which was able to identify as many as 20 diseases.

In another study titled dermatological classification using deep learning of skin image and patient background knowledge Kittipat et al. [16] proposed an automatic method for skin disease classification using deep learning model of convolution neural network (CNN). In order to increase the classification performance of CNN, they employ both image data and background knowledge of the patient in the modeling process. The experimental results performed on a public dataset showed that the CNN model can classify skin diseases with 79.29% accuracy, while the proposed model which incorporated background knowledge of patient in the modeling phase improved the accuracy up to 80.39%.

Dai et al. [17] proposed an on-device inference App and demonstrated a proof of concept using a dataset of skin cancer images. Skin cancer dataset was used to train the Convolutional Neural Network model.

After then, the model is deployed on a mobile device, where the inference process occurs. When a new test image is shown, all computations are performed locally, and the test data is retained. An accuracy of 75.2% was achieved and the method lowers latency, conserves bandwidth, and enhances privacy.

Kumar et al. [18] proposed a method for determining whether or not a set of skin photos contains Melanoma. They gathered labelled data from pre-processed photos, flattening them and extracting the pixel intensities into an array, adding all such arrays to a database, training the SVM with labelled data using an appropriate kernel, and correctly classifying the samples using the trained data. The results reveal that the categorization accuracy achieved is around 90%.

From the literatures, the following observations were noted: Firstly, it has been identified that cardiovascular disease has obvious dermatologic manifestations. Secondly, that various machine learning and deep learning techniques has been employed to classify some skin issues. Thirdly, a major drawback is observed in some previous studies, that the overall accuracy from the methods employed is still low and could be improved. Finally, no work was done to classify the dermatologic manifestations of cardiovascular disease using deep learning approach.

3. The Proposed Method

The architecture of the proposed method consists of three phases: data description, data preprocessing to suit the efficientNetV2 model, and classification to determine one of the eight classes the image belong to, as shown in Figure 1. The details of each phase will be discussed in the following subsections.

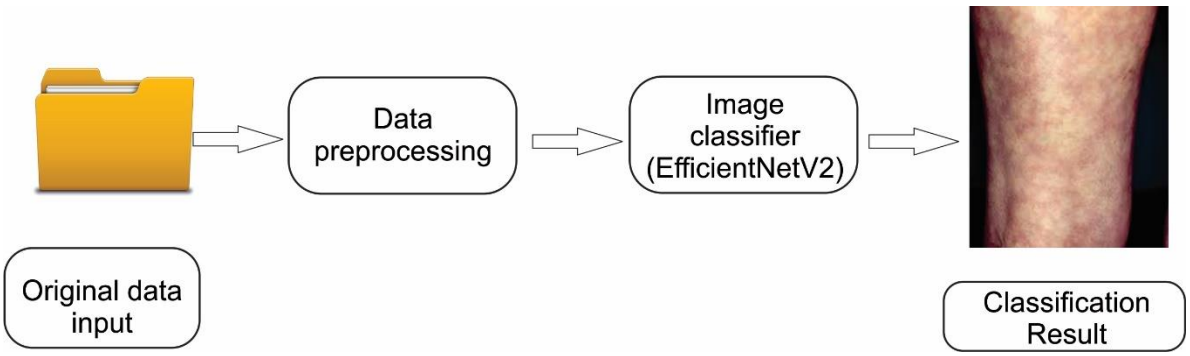

Figure. 1: The proposed method architecture

3.1. Data description

The total images of the selected classes of dermatologic manifestation of cardiovascular disease which are in the dataset gathered are 2665 images consisting of 430 for Cyanosis, 480 for Liverdo reticularis, 780 for Xanthoma, 430 for Stasis dermatitis, 540 for fingernails clubbing, and other 1100 images of both normal skin and general objects images classified as not recognized. The images were gathered from DermNetNZ [19], Kaggle [20], Dermnet [21] (which are among the largest dermatology source online built for the purpose of providing online medical education) and locally. Below is the brief description of the dataset.

3.1.1 Cyanosis

A bluish-purple colouring to the skin is referred to as cyanosis. It is most visible in areas with thin skin, such as the lips, mouth, earlobes, and fingernails. Cyanosis is a condition in which the oxygen in the bloodstream is reduced. It is a sign of a cardiac condition [22]. Figure 2 shows the photo of cyanosis.

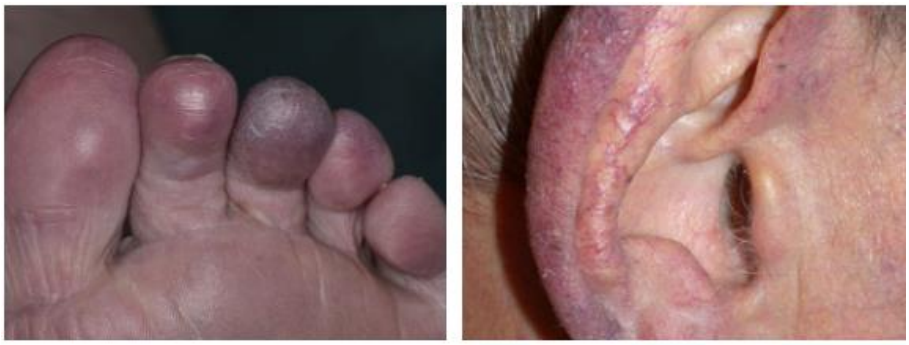

Figure. 2: Cyanosis [23]

3.1.2 Liverdo Reticularis

The skin symptom liverdo reticularis (LR) is a net-like pattern of reddish-blue skin discolouration. Legs are frequently affected. Inflamed blood vessels are identified as the cause of the illness. Figure 3 shows the photo of Liverdo Recticularis. It may worsen if the weather is cold. As blood circulates through the body, arteries transport blood away from the heart and veins transport blood back to the heart. LR skin discolouration is caused by veins in the skin that are loaded with more blood than usual [24].

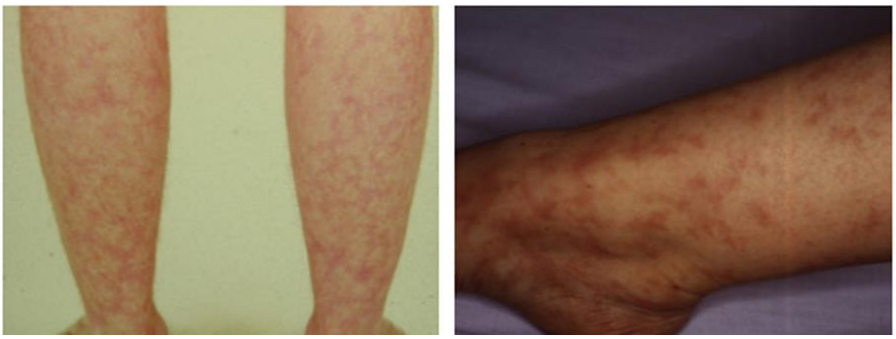

Figure. 3: Liverdo Reticularis [25]

3.1.3 Xanthoma (Xanthelasma)

Xanthomas are fatty lumps beneath the surface of the skin. They might be as small as a pinhead or as large as three inches. Xanthomas can appear anywhere on the body. The most usually affected areas are the elbows, buttocks, tendons, hands, knees, feet, and joints. Fatty tumors on the eyelids are known as xanthelasma. Figure 4 shows the photo of Xanthoma (Xanthelasma). Excess blood fat levels are connected to xanthelasma [26].

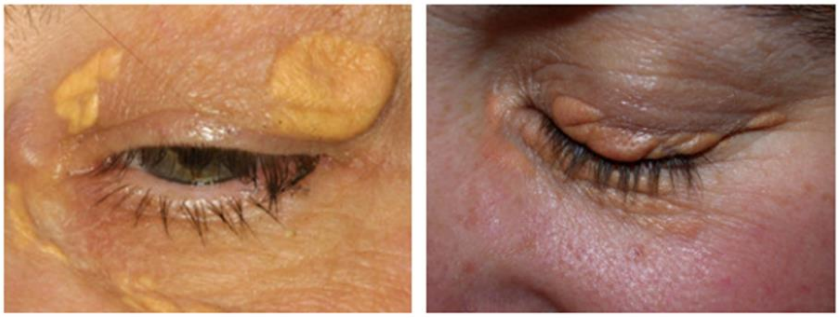

Figure. 4: Xanthoma (Xanthelasma) [27]

3.1.4 Fingernails clubbing

Fingernails clubbing, also known as digital clubbing or clubbing, is a malformation of the finger or toe nails linked to a variety of illnesses, the most common of which are heart and lung ailments. Clubbing is as a result of chronic low blood-oxygen levels [28]. Figure 5 shows the photo of Fingernails clubbing.

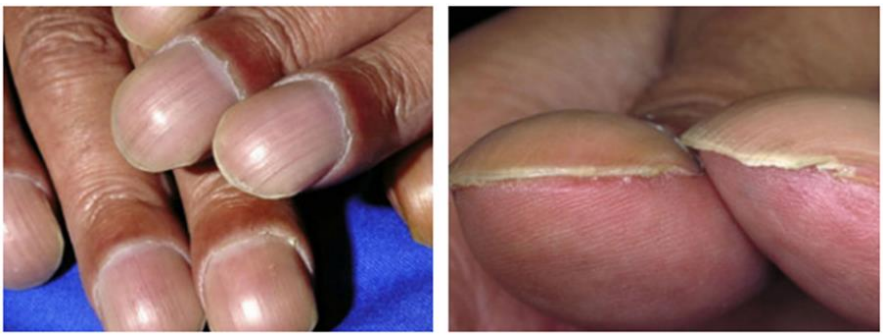

Figure. 5: Fingernails clubbing [28]

3.1.5 Stasis dermatitis

When there is venous insufficiency, or impaired circulation in the lower legs, stasis dermatitis develops. It occurs when the valves in the leg veins that enable the return of blood to the heart fail and leak fluid. This causes the accumulation of fluids and blood cells in the lower legs. Stasis dermatitis might indicate the presence of a major underlying medical issue, such as heart or renal illness [29]. Figure 6 shows the photo of Stasis dermatitis.

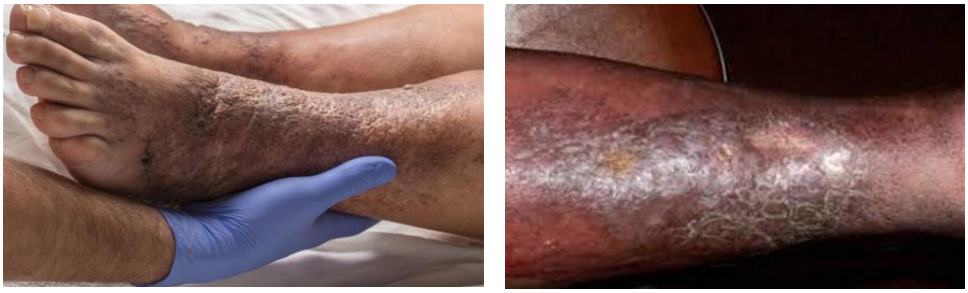

Figure. 6: Stasis dermatitis [29]

3.2. Data Preprocessing

Each image from the dataset collected was preprocessed according to requirement of the pre-trained deep neural network architecture used. The standardization of the EfficientNetV2 architecture requires the

input images to be of size 224 × 224 [30], but the dataset consisted images of varying sizes. Hence, all the images were resized to fulfill the requirement by setting the input image size to 224 × 224. As an additional preprocessing step, RGB values in each image was also normalized to be in range [1.,225] using a normalization layer as part of the model itself. The dataset was divided into training, validation and testing split using 60%, 20%, 20%. Data augmentation was employed during training to compensate for the amount of training data by creating modified versions of images in the dataset. Random rotation (40), and random flip (horizontal) were the parameters that was used in the image augmentation as they don't make any changes to the image texture and colour.

3.3. Transfer Learning and fine tuning

After the data pre-processing, transfer learning was done since the pretrained model (EfficientNetV2) which was trained previously on a very large ImageNet dataset was used to further train the dataset for this paper. The EfficientNetV2 model was loaded without the top layers and with the weights from the desired datasets. This was used as feature extractor. A new classifier that would handle multi-class classification of the dataset of dermatological signs of cardiovascular disorders was used as the classifier for this work. Finally, the base model was unfrozen and some layers of the model was trained at a low learning rate this is referred to as finetuning.

3.4. Setup

The dataset used for the training of the new top layer of the efficientNetV2 model comprise of five different classes of the selected skin disorders, a normal skin and general object classes and was organized into the train, validation and testing split with 2259 (6777 with augmentation) 753 and 753 images respectively as shown in table 1. The architecture of efficientNetV2 was loaded using the open-source Keras deep learning framework with TensorFlow as the backend, and the top layer was changed to a new classifier to produce a new model from the base model. In order to prevent overfitting, data augmentation techniques were used to generate numerous variations of the training dataset that was already accessible. The multiclass cross entropy loss function and Adam optimizer were both employed for the training. The Google Colaboratory, which has a 12GB RAM, 16GB NVIDIA Tesla T4 GPU, and an Intel(R) Xeon(R) CPU @ 2.20GHz processor was used for all processing. The weights of the convolutional base were initialized with the ImageNet pretrained weights while building the new classifier on top of the efficientNetV2 model. To get the feature vector, the output tensor of the base model was passed through a global average pooling layer, a dropout layer for regularization with a rate of 0.5, and then a fully connected classifier layer. The mechanism of transfer learning was used.

Table. 1: Total number of training, validation and test data used per class

s/n	Classes	Training (with augmentation)	Validation	Testing
1.	Cyanosis	783	87	87
2.	Fingernails clubbing	972	108	108
3.	Liverdo recticularis	864	96	96
4.	Normal skin	900	100	100
5.	Stasis dermatitis	774	86	86
6.	Xanthoma	1404	156	156
7.	Not recognized	1080	120	120
	Total	6777	753	753

3.5. Performance Metrics

The confusion matrix is a much better approach to evaluate a classifier's performance [31]. The accuracy, recall, precision, and F1 scores was used to validate the model's performance. Below are the equations of all the performance measures that was used in this paper. While classifying dermatologic signs of cardiovascular disease using skin images, the following definitions and equations are used. True Positive (TP) indicates the number of images identified as dermatologic manifestations of cardiovascular disease, True Negative (TN) indicates the number of images identified as not it, False Positive (FP) indicates the number of images incorrectly identified as dermatologic manifestations of cardiovascular disease images, and False Negative (FN) indicates the number of dermatologic manifestations of cardiovascular disease images incorrectly identified as not it.

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \qquad \text{Eq. (1)}$$

$$\boldsymbol{Precision} = \frac{TP}{TP+FP} \qquad \text{Eq. (2)}$$

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \qquad \text{Eq. (3)}$$

$$\boldsymbol{F1} = 2.\frac{Recall*Precision}{Recall+Presicion} \qquad \text{Eq. (4)}$$

4. Results and Discussion

The section below covers the results from the proposed method and the discussion.

4.1 Training image augmentation

Before training the model classifier layer with the images, the image was augmented and the augmentation result is as shown in figure 7. Which shows the horizontal flip and rotation (40) augmentation parameters.

4.2. Model result in terms of accuracy and loss

The EfficientNetV2 model was able to achieve a training and validation accuracies of 97.98% and 96.04% respectively with 40 epochs and fine tuning. The accuracy and loss curves for the training and validation sets produced after training the models are shown in Figure 8 and 9. The classifier's learning rate was held constant at 1e-5 during training. Because dropout which have an impact on training accuracy is activated by the network when analyzing the validation set, the validation accuracy is lower than the training accuracy.

4.3. Actual and predicted results of the efficinetNetV2 model

After completely training the model, different images from the validation dataset were used randomly to check the model’s classification result. The result is shown in figure 10. The model was able to classify the real labels and predicted labels of most of the images correctly only a few images were classified wrongly.

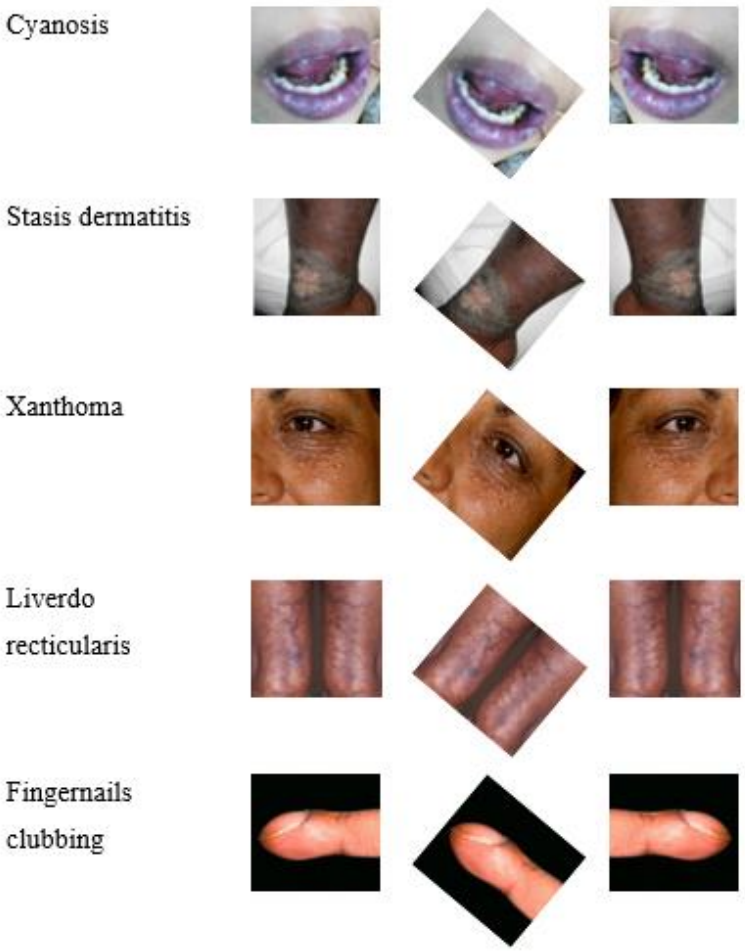

Figure. 7: Image augmentation results

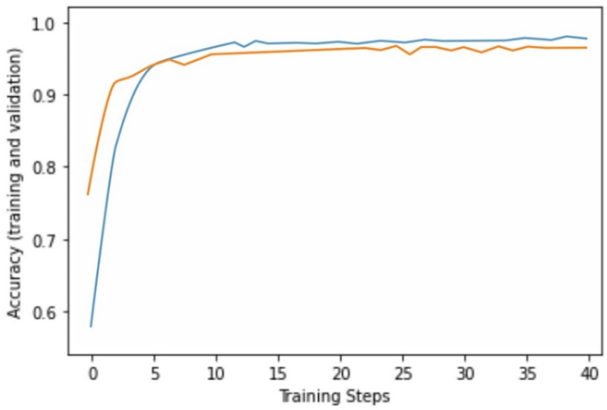

Figure. 8: Training and validation Accuracy curve

4.4. Performance analysis of the model using the test dataset

The efficientNetV2 model was trained using an imbalanced dataset. Figure 11 show the confusion matrix of the model which shows how the model classified and misclassified the various classes of the dataset

while compiling the model using the test dataset which comprise 753 images. From the confusion matrix, the accuracy of the test dataset was 92.96% other performance metrics of the model was measured such as the precision, recall, F1-score and support values are as shown in table 2.

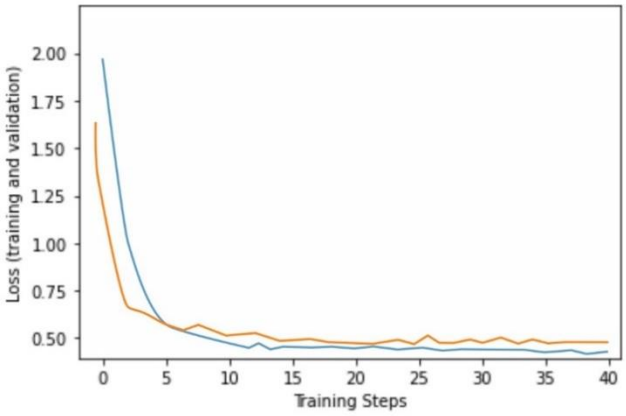

Figure. 9: Training and validation loss curve

Figure. 10: Result from model classification accuracy using test data

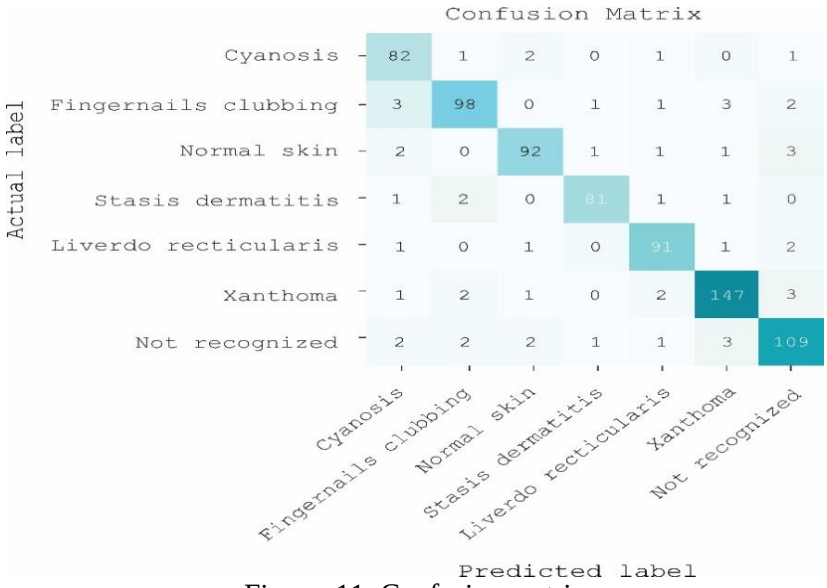

Figure. 11: Confusion matrix

Table. 2: Performance metrics of the model

	Precision	Recall	F1-score	Support
Cyanosis	0.94	0.89	0.91	87
Fingernails clubbing	0.91	0.93	0.92	108
Normal skin	0.92	0.94	0.93	100
Stasis dermatitis	0.94	0.96	0.95	86
Liverdo recticularis	0.95	0.93	0.94	96
Xanthoma	0.94	0.94	0.94	156
Not recognized	0.91	0.91	0.90	120
Accuracy			0.93	753
Macro avg	0.93	0.93	0.93	753

4.5. Discussion

In this paper, the model which was pretrained on a vast quantity of image data, was employed to extracts the colour and texture features of the skin disorder images at the convolutional layer, and the images was classified at the final layer. The trained model achieved an accuracy of 96.04% with fine tuning. In comparison to previous study, the proposed model performed satisfactorily as show in table 3.

Table. 3: Comparison between the Proposed Model and Related Studies

s/n	Study	Dataset	Classification	Accuracy
1.	Kittipat et al. 2019	Skin images, Patients background knowledge	CNN	80.39%
2.	Dai et al. 2019	Skin cancer images	CNN	75.2%
3.	Kumar et al. 2019	Skin images	SVM	90%
4.	**Proposed model**	Skin images	EfficientNetV2	96.04%

5. Conclusion

Transfer learning is a useful strategy for dealing with the lack of data that plagues models trained to classify skin condition images. In this paper, it was demonstrated that pretrained convolutional neural networks (CNN) on a large image dataset significantly enhances target task performance, effectively lowering the number of expensive iterations necessary to achieve the same performance level as CNNs that are not pretrained. The EfficientNetV2 model worked well for categorizing dermatologic signs of cardiovascular disease with little computing work. The results are encouraging, with the model achieving an accuracy of 96.04%. The proposed model is intended to support rather than replace current dermatologic disorder-diagnosis procedures. For future work, since this paper used the EfficientNetV2 architecture which achieved an accuracy of 96.04% this can be improved in the future work. The model was to classify the dermatologic manifestation of cardiovascular disease but it can be extended to include other dermatologic disorders. An imbalance and small sized dataset were used which may have certain impact on the result obtained in the future, the dataset size can be increased and balanced to check for improvement in the accuracy.

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