2024 International Conference on Recent Innovation in Smart and Sustainable Technology (ICRISST) | 979-8-3503-0914-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICRISST59181.2024.10921758

Image-Based Skin Diseases Detection and Classification Using Convolutional Neural Network

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***Abstract*—The outermost layer of the human body is the skin. Skin diseases can be caused by viruses, bacteria, allergies, fungal infections, and more. It causes serious physical, social, and psychological effects, even though some people do not pay attention to it. Several research studies have been conducted regarding skin disease classification. However, there are a few issues that those research studies fail to address in a way that yields easy and most accurate results. This research study is to design an easy and accurate system using a convolutional neural network to detect and classify skin diseases. The performance of the proposed system was then assessed using the accuracy, precision, recall, and F-measure metrics. The system has been conducted within three data splitting ratios which are 70/30%, 80/20%, and 90/10%. The accuracy of the result interpretation is 93.76%, and the precision, recall, and F-score all have a value of 93%. This indicates that the system has performed very well in detecting and classifying skin diseases, particularly with the 90/10% data splitting ratio. Overall, the results suggest that the system is accurate and effective in its classification performance.**

Keywords— Skin diseases, Convolutional Neural Network (CNN), HAM10000, detection, classification

I. INTRODUCTION

The skin is the largest and most delicate part of the human body, protecting important internal parts and organs from the external environment and preventing contact with bacteria and viruses [1]. And it functions to retain fluid and avoid dehydration, help human experience sensations like pain or temperature, keep out bacteria, viruses, and other infection-causing agents, maintain a constant body temperature, and produce vitamin D in response to sun exposure [2].

More people than any other health issue suffer from skin issues. Bacteria, viruses, allergies, fungal infections and more are the cause of skin diseases. It can change the texture or tone of the skin. Skin conditions are often infectious, chronic, and sporadically carcinogenic. So, early diagnosis is essential to stop skin diseases from developing and spreading. Diagnosis and treatment of skin diseases can be time-consuming and costly[3]. In general, most people are unaware of the type of skin diseases. Part of it becomes symptomatic after a few months and causes the disease to progress and spread further. This is due to the lack of medical knowledge for public. In addition, it can be difficult for a dermatologist to diagnose the problem of the skin, and expensive clinical tests may be required to properly determine the type of the condition of the skin. Advances in laser and photonics-based medical techniques have made it possible to diagnose skin diseases much faster and more accurately [4][5].

Skin diseases cause serious physical, social, and psychological effects, even though some people ignore it. Skin diseases, which can be cured with low cost and easy treatment before the skin is more affected, are causing a lot of damage to the skin due to negligence. Although various studies have been done; a better skin diseases classifier system is needed to help society. The motivation of the research is to replace the existing methods by CNN based deep learning methods with more accurate, and simple skin diseases classifier system. So more research studies are needed to a person with a skin problem can easily identify the type of skin disease [6-7]..

II. LITERATURE REVIEW

Alenezi et.al.have proposed a method of skin disease detection using image processing and machine learning. The proposed work's main goal was to detect and classify three skin diseases and one healthy skin [8]. N. Leelavathy S have proposed approach, hybrid strategy that combines approaches from computer vision and machine learning. A classifier model predicts the illness and image processing techniques are used to extract the feature values [9]. A. V. P. S. O. K has proposed in use deep learning methods to recognize images of skin diseases. In this paper, dermoscopy images are used to detect and classify melanoma using an appropriate classifier. This project is built with MATLAB. Using Hybrid SVM classification, we achieved 95% accuracy [10]. Latha A. et al. have proposed a system making use of image processing methods. As a result, using CNN, skin disorders can be detected and classified. A preliminary training result in approximate output accuracy of 82% is obtained. This may be further boosted by expanding the deep learning model's training data set [11]. N. Vikranth Kumar and colleagues proposed a method for identifying melanoma in a given sample. They showed the effective classification of samples like melanoma and non-melanoma using SVM. According to the findings, the achieved categorization accuracy is around 90% [12]. M. Vidya and M. V. Karki used KNN, SVM, and Naive Bayes Classifiers to create a skin disease detection model. They were able to obtain an area under the curve of 0.94 and a classification accuracy of 97.8% using SVM classifiers [13].Srujan S. Ahave proposed Convolutional Neural Network system to detect seven types of skin cancers. The proposed system exhibited a 74%-75% accuracy in predicting the aforementioned diseases [14]. S. Hosseinzadeh K. et al. used a variety of deep learning architectures that were trained on an augmented HAM10000 dataset. They discovered that VGGNet 19 and VGGNet 16 both had higher accuracy ratings than AlexNet model, which had the lowest accuracy rating at 84%. ResNet50 had the highest accuracy in this study, 92%, while Xception had the lowest accuracy, 90% [15].

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In related work, some papers are used only a limited number of datasets and some are with low accuracy and complex system. In this work, by using large dataset, simple methods, and seven types of skin diseases to get a more accurate results.

III. Proposed System

The proposed system imports the skin disease images from HAM10000 into the system. By addressing the crucial issues, the suggested architecture fills in a research gap. The first step entails importing a preexisting dataset with images for analysis and their associated metadata in CSV format. Fig .1 shows the proposed architecture.

IMPORTANT DATA

The initial step in categorizing skin diseases involves importing datasets. The HAM10000 dataset is comprised of 10,015 dermatoscopic images with a resolution of 450 ×600. This dataset includes seven different skin diseases and a wide range of crucial diagnostic categories for pigmented lesions. Numerous images from this varied dataset illustrate seven different types of skin diseases.

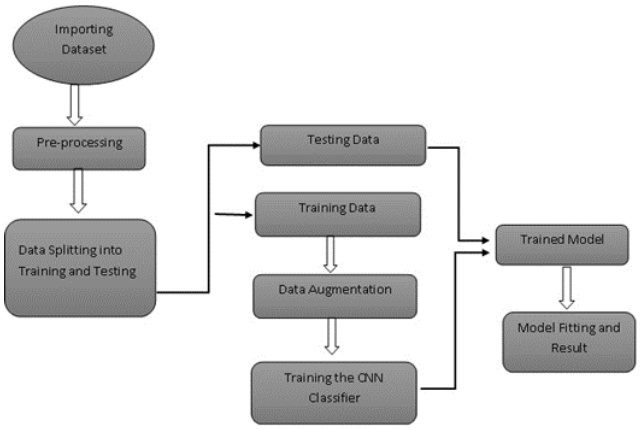

Fig 1. Proposed Architecture

DATA ANALYZING

Since analyzing the dataset, this study came up with Table I, which shows how many types of skin diseases the researcher has identified. In this study, the datasets are categorized as seven different types of lesions, including melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratosis, vascular lesions, and dermatofibromas.

Count value shows the number of images for all seven skin diseases from Table 1. Of the 10015 images, Melanocytic nevi accounted for the majority. The second one with the most images is melanoma. The third number of sizes is benign keratosis-like lesions.

TABLE I. SKIN DISEASES NAME AND COUNT VALUES

Skin diseases name	Count value
Melanocytic nevi	6705
Melanoma	1113
Benign keratosis- like lesions	1099
Basal cell carcinoma	514
Actinic keratosis	327
Vascular lesions	142
Dermatofibroma	115

IMAGE RESIZING

The following import data are resized by the system 36 × 36. The HAM10000 dataset is used in this study. However, feeding these images into the proposed CNN system's convolutional neural network classifier results in high memory space utilization and processing power requirements.

LABELING AND PROPER ABBREVIATION

The needed datasets for this study have seven class labels. They are all shortened because each skin condition needs its abbreviation. These also came in the form of strings. With these string values were machine-readable, they were converted to numerical values. Additionally, a corresponding numerical value was created from the class labels. The corresponding values of each class label are shown in Table II.

TABLE II. LABELING AND PROPER ABBREVIATION

Skin diseases name	Abbreviation	Numerical value
Melanocytic nevi	Nv	0
Melanoma	Mel	1
Benign keratosis-like lesions	bkl	2
Basal cell carcinoma	bcc	3
Actinic keratosis	akiec	4
Vascular lesions	vasc	5
Dermatofibroma	df	6

TRAIN-TEST DATA SPLITING

The entire dataset was then divided into a training dataset and a test dataset. It is divided into three scenarios which are 70:30, 80:20, and 90:10 train-to-test ratio.

DATA AUGMENTATION

Because it reduces model overfitting, data augmentation is used in this study to increase the size of the training and testing datasets by changing the adaptations of the image in the dataset. In this study, the collected datasets were enhanced using the data augmentation technique because large datasets reduce the problem of overfitting and improve model performance.

PROPOSED CONVOLUTION NEURAL NETWORK

Three layers--convolutional layer, a max-pooling layer, a ReLu activation function, and fully connected layers--of the convolutional neural network system were proposed as described in Table III.

Convolutional layer necessitates a few components, including input data, a filter, and a feature map. Assume the input is a color image composed of a 3D matrix of pixels. This means that the input will have three dimensions: height, width, and depth, which correspond to the RGB color space in an image. And also a feature detector, also known as a kernel or a filter, which will move across the image's receptive field, checking for the presence of the feature. This process is known as convolution [16].

The same padding ensures that the output layer and the input layer are the same size. After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model. Max pooling; the filter moves through the input, it chooses the pixel with the highest value to send to the output array [17].

TABLE III.THE PROPOSED CONVOLUTIONAL NEURAL NETWORK MODEL PARAMETERS

Layer Type	Filter size	Number of filters	Stride	Padding
Convolutional layer	3x3	16	1	Same
Activation function	Relu			
Convolutional layer	3x3	32		
Activation function	relu			
Max pooling	2x2			
Convolutional layer	3x3	32	1	Same
Activation function	Relu			
Convolutional layer	3x3	64	1	Same
Activation function	Relu			
Max pooling	2x2			Same
Convolutional layer	3x3	64	1	Same
Activation function	Relu			
Convolutional layer	3x3	128		
Activation function	Relu			
Max pooling	2x2			same
Flatten	It has 512 neurons			
Dense 1	It has 128 neurons with a Relu activation function			
Dense 2	It has 64 neurons with a Relu activation			
Dense 3	It has 7 neurons with a softmax activation			

The final convolution or pooling layer's output feature maps are typically flattened, that is, transformed into a one-dimensional (1D) array of numbers (or vector), and connected to one or more fully connected layers, also known as dense layers, in which every input is connected to every output by a learnable weight.

TABLE IV . IMPLEMENTED PARAMETERS IN FULLY CONNECTED LAYERS FOR THE PROPOSED CONVOLUTIONAL NEURAL NETWORK MODEL

Parameters	Values
Number of epochs	50
Batch size	128
Optimizer	ADAM
Learning rate	The default learning rate of the ADAM optimizer
Network type	Feed-forward
Algorithm	Backpropagation
Loss function	Categorical cross-entropy

In Table IV, here, 128 images are used at a time because as batch sizes grow, more memory space is required. As a result, it requires a lot of memory and processing time. Additionally, the categorical cross-entropy loss is implemented as a loss function to assess the training set through forward propagation, and the Adam optimizer is chosen to update the weights. Modified learnable parameters like weights, the number of hidden neurons, and bias are used to train a feed-forward neural network or a multilayer perceptron neural network [18].

CLASSIFICATION

Based on the characteristics of the image, the classifier differentiates the images of skin diseases into one of seven types of diseases. After learning and extracting the distinguishing characteristics, it is carried out. Seven classes are created using the SoftMax classifier based on their origin.

PERFORMANCE EVALUATION

The next step is to assess the models efficacy after they have been built as classifier models. Accuracy, precision, recall, and F-measure rate are used to assess the models' performance.

$$\text{Recall} = \frac{t_p}{t_p+f_n} \quad (1)$$

$$\text{Precision} = \frac{t_p}{t_p+f_p} \quad (2)$$

$$F = 2 \times \frac{t_p}{t_p+f_p+f_n} \quad (3)$$

$$\text{Accuracy} = \frac{t_p+t_n}{t_p+t_n+f_p+f_n} \quad (4)$$

Pseudo code for image-based skin diseases detection and classification

Step 1: Import HAM10000 dataset

Step 2: Analyze data

Minimize the size of each data from 450×600 into 36×36

Abbreviate “Melanoytic nevi” into “Nv” and give numerical value “0”

Abbreviate “Melanoma” into “Mel” and give numerical value “1”

Abbreviate “Benign keratosis-like lesions” into “bkl” and give a numerical value “2”

Abbreviate “Basal cell carcinoma” into “bcc” and give a numerical value “3”

Abbreviate “Actinic keratosis” into “akiec” and give numerical value “4”

Abbreviate “Vascular lesions” into “vasc” and give a numerical value “5”

Abbreviate “Dermatofibroma” into “df” and give numerical value “6”

Step 3: Split the whole data into two groups with 70:30 ratio

Augment data

Step 4: Apply a convolutional neural network to:

Number of epoches is 50

Batch size is 128

Optimizer of ADAM

Learning rate of 0.001

Step 5: Classify the data using SoftMax classifier based on their origin

Step 6: Evaluate the performance of the classifier model using accuracy, precision, recall, and F-measure rate

IV. Results and Discussion

When using deep learning techniques, all hyper-parameters and convolutional parameters, including the number of layers, neurons, activation function, and fully connected layers with optimizers and learning rate were chosen optimally. The proposed convolutional network classifier model fed augmented images that were 36×36 in height, width, and three channels deep during the experiment. In addition, the proposed convolutional neural network system experiment has been tested by dividing the entire dataset into training and testing splits of 70% and 30%, 80% and 20%, 90%, and 10%, respectively [19] [20].

Scenario One: 70:30% Percentage Split Test Option

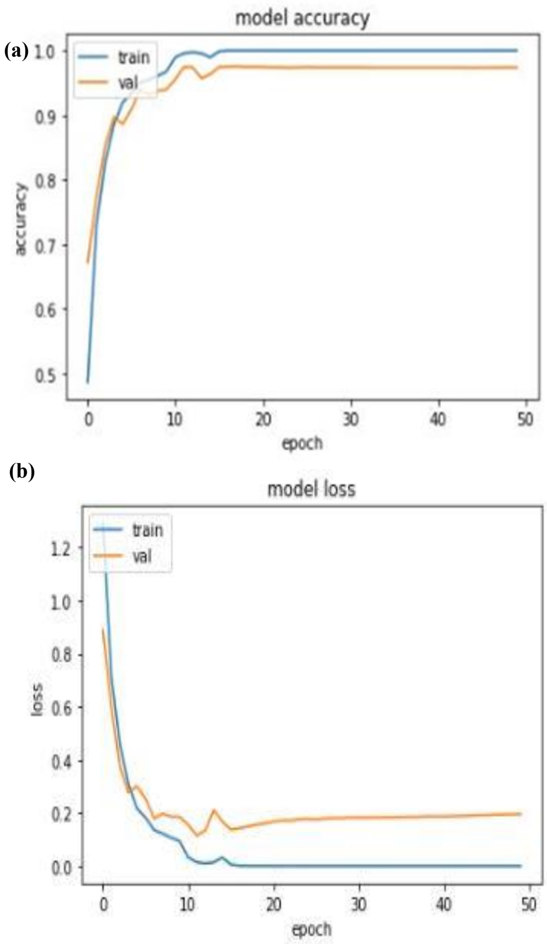

Fig. 2(a)-(b) The accuracy and loss of model 70:30 % split test

As shown in Fig. 2(a-b), the total dataset was split into 32,853 (70%) for training and 14,081 (30%) for testing. The result is 92.54 % of accuracy.

Scenario Two: 80:20% Percentage Split test option

As shown Fig. 3(a-b), by splitting the total image datasets into 80% for training and 20% for testing, the proposed convolutional neural network classifier system has been developed and evaluated in this scenario. The result is 93.08

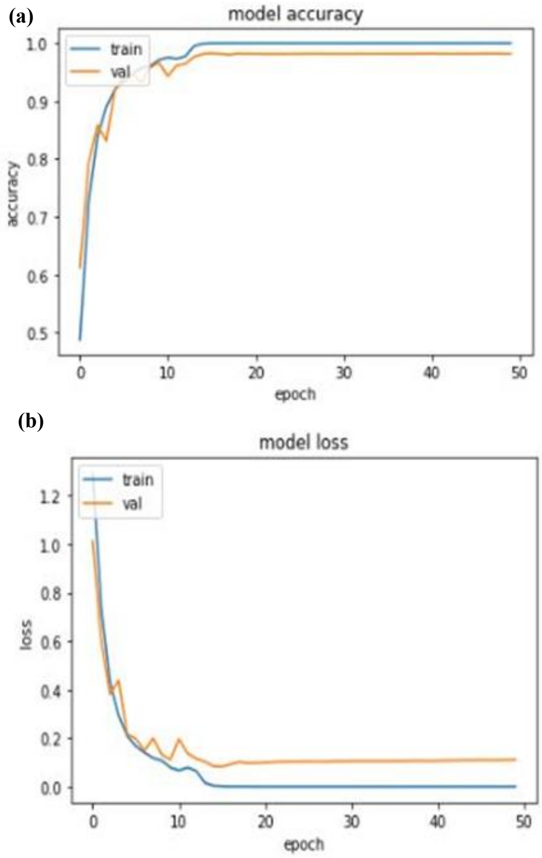

Fig. 3 (a) - (b) The accuracy and loss of model 80:20 % split test

% of accuracy.

Scenario Three: 90:10% Percentage Split Test Option

In this option, as seen Fig. 4(a-b), the image dataset was split into two sets, with 90% of the dataset used for training and 10% used for testing the classifier model. As a result, 93.76 % of the accuracy is obtained. To sum up, the results of experiments for all scenarios are presented below in Table 5 as a weighted average. In the scenario 2 and 3 the false positive rate is less compare to the scenario 1.Similarly the accuracy rate of scenario 3 is outperformed the remaining scenarios.

Table 5. Experimental Result Analysis summary of the Proposed CNN Classifier

Scenarios Test option	Test images	Accuracy	Precision	Recall	F-score	True positive rate	False positive rate
70%:30%	3004	92.541 %	92%	92%	92 %	92%	8%
80%:20%	2003	93.087 %	93%	93%	93 %	93%	7%
90%:10%	1001	93.763 %	93%	93%	93 %	93%	7%

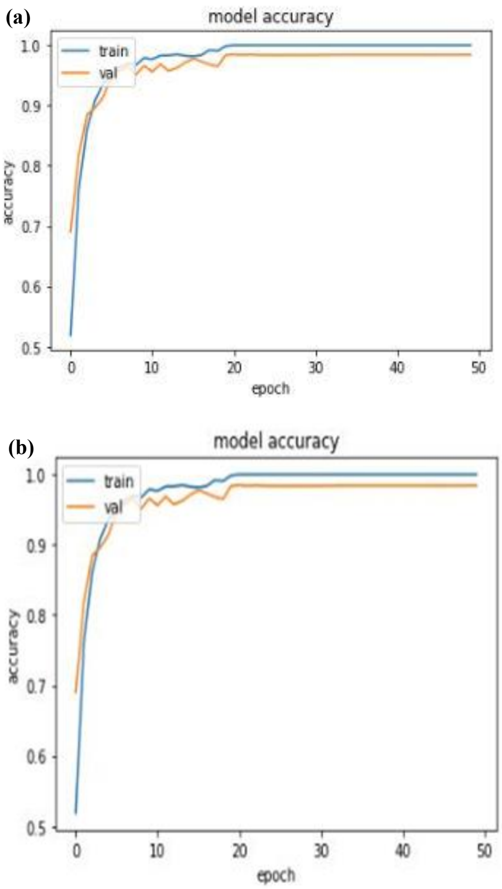

Fig. 4(a)-(b) The accuracy and loss of model 90:10 % split test

Comparison of This Study to Other Research Works

No.	Author	Title	Proposed method	Accuracy	Remark
1.	Anagha V.P and Safoora O.K.	Skin Disease Image Recognition Using Deep Learning Techniques	SVM	95%	
2.	Latha A. et.al.	Detection and Classification of Skin Diseases	CNN	82%-90%	
3.	N.V. Kumar et.al.	Classification of Skin diseases using Image processing and SVM	SVM	90%	
	Proposed method			98.25 %	

V. Conclusion

The detection and classification of seven different skin diseases using convolutional neural network is the key contribution of this research study. Three distinct results were obtained as a result of the various percentages split test options. Accuracy, recall, precision, and F1 measures were used to compare the best-performing system. The accuracy of the 90%:10% percentage split test is 93.76%, making it more accurate than the other two percentage split tests.

In the further work, seven different types of skin diseases have been classified by the researcher in this study using a system. The created system, however, does not determine how serious the discovered illness is. As a result, one area of research could be automatically estimating the severity of the diseases that have been identified. It is better to suggest the right course of treatment after skin diseases have been identified. Therefore, another research area is to automatically recommend the appropriate therapy for the identified diseaseexpression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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