Derma-Speziale: An Image-Based Automated System for Skin Disease Identification Using Convolutional Neural Networks

Neethu C Sekhar[1], Rosmin Augustine[2], Johny Xavier Fernandez[3], Midhlaj Ahammed T K[4], Serene Anna Giji[5]

[1]Assistant Professor, Department of Computer Science and Engineering, Amal Jyothi College of Engineering (APJ Abdul Kalam Technological Kalam Technological University) Kottayam, India

[2,3,4,5]Department of Computer Science and Engineering, Amal Jyothi College of Engineering, (APJ Abdul Kalam Technological, Kalam Technological University) Kottayam, India

***Abstract* - Skin disease is perhaps the most well-known kind of human illness, which may happen to everybody regardless of any demographic characteristics and skin diseases are becoming one of the most common health issues in all countries worldwide. Multiple tests should be carried out to determine the skin diseases faced by patients. This takes a while, depending on the prediction of the diagnosis. As a result, a framework is required that can analyse skin diseases without any of these requirements and provide superior results in seconds. An automated image-based system based on convolutional neural networks (CNN) for skin disease recognition is proposed in this paper. Training dataset is required for various skin diseases. The dataset includes all forms of skin diseases, however we focused on nine main types of skin diseases, with each class including between 150 and 300 samples. Users can enter images and system processes, use CNN algorithm to extract features, and use softmax classifier to diagnose diseases. The proposed CNN model is compared with a recurrent neural networks(RNN) model to ensure CNN model is more accurate in classification and prediction of the input images.**

***Index Terms* – Deep Learning, prediction modelling, CNN, TensorFlow.**

I.INTRODUCTION

Dermatological diseases are the most common. Proper knowledge and experience in dermatology is required for accurate diagnosis. Skin diseases can be controlled to a significant extent by taking precautionary and preventive measures. Early detection of skin diseases is the very need of the hour. Skin disease can impact on quality of life for patients. Some diseases are malignant and need proper care and attention. As skin is one of the sensory organs, utmost care is required. The development of readily available detection techniques will make early skin disease diagnosis easier. This work aims to treat the main skin diseases such as squamous cell carcinoma, nevus, basal cell carcinoma, melanoma, seborrheic keratosis, benign pigmented keratosis, dermatofibroma, vascular disease and actinic keratosis. To classify diseases, we developed a system based on convolution neural networks. To bring the image to the required dimension, it is preprocessed, and feature extraction is performed. The feature extraction unit's output is passed onto the classifier unit. The classifier used is softmax classifier which is based on probability. The testing data and training data are compared based on probability. Each disease is given its own classification. If the disease belongs to one of the training data sets, then the software forecasts what disease it is; otherwise, the image does not match the dataset, and a message is displayed.

II. LITERATURE SURVEY

Certain researchers have proposed image processing-based techniques for detecting the type of skin disease. Some of the strategies referenced in the literature are briefly summarised here.

The system takes a two-step technique. Image processing for identification is the first stage of this approach, followed by machine learning [1].The system acts as an effective learning tool and helps to review the results because it has access to clinical data. The training data set has attained a greater level of precision thanks to the machine learning data repository. The system is able to detect six diseases to recognize, namely Seborrheic Dermatitis, Pityriasis Rosea, Lichen Planus, Chronic Dermatitis and Pityriasis Rubra Pilaris, Psoriasis; The system refines the image classification in the second stage using various machine learning techniques; the second level of prediction is made available to health professionals with access to various histopathological features such as acanthosis, hyperkeratosis, parakeratosis, exocytosis and other features. In the medical field, it can be a useful teaching tool. In addition, the application can also be used by normal users, as they could only achieve a fairly accurate recognition rate with computer vision techniques.

Authors proposed an automated computer-aided diagnosis (CAD) for meatoscopic images was required to accurately classify skin lesions [2]. In order to segment skin lesions, many researchers have developed different methods for melanoma skin lesions (MSL) and few methods for non-melanoma skin lesions (NoMSL), while accurate segmentation for the different lesions is somewhat risky. is used for segmentation. After segmenting the lesion, extract the features such as color, text, and shape. Many methods are used for classification, but focus only on the melanocytic skin lesion, a new approach The Support Vector Machine (SVM) classifier has been used to classify skin lesions such as melanoma, basal cell carcinoma (BCC), seborrheic keratosis (SK), and nevus .The dataset collected by Dermweb. Here the researchers used 100 NoMSL and 220 MSL image sets. This classification method has achieved a higher level of precision compared to others.

Authors proposed a method that uses computer vision-based techniques to detect different types of dermatological skin diseases [3]. Here different types of image processing algorithms are used for feature extraction and artificial neural feedback. The system works in two phases, first it processes the images of the skin in color to extract significant features and then it identifies the diseases. The system successfully detects 9 different types of dermatological skin diseases with an accuracy of 90.

This research describes the detection of skin diseases through the use of a neural network based on texture analysis [4]. There are many skin diseases that have many symptoms in common, such as measles (rubeola), German measles (rubella), and chickenpox, etc. In general, these diseases have similarities in infection patterns and symptoms such as redness and rash. Diagnosing and detecting skin diseases requires a very long-term process, requiring the patient's medical history, physical exam, and appropriate laboratory diagnostic tests. It requires a large number of clinical and histopathological features for analysis and additional treatment. Diagnosis and detection of the disease become difficult as the complexity and number of disease features increase. Therefore a computerized detection and diagnosis system is introduced. It was implemented with the help of a classifier such as the artificial neural network (ANN). KNN can learn symptom patterns of certain diseases and enables faster diagnosis and detection than a human doctor. This enables patients to carry out the treatment of the skin condition immediately because of the observed symptoms.

An automatic Computer-Aided Diagnosis (CAD) for dermoscopy images was required to accurately diagnose the skin lesions [5]. In the categorization phase, lesion segmentation is critical. Many researchers have created numerous ways for segmenting skin lesions on melanocytic skin lesions (MSLs) and a few approaches for non-melanocytic skin lesions (NoMSLs), however correct segmentation for a variety of lesions is relatively problematic. For segmentation, K-means clustering is used. Extract attributes such as colour, text, and form once the lesion has been segmented. For this, a variety of strategies are employed.

III. DATASET

Datasets are collected from the images available from the site "KAGGLE". Here, we have collected 160 images of actinic keratosis (Fig 1), 554 images of melanoma (Fig 2), 203 of dermatofibroma (Fig 3), 478 of pigmented benign keratosis (Fig 4), 80 of seborrheic keratosis, 461 of basal cell carcinoma, 573 of nevus, 197 of squamous cell carcinoma, 232 of vascular lesion. To eliminate the presence of distortions in the images, Normalization is used which is done by normalizing the RGB values of the picture.

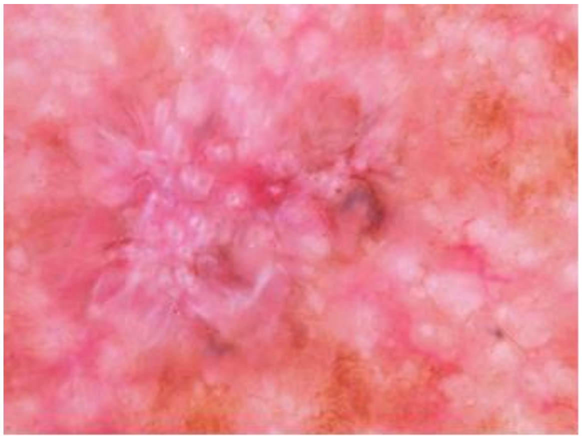

Fig. 1. Actinic Keratosis

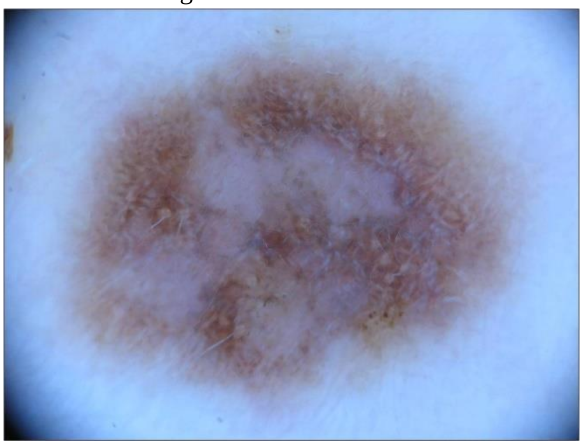

Fig. 2. Melanoma

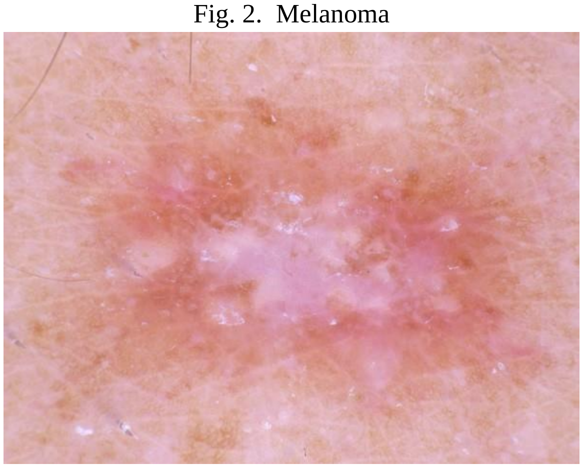

Fig. 3. Dermatofibroma

IV. PROPOSED SYSTEM

Module 1: The home page of the web application Derma - Speziale. When 'Login' is clicked it goes to the login page,where existing or already registered users can login. The login page requires the username and password for authentication. These pages are the same for both admin and users. If not an existing user it goes to the registration page. Here the user needs to fill out details to create an account.

Module 2: After logging in, the user is directed to a page which is called the predict page.If the user clicks the predict button then it will be directed to the next page where the user has to upload the image of the infected area of their skin.

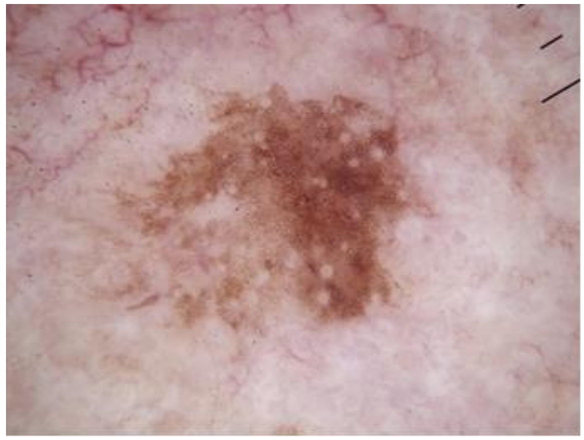

Fig. 4. Pigmented Benign Keratosis

Module 3: Here,the user can see the name of the predicted disease along with a picture that the user has uploaded.This is where the result analysis comes in.

A. CNN Architecture

The proposed system uses a convolutional neural network (CNN). The user provides the skin disease information being processed by the system, uses the CNN for feature extraction, and uses the Softmax classifier for disease diagnosis. The main parts are provided with an extraction and classification unit. The feature extraction unit improves the image by casting off noise and undesirable skin parts. First, the image preprocessing is done and transformed to a normal size. The image is then fed to the first layer as input. The convolutional neural network is applied until high-level properties such as color, shape and texture are obtained. The system basically consists of two modules:

- Feature extraction module
- Classifier module

B. Feature Extraction Module

Convolution, Max pooling, and ReLu are the operations performed by this module. This layer may be extended depending on the requirements. The convolution operation's goal is to extract high-level properties from the input image, such as shape and texture.The maximum value from the picture covered by the Kernel is returned via pooling. Max Pooling works as a Noise Suppressant as well. It removes sounds and conducts de-noising and dimensionality reduction at the same time. ReLU is a biological and mathematical activation function with powerful biological and mathematical activities.

a certain amount; if the input is less than zero, the output is zero; however, if the input is greater than a certain threshold, the output is linear. The primary goal is to eliminate all negative values got from convolution and max pooling. The positive values are all unchanged.

C. Classification Module

The module is made up of three layers: dense, dropout, and softmax. A dropout layer is a strategy for improving neural network overfit. The dropout layer is turned off during prediction. A non-linear activation follows the dense layer.

Convolution

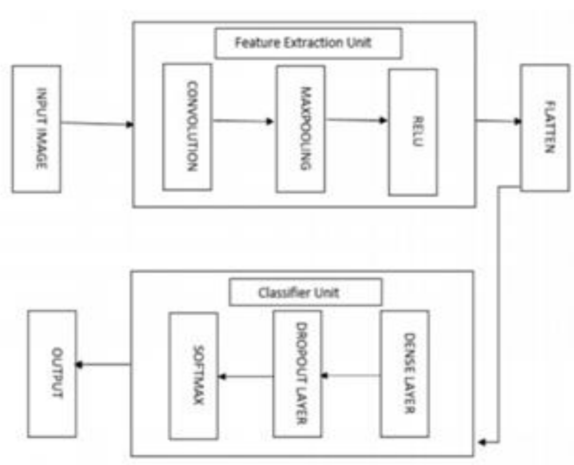

Fig. 5. CNN Architecture

1) Dense Layer

In a neural network, a dense layer is simply a regular layer of neurons. Each neuron in the preceding stage takes inputs from all neurons in the layer just above, resulting in a dense network. A weight matrix W, a bias vector b, and the activations of previous layers make up the layer. The dense layer takes into account the number of input neurons and the activation function.

2) Dropout Layer

Dropout is a technique used to correct overfitting.

Convolutional layers are the basic building blocks used in neural convolutional networks. Convolution is the simple process of applying filters to inputs to create triggers. There are 4 steps to a Convolution:

1) Line up the features and the images.
2) Multiply each pixel in the image by the corresponding pixel of the function.
3) Add the values to the sum.
4) Divide the sum by the total number of pixels in the function.

Convolutional layer imported from Tensorflow module. The network uses training to determine which attributes it believes are important for scanning images and classifying them more accurately. On this basis, it developed its own feature detector. In many cases, the features seen by the network are not perceivable by the human eye.

Max Pooling The pooling layer is used to reduce the size of the representations, speed up calculations, and improve the robustness of some of the traits it finds. The max pooling process is broken down into four steps:

1) Pick a window size
2) Pick a stride.
3) Walk your window across your filtered images.
4) From each window, take the maximum value.

The convolution and max pooling layers gather features from the input images and pass them along to the ReLu activation layer.

ReLu Layer The Rectified Linear Unit (ReLU) transform function only activates a node if the input is greater than The dropout method in the keras.layers module takes a floating point number between 0 and 1, which corresponds to the fraction of the neurons to be killed. Dropout prevents overfitting by setting a fraction rate of input units to 0 in each update during training.

3) Softmax Classifier

The purpose of the Softmax classification layer is simply to convert all net activations in their final output layer into a series of values that can be interpreted as probabilities. The last layer takes parameters such as the number of output labels and the activation called Softmax.

V. COMPARISON WITH RNN

The proposed CNN model is compared with a recurrent neural networks (RNN) model to ensure CNN model is more accurate in classification and prediction of the input images. When input images are trained and tested using RNN model, very low accuracy is obtained. It is shown in figure 11. From this, it is clear that RNN is not best suited for the classification of data in the form of images.

VI. RESULT AND DISCUSSIONS

A. The Web Server Based API

The figure 11 shows the home page of the web server. Figure 12 shows the sign-up page and Figure 13 shows log-in page.

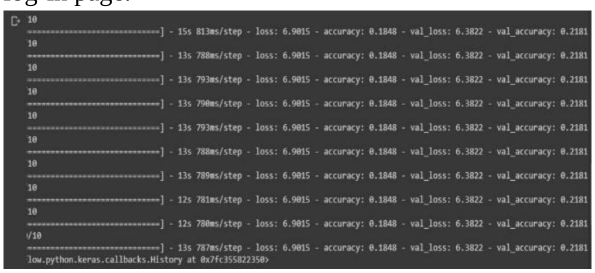

Fig. 6. Training of images with RNN model

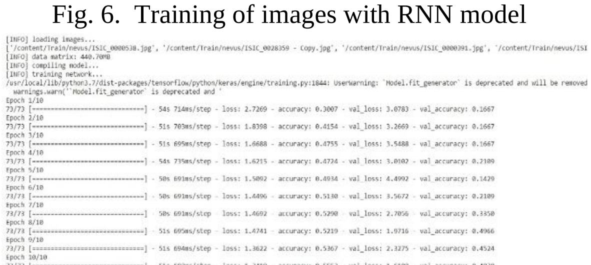

Fig. 7. Training of images with CNN model

The sign-up page requires the name, age, email. Figure 14 shows the page to upload image and Figure 15 shows the result of the uploaded picture.

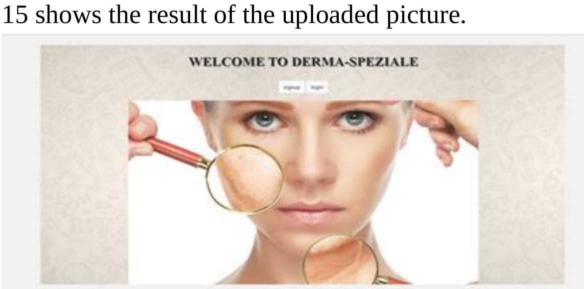

Fig. 8. Home Page of the Web Server

Fig. 9. Login Page of the Web Server

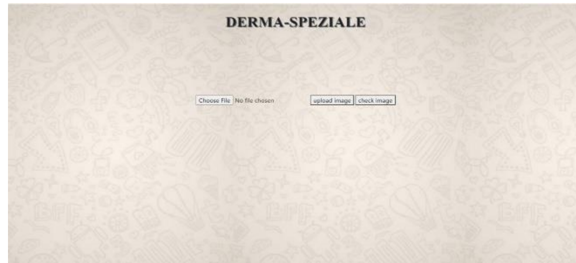

Fig. 10. Page to Upload Image

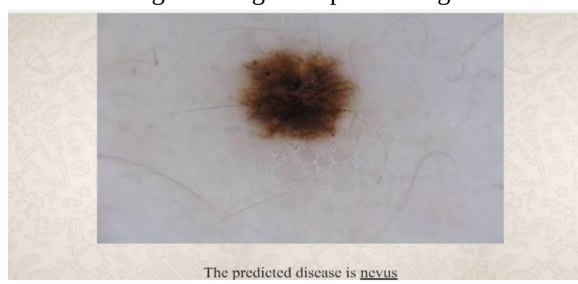

Fig. 11. Result of the Uploaded Image

B. Performance Evaluation

The images in the dataset are preprocessed using normal- ization techniques before it is trained with the CNN model and the different classes in the dataset are shown in Figure 12.

Index	Classes	Count
0	Nevus	573
1	Dermatofibroma	203
2	Melanoma	554
3	Basal Cell Carcinoma	461
4	Seborrheic Keratosis	80
5	Squamous Cell Carcinoma	197
6	Pigmented Benign Keratosis	478
7	Actinic Keratosis	160
8	Vascular Lesion	232

Fig. 12. Classes of Images in the Dataset

The system predicted the data and obtained very accurate results using the CNN network. Nevus, Melanoma and Pig- mented Benign Keratosis has the most numbered images in the dataset, hence these classes have greater level of accuracy in prediction.

VII. CONCLUSION

We were able to design a neural network-based system for diagnosing skin diseases with lesser drawbacks. Methods for detecting skin diseases that are used in the system produce better results and accuracy. Users can use the system to find out what type of skin disease they have. This enables users to take preventive measures to control the spread of disease and prevents them at an early stage. Neural networks have many uses in the medical field that aid in the early detection and prevention of disease. Convolutional Neural Networks have proved that a large number of records can be trained in a short time and provide higher precision. With the help of advanced computing techniques and a large data set, the sys- tem can match the results of a dermatologist, thus improving the standard quality in this field of improving medicine and research. With a huge data set, the system could detect various diseases in addition to those mentioned in work. The real-time application of the work with an Android platform could help people analyze the disease in a split second and the location of the nearby dermatologist could also be included.

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