

UTILIZATION OF NN STRUCTURE IN PREDICTION AND CLASSIFICATION OF SKIN DISEASES FOR PERFECT ACCURACY

¹M Sandeep, ²Chitram Pooja, ³Yedla Sandhya, ⁴B Manasaveena

^{1,2,3}Assistant Professor, ⁴UG Student, ^{1,2,3,4}Department of Computer Science and Engineering, Brilliant Institute of Engineering and Technology, Hyderabad, India.

Abstract

According to this survey, dermatological conditions are among the world's most prevalent diseases. Therapy is universal, but it's also really challenging and takes a lot of subject knowledge. Bacteria, fungus, viruses, allergies, etc. are the main causes of most skin diseases. With the advancement of lasers and photonics-based medical technologies, skin diseases may be treated quickly and precisely. Yet, there are very few and very expensive medical equipment required for such a diagnosis. Deep learning techniques are advantageous in these situations. An important component of treating skin diseases is early diagnosis. Deep learning technique like Convolution Neural Network (CNN) may help to find the problem at an initial stage. Computer vision and Deep learning are dual stages which we used to identify diseases accurately. The utilization of Deep Learning methods have decreased the requirement for human supervision on a regular basis. A Dataset of 5,633 images which are divided into 5 categories have been taken for Skin diseases classification. They comprise Acne, Eczema, Melanoma, Psoriasis and urticaria Hives. The model also provides the precautions needed to be taken and some recommended medicines for the skin disease. By utilizing CNN algorithm, 83% accuracy is achieved in classification of skin disease.

Keywords: Deep Learning, Skin Disease, CNN.

1. INTRODUCTION

Skin conditions affect people of all ages and are a fairly common form of disease. The hardest disease to understand may be skin conditions because of their unpleasantness and associated challenges, especially when they affect the face where they are impossible to conceal, even with cosmetics. The concept of skin disease's "weight" encompasses the psychological, societal, and financial costs to individuals, their families, and society as a whole. Most skin disease treatments need a lot of time and effort to display the patient's belongings. If the condition doesn't respond to medications for skin problems, the situation becomes more problematic. Persistent and serious skin infections, like psoriasis and dermatitis, are related with critical horribleness as actual inconvenience and weakness of patient's quality of life. Chronic skin conditions, like vitiligo, psoriasis, eczema, and leg ulcers, while not immediately fatal, are known to cause significant health problems, including physical, emotional, and financial consequences. whereas malignant diseases, like carry substantial mortality, malignant melanoma. There are 3000 and more obscure skin infections. Individuals of practically 73% are influenced with skin problem don't look for clinical guidance for different reasons. There are relatively few measurements to demonstrate the specific recurrence of skin infections in this nation, however broad impression is 10-20 percent of patients looking for clinical counsel experience the ill effects of skin sicknesses. CNNs (convolutional neural networks) are a type of deep learning neural network. The CNN model is a significant advancement in image recognition. They are used to investigate visual pictures and image classification. A CNN model is built by feeding it a large number of images. The CNN model pulls features from images using convolutional neural networks. This eliminates the need for manual feature extraction. While the network trains on a set of images, the features from the set of images are not trained; instead, they are learned. It ensures that deep learning models are extremely accurate. CNN learns the feature detection through number of hidden layers. CNN model comprises of different layers like pooling layer, convolution layer, output layer, Fully Connected layer,. Each layer performs a specific task and finally at the end the input is classified under one output class.

2. LITERATURE SURVEY

Numerous investigations have applied profound learning calculations in arrangement of skin infections. Every day soft drink utilization mainly expands the danger of moderate-to-serious skin inflammation in young people, particularly

when the sugar admission from any kind of soft drink surpasses 100 g each day [2]. Skin Diseases are turning out to be exceptionally normal now days. Many people influenced by skin illnesses is expanding quickly. Human judgment on conclusion of skin infections is normally abstract and not reproducible. To accomplish more solid and target exactness computer aided helped conclusion might be utilized in [3]. The outcomes show that leptin assumes a basic part in the improvement of immune system problems and exhibit that the transgenic leptin pigs will be go about as a significant model of SLE. Certain outcomes contend firmly to incorporate skin illness anticipation and treatment in future worldwide wellbeing techniques as an issue of desperation [1]. The outcomes in [4] show that leptin assumes a basic part in the advancement of immune system problems and exhibit that our transgenic leptin pigs might go about as a significant method of SLE. Samples from nine normal skin analyzed by IHC in expression of ATP5B and K10 such as, 6 chronic dermatitis, 5prurigonodularis, 7 keratosis seborrheic, 9 verruca vulgaris, 25 psoriasis, 5keratoacanthoma, and 9 SCC in [5]. Skin sicknesses associate with society, and both are influenced by one another. Incorporating its relationship to aesthetic angle [6] gave it more significance and focused of numerous specialists in different nations of the world to investigate the programmed analysis of skin illnesses, providedextraordinary significance of skin sicknesses in pathology from one viewpoint. Then again, quick mechanical turn of events and its part in all fields, the most significant of which is the clinical field [7]. The professionals engaged 46 and 105 Chinese Han psoriasis vulgaris patients for disclosure and approval stages to study the association between polymorphisms and acitretin viability [8]. This study [9] looks at the relationship between the rs1802073 polymorphism in Frizzled-related proteins 4 (SFRP4) and the progression of serum lipids in Chinese psoriatic patients treated with acitretin. In [10], the usefulness of ImageNet is represented by three simple applications in object recognition, picture grouping, and programmable object bunching. The project to characterise skin malignancies using the Inception-v3 network, for example, has reached the arrangement level of professional dermatologists. A PC achieved an accuracy rate of 55.4 percent for particular nine kinds of malignancies, while two dermatologists achieved accuracies of 53.3 percent and 55.0 percent [11]. The clinical information made in tolerant records can be utilized to investigate the reasons for illnesses and how they spread, to foster fitting plans and approaches, and to get ready and foster medications and clinical medicines [12]. The work [13] planned a profound learning calculation called Deep Gestalt and it prepared the model on in excess of 17,000 facial pictures of hereditary disorders, and this model recognized more than 200genetic conditions utilizing skin pictures with high accuracy. In towns and provincial regions, patients don't get satisfactory medical care, and there is an absence of dermatologists in those spots, and the conclusion is made via prepared staff [14]. At first, examination of extent of skin pictures in most ordinarily utilized public datasets for skin sickness, which incorporate Dermnet [19], AtlasDerm [15], ISIC Archive [17], DermIS [16], and Derm101 [18]. The vast majority of these datasets [15]–[18] didn't give data about body parts. The work [19] gives body parts data; there were just 195 facial pictures.

3. METHODOLOGY

Figure 1 [7]represent the overall architecture of proposed system also methodology of CNN model can be explained with it. The system might be generally classified into Data Collection, Image Processing, Feature Extraction and Image Classification modules.

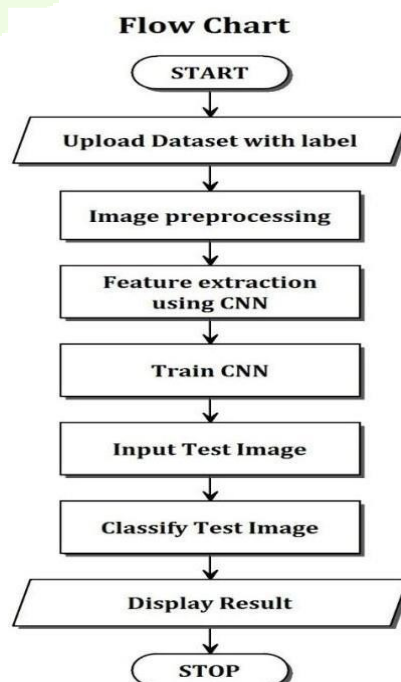


Figure.1. Overall architecture of suggested system

First the model is fed with a dataset which have different classes with output labels. In the next stage Image processing is applied to the images. There may be presence of some distortions while taking a picture, at times; you need to dispose of twists brought about by lights and shadows in a picture. Normalizing the RGB upsides of a picture can now and again be a straightforward and powerful method of accomplishing this. Picture information increase is a strategy, which might be used to misleadingly extend preparation dataset size by making altered adaptations of pictures in dataset. Feature Extraction in CNN is done using convolution layers, pooling layers. Later model is trained after providing images, adding layers to the model which in turn extracts features. After the model is trained, testing is done by providing a input image. The model classifies the image into one of the output class based on the training. Finally result is displayed.

A. DATA SET

Dataset contains 5,633 photos of Five Classes of Skin Diseases in the proposed Skin Disease classification methodology. The dataset is divided into two parts: training and testing. There are 4,449 photos in the training set and 1,184 images in the test set. Each set includes five different ailments, including acne, eczema, melanoma, psoriasis, and urticaria hives. For the training system, training data is used.

Finally image is classified into above mentioned five categories. Here are some sample images of the dataset. Fig 1.a,b,c,d,erepresent Acne, Eczema, Melanoma, Psoriasis and Urticaria Hives respectively.



Figure.2.sample images of the dataset

4. CNN for Skin Disease Classification

In the areas of speech recognition, picture identification, and natural language processing, neural networks and deep learning are already giving superior solutions. A neural network is a deep learning technology that allows a computer to learn by incorporating fresh data. CNN is particularly useful in image recognition for examining visual imagery and is frequently employed in picture classification. The input to our suggested system model includes five classes of skin disease photos, and the output is a probability that the input corresponds to a specific class. On any image-related topic, CNN is now the favoured solution. CNN has a big advantage over its predecessor in that it automatically detects the main features without the need for human supervision. For example, given a large number of photos of dogs and cats, it learns the characteristics of each class on its own. CNN is also efficient in terms of computing. Convolution layers, pooling layers, ReLU layers, and fully connected layers are all layers of a CNN. Convolution layers are the major building blocks utilized in CNNs. In this layer, the features of the image are extracted. The extraction of the features is done using various filters. The filters are values represented in matrix form. Now these filters are strided over input matrix. The task of filter is to increase its qualities by the main pixel values, all these multiplications are summarized. One number is acquired in end. Since filter has observe picture just inside the upper left corner, it moves further right by 1 unit executing an indistinguishable activity. After passing the filter across all positions, a lattice is acquired, yet smaller than input matrix. Convolution of a picture with numerous channels might execute tasks, like edge identification, obscure and hone by applying various filters. ReLU or Rectified Linear Unit, it's anything but a

non-linear operation. ReLU acts on an elementary level which means an activation function. In other words, here all the pixel value which has negative value is converted to zero. Spatial pooling which is also named as sub sampling or down sampling is utilized to decrease the dimensions of each feature map but even while doing so, retains the most consequential information of the map. Max pooling, sum pooling, and average pooling are examples of different types of pooling. Average pooling takes the feature's average. Sum pooling refers to the sum of all elements in a feature map. Pooling to the limit, retrieves the maximum value in a $k \times k$ matrix. After completion of series of convolution, nonlinear and pooling layers, it's necessary to connect a totally connected layer. The Fully connected (FC layer) takes the output information from convolution networks and convert it to a single vector form. The output of FC layer is given to output layer, where image is classified into one of the class. Here input is the skin disease dataset which has 5 different classes. Convolution layer extracts important features from the images. ReLU unit suspends all negative values from matrix and converts them to zero. Pooling layer samples down the size of the matrix. The final fully linked layer allows us to vote on the five dataset classes we're interested in. Training is done using both forward and reverse propagation, and the process is repeated until we have a well-defined neural network with trained weights and feature detectors.

The following figure 4.1 shows the basic architecture of CNN. At initial stage model is trained with number of different images of different classes. A layer one by one in model learns about the image. First convolution layer finds the important features of image using filter matrices. Next, pooling layer reduces the size of input matrix. By doing this pooling layer also helps in decreasing computational capacity. Later fully connected layer converts matrix into a single vector, which in turn is given to a output layer. The output layer is where; the output class of the image given is predicted.

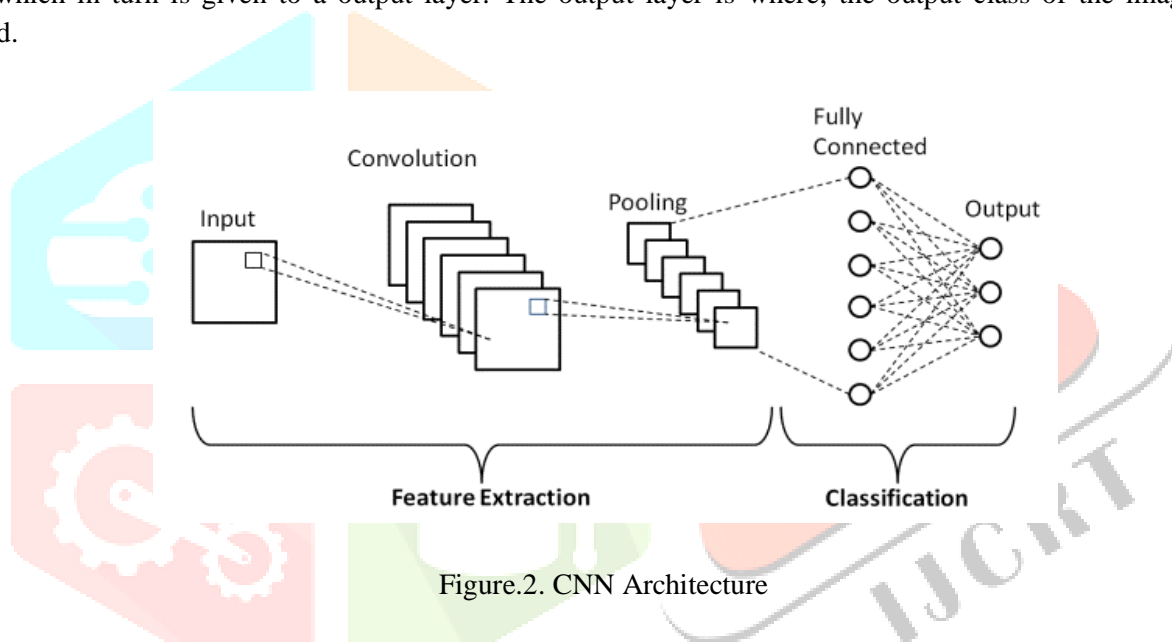


Figure.2. CNN Architecture

5. Results and Discussion

First and foremost, the CNN algorithm is used to train and identify clinical pictures of all types. We've looked at five different forms of skin problems. Acne (1,412 pictures), Eczema (1,593), Melanoma (579), Psoriasis (1,327), and Urticaria (hives) are the conditions (727). Transfer learning is when we train the system using a set of data and use the parameters from the pre-trained set as the first elements for new input. Sets that have been pre-trained with images frequently outperform sets that have been taught with the next batch of inputs. An input image is provided to the model and the model classifies the input image into any of the 5 categories of skin diseases considered based on the training. We also provide the necessary precautions, some medicines needed to be taken for the predicted skin disease. According to us, there were numerous variances among images in diverse parts of body. Though, for most diseases, the symptoms on different body regions are not the same. As a result, while training the approach for skin disorders, the optimal method may be to train the model with datasets of skin diseases in various body parts and then retrain the model on photos of specific body parts. The specific method might then be used to diagnose the disease in any location of the body. We achieve an overall accuracy of 82 percent.

The findings demonstrate that, in general, CNN formed predictions based on traits and attributes learnt from aberrant lesion areas rather than the textures or other aspects of normal skin. The training set is used to teach the procedure, but the test set is merely used to evaluate it. The training and validation accuracy of the CNN algorithm in skin disease categorization is shown in Figure 4. The training and validation loss are depicted in Figure 5.

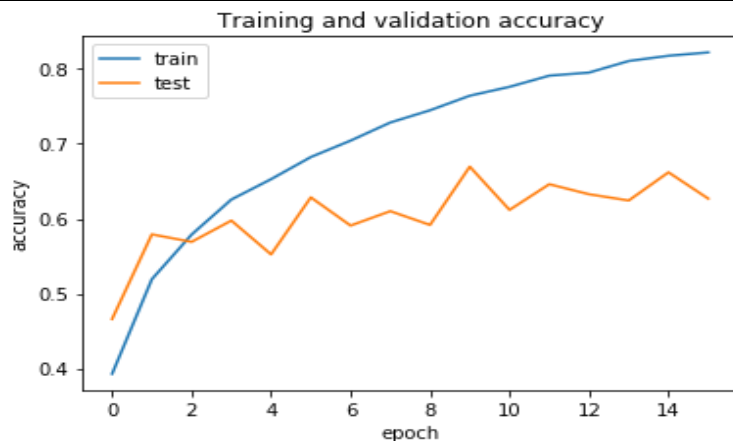


Figure.3. Training and validation accuracy

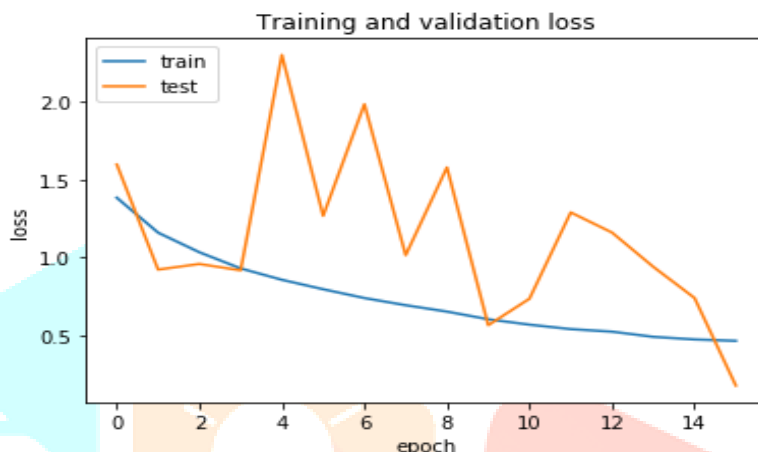


Figure.4. Training and validation loss

We trained the model varying the number of epochs. The accuracy in each of the epochs is as follows

ARCHITECTURE	ACCURACY		
	10 Epochs	12 Epochs	16 Epochs
CNN	76%	78%	82%

Table.1 Accuracy for CNN

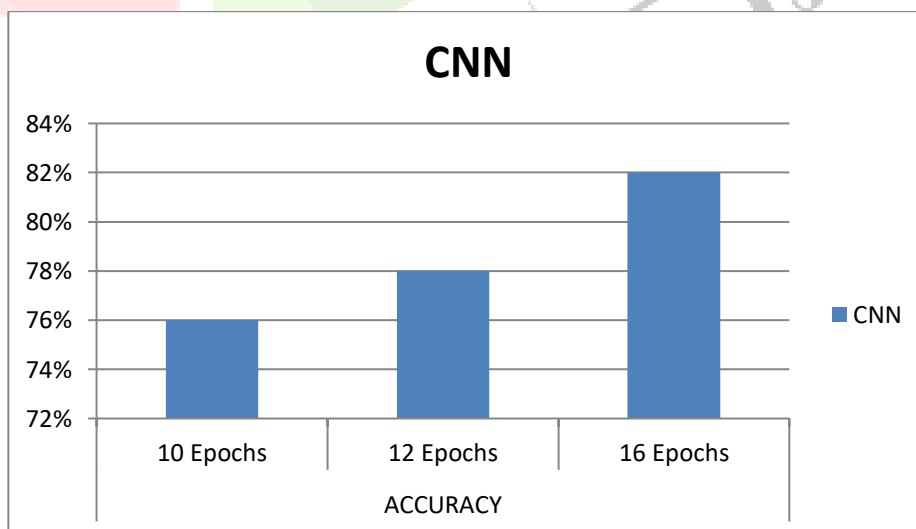


Figure.5. Graphical representation of accuracy for CNN

Conclusion

This research produced a dataset that was mostly made up of images of skin infections and used CNN structure for the analysis of skin photographs of five common skin diseases. The findings support CNNs' ability to recognize and diagnose skin diseases. Furthermore, our testing also demonstrated this pertinent data; network development might

advance the method's presentation. Although the NN structure's presentation is used to characterize some diseases, the whole implementation needs to be improved. Thus, if individuals need to really utilize this method to check their skin wellbeing in their everyday life, specific upgrades ought to be finished. As we would see it, with the expanding measure of picture information of different skin infections will keep on improving the model execution.

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