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Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images

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Abstract: *Skin disease is a major problem nowadays all over the world and due to the technology era, it is important to solve the problem through machines instead of human. Deep learning is one of the best ways to solve the skin disease problems. Deep learning is a new research area within the modern technology using micro services with big data, virtual reality and also augmented reality. Due to the development of huge computing capacity, technologies such as deep learning application using(CNN) has revolutionized image classification. Deep learning can be used to classify the different types of skin disease types. This learning technique uses different algorithms such as CNN algorithms. MobileNet algorithms are the suitable ways to recognize the images from the input and gives accurate results. In this current work CNN is used to our data set to classify skin diseases types according to our input. The study showed that the implementation of Deep learning within the field of disease diseases can be the most suitable way to classify and recognized skin disease images, which can be very beneficial in the field of medicine for early diagnosis and improve the accurate diagnosis result. This current work showed and output result of 90 % accuracy.*

Keywords: Actinic_kerotosis,Basel_cell_carcinoma, Haemangioma, Melonocytics_nevous etc

I. INTRODUCTION

Skin disease is one of the most common and difficult disease for diagnosis because of its lack of awareness and ignorance. In many developing countries also people consult dermatologist for skin disease and prevention measures. The people are uncertain of the medicinal prescriptions provided by the dermatologist and there is no justification in the current system. Importance of skin disease without ignoring at the early stage is very important as skin plays a major role in protecting the human body against fungal and harmful bacterial infections. Many people get skin disease through their inheritance, job, lack of nutrition, regular habitats, exposed to chemicals etc.

Environmental factors also influence the existence of skin disease like climate, summer season, winter season. Thus identifying skin disease and diagnosis at the early stage is very crucial. Thus to provide feasible and efficient system and due to the emergence of smart phones, image processing based disease analysis is more remindful as this could provide promising results in less time. Utilization of camera technique, the people can provide the input and integration of image processing and machine learning techniques the respective skin disease is identified and = diagnosis is recommended.

The identification of skin disease from the microscope images are provided to image processing model. Pre-processing, feature extraction are performed in the image processing stage. In the image processing model, color, texture and share of the features are extracted and analyzed. Then processed to the classifier model. This classifier model predicts whether its normal, benign and malignant skin type of diseases.

1.1 Integumentary System of skin cancer

The skin is the body's largest organ and consists of two layers — the epidermis (the outer layer) and the dermis (the inner layer). The epidermis is a meager layer of cells and over the inner dermis forms a defensive layer.

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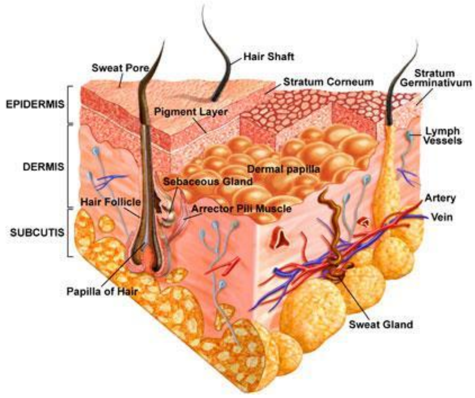

It acts to prevent ailments on the inner layers of the skin. Melanocytes (skin cells) contain melanin that assimilates light vitality and protects against the harmful effects of the sun's bright rays. Melaninprovides the skin with a form of shade.

II. LITERATURE REVIEW

(Sasikala et al., 2018) propose one of the most popular articles that uses CNN for the recognition and classification of malignant growth. They state that the accuracy of their proposed CNN is more efficient than most of the neural systems. Thus CNN can be a good alternative for classification malignancy grouping andthe accuracy of the CNN method is 96% but the dataset for this scheme was reasonably small 1000 images.

(Pomponiu et al., 2016) use only 399 images to arrange melanomas versus nevus typed.In this study that use a pertained deep neural network (DNN). Once again, this dataset is unreasonably small for a scheme that should characterize such sensitive client data. This method achieves 92.1 % affectability, 95.18 %explicitness, and 93.64 % accuracy.

(Codella et al., 2015) use 2624 Universal Skin Imaging Coordinated Effort (ISIC) dermatoscopic images. They apply transfer karnmy using AlexNet; in addition they apply scanty coding, deep leftover scheme, and convolutionary U-organization. After extraction factures using transfer learning a support vector machine is used for classification. They achieve 93.1% accuracy, 94.9% affectability, and 92.8% peculiarity for grouping melanoma versus non melanoma. An accuracy of 73.9 percent, an affectability of 73.8 percent, and an explicitness of 74.3 percent were accounted for more troublesome segregation between melanomas and atypical nevi.

(Kawahara et al, 2016) utilize a multi-class classifier with 10 labels using AlexNet (transfer learning) extract features. The creators used 1300 images of 10 skin lesions and announced 81.8% accuracy.

(Brinker et al., 2019) use in-depth information on how to prepare CNN with 12,378 opensource dermoscopic images and used 100 images to evaluate the performance of CNN with 157 dermatologists from 12 different college emergency hospitals in Germany. The standard affectability and Particularity performed by dermatologists with dermoscopic images (which were the evaluation measurements used in their journal) wasterritory74.1%and 91.3 %.

(Hosny et al., 2019) study skin injury techniques (melanoma and so on) using a preprepared CNN model using transfer learning with AlexNet. They use ph2 dataset and the accuracy is accuracy (98.61%), affectability (98.93%), explicitness (98.93%)and accuracy (97.73%).

(Mendes et al., 2018) examine the significance of programmed characterization technique to help skin sores conclusion utilizing CNN. The scheme was tested with 956 clinical images and accomplishes a territory of 96% for Melanoma under the Area under the Curve (AUC) and 91% for Basal Cell Carcinoma.

(Ramlakhan et al., 2011) introduce a prototype of an automated image-based melanoma identification scheme for Android smartphones. The scheme comprises of three main parts: segmentation of images, calculation of features and classification.

A skin lesion image is converted to a monochrome image for outline contour detection. They are used as an input KNN for classifier; in that work just two classes used melanoma and convenient automated diagnosis of skin. They achieve an average precision of 66.7%, with an average recall / sensitivity of malignant class of 60.7% and a specificity of 80.5%.

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(Ruiz et al., 2011) present a clinical decision support scheme for diagnosing melanoma using in pictures set of the skin lesion to be diagnosed as input. In order to extract the impacted region, the scheme analyses the picture sequence, determines the features that show the degree of harm and it makes a choice according to them; they are used as an input KNN for classifier, a multilayered perceptron, a Bayesian classifier and the K- Nearest Neighbour (K-NN) algorithm. They are achieves approximately 87% and accuracy are 73.47%, 80.6% and 86.73%.

III. METHODOLOGY

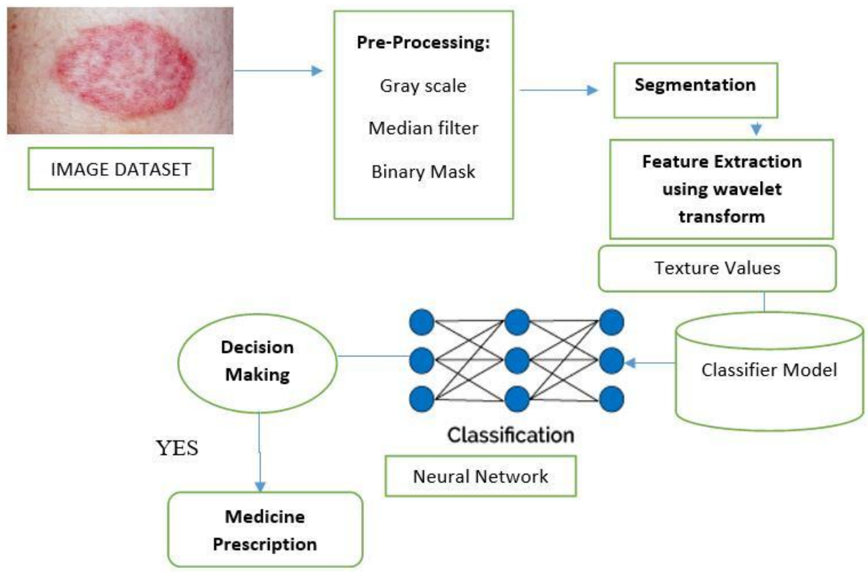

Fig 1 explains the overall experimental approach for skin disease detection using image processing andcomputer vision techniques. In this the skin images are given into the system for processing. The inputimage is subjected to image processing process like pre-processing, feature extraction and machinelearning based classifier to predict skin disease or not and recommend medicinal guidance based on theskin disease stage.The Proposed methodology is an effective tool which can analyze the people input skin disease to predictskin disease. In this proposed system, hybrid architecture with image processing and machine learningtechniques are used to predict type of disease with promising accuracy in a short period of time.

The image processing phase invokes preprocessing, segmentation, feature extraction steps. The machine learningphase invokes 3 steps: processing, training and detection steps. The proposed system uses 2D WaveletTransform algorithm for feature extraction in which color, texture and shape features are extracted fromthe skin input images. The correlation values are also been extracted from the input image.

IV. FACILITIS REQUIRED FOR PROPOSED WORK

An CNN uses a feed-forward method for neurons feeding and back propagation for parameters training. The main advantage of the CNN approach is its ability to extract topological properties from the raw gray-scale image automatically and generate a prediction to classify high-dimensional patterns. An CNN is composed of two distinct parts.

The first part consists of several layers that extract features from the input image pattern by a composition of convolutional and sub-sampling layers. Conceptually, visual features from local receptive fields [15] are extracted by an extended 2D convolution approach to gain the appropriate spatially local correlation present in the input images. Since the precise location of an extracted feature is inconsequent and dispensable, resolution reduction by 2 of the features is followed through the sub-sampling layers. The second distinct part categorizes the pattern into classes.

In general, an CNN consists of three different layers: convolution layer, sub-sampling (max-pooling) layer and an ensemble of fully connected layers. In the current study, we use an CNN with the architecture of LeNet5 [15], see Fig. 5.

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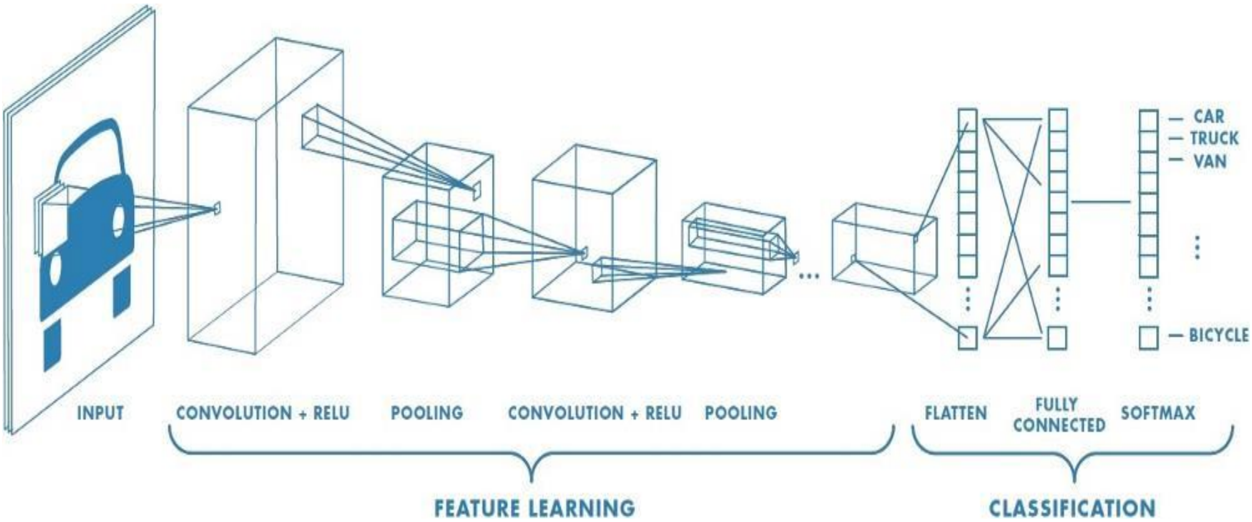

Fig. 5. LeNet-5 structure in modelling *CNN* for a 28×28 input image

In the first layers (properties extractors) convolutional filters in a 5×5 pixels window are applied over the image. It is highly recommended to add two blank pixels at each four directions to avoid missing real data at each border in convolution computations

The number of alternative three main layers depends on input database and can be varied between different input size to get better performance and confidence. In this work a LeNet5 with eight layers is used (including first layer as input gray-scale image and also output layer). Each convolution layer (C-layers) has different feature maps, C1 is composed of 6 units while C3 has 16 and C5 has 120 units. Also because of convolution windows size (5×5) and input size (28×28), the size of each convolution layer is defined as shown in Fig. 3: C1 is 28×28, C3 10×10, and C5 is 1×1, a single neuron.

V. RESULTS AND DISCUSSION

5.1 Accuracy and Loss with 10 Epochs :

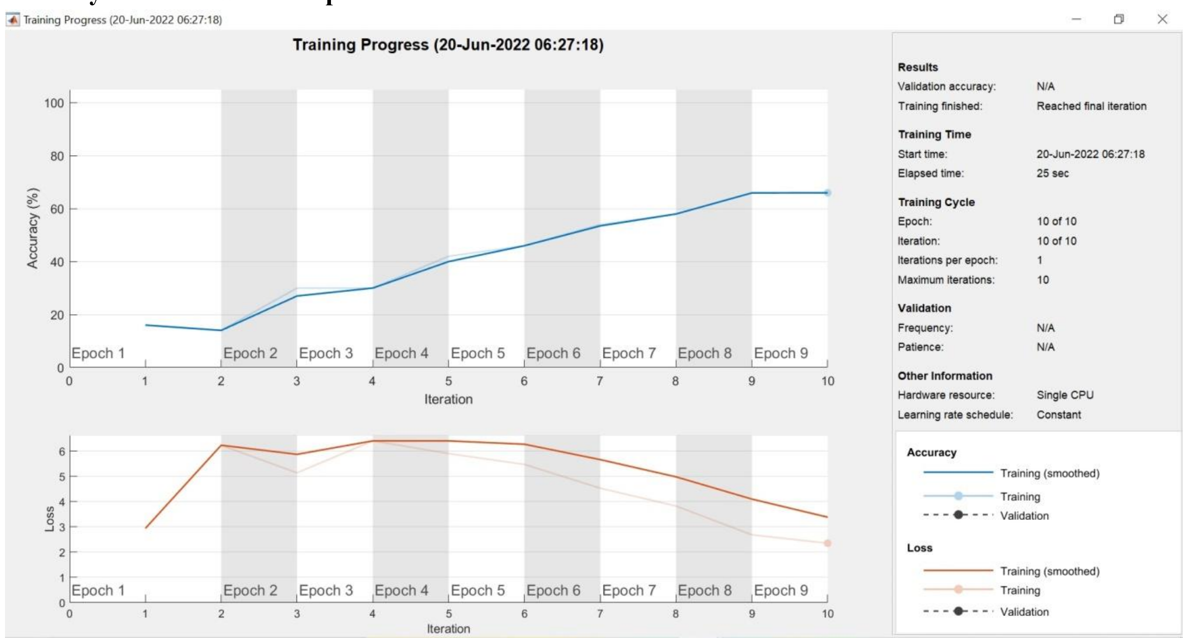

Figure 5.1 : Accuracy and Loss with 10 Epochs

HeretheMobilenetuse3x3filterssizeforthreeconvolutional layers and 1x1filter size for deptwiselyer of our model. Results show that comparing to the model with two layers, categorical accuracy increase 75% and loss will be the 25% maintained across it.

5.2 Accuracy and Loss with 15 Epochs

Figure 5.2 Accuracy and loss with 15 epochs

HeretheMobilenetuse3x3filterssizeforthreeconvolutional layers and 2x2filter size for deptwiselyer of our model. Results show that comparing to the model with two layers, categorical accuracy increase 94% and loss will be the 6% maintained across it.

5.3 Classfication of Blood Cells using CNN:

Figure 5.3 Detection of skin disease using CNN (HAEMANGIOMA)

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Figure 5.4 Detection of skin disease using CNN (SQUOUMMOUS CELL CARCINOMIA)

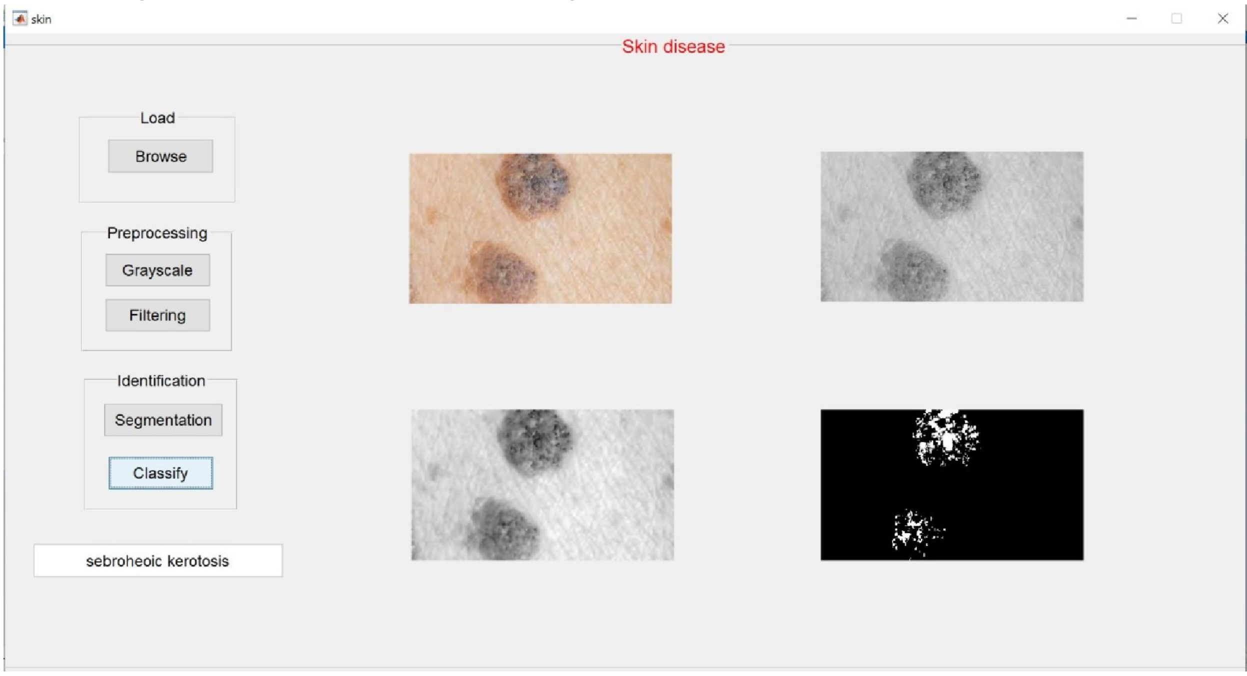

Figure 5.5 Detection of skin disease using CNN (SEBROHEOIC KRROTOSIS)

5.4 Confusion Matrix

A confusion matrix also recognized as an error matrix in the field of machine learning and specifically the issue of statistical classification. A confusion matrix is a table that is of tenused to define the performance of an algorithm's classification system (or "classifier") on a collection of test information for which the real values are known. It enables confusion between classes to be easily identified, e.g. one class is frequently mislabelled as the other. Most efficiency measurements are calculated from the matrix of confusion. Following figure shows the confusion matrix of our result which was gotten it from our data setsimulation test.

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The network sections speak to the expectation names and the columns speak to the genuine marks. The perplexity lattice is consistently a 2-D exhibit of shape [n, n], where n is the quantity of substantial names for a given grouping task. Both forecast and names must be1-Dvarieties of a similar shapeall together for this capacity to work.

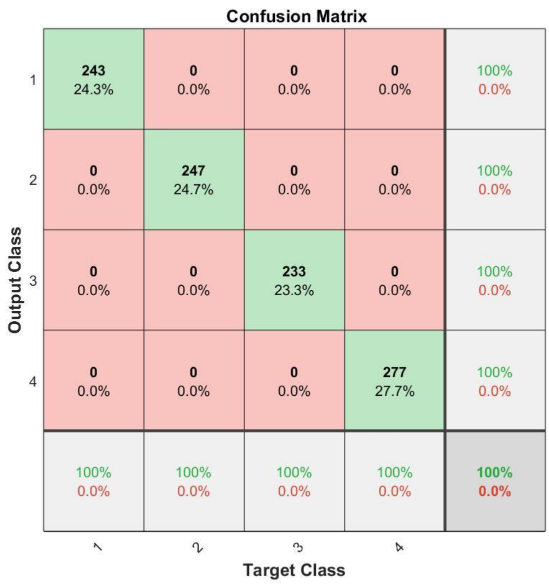

Figure 5.6 Confusion Matrix

VI. CONCLUSION

The system is able to classify 10 most common skin diseases efficiently. An initial training gives the output accuracy of 97% approximately. This can be definitely increased by increasing the training data set in the deep learning model. A large data set can increase the accuracy to more than 90 percent.

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