JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Melanoma Disease Detection and classification using deep learning

[1] **Md. IRSHAD HUSSAIN B , [2] HEMALATHA B, [3] SHOBHA H ,[4] SUPRIYA K U ,[5] SYEDA UZMA**

[1] Asst. Professor, Department of MCA, UBDTCE, Davanagere
[2,3,4,5] Department of MCA,UBDTCE, Davanagere

Abstract: The people health more than any other diseases. Skin diseases are mostly caused by fungal infection, bacteria, allergy, or viruses, etc. The lasers advancement and Photonics based medical technology is used in diagnosis of the skin diseases quickly and accurately. The medical equipment for such diagnosis is limited and most expensive. So, Deep learning techniques helps in detection of skin disease at an initial stage. The feature extraction plays a key role in classification of skin diseases. The usage of Deep Learning algorithms has reduced the need for human labour, such as manual feature extraction and data reconstruction for classification purpose. A Dataset of 10015 images has been taken for the Classification of Skin diseases. They include Melanoma, Nevus, and Sebborheic Keratosis. By using CNN algorithm, 92% accuracy is achieved in classification of skin disease
.

***Keywords*— Melanoma, Nevus, Sebborheic Keratosis, CNN and Deep Learning.**

i. INTRODUCTION

Skin is one of the largest and fastest growing tissues in the human body. Skin diseases are the common health problems in the worldwide. The burden of skin disease is viewed as a multidimensional concept that comprehends psychological, social and financial importance of the skin disease on the patients and their families and also on society. It is the infections that occurring in people among all the ages. Skin is frequently damaged because it is very sensitive part of the body. There are 3000 and more unknown skin diseases. A cosmetically appearance spoiler disorder can have a significant impact, and can cause considerable pain and permanent injury. Most of the chronic skin conditions, such as atopic eczema, psoriasis, vitiligo and leg ulcers, are not immediately lethal, they are recognized as a considerable trouble on health status including physical, emotional and financial outcome. On the other hand, skin cancers, like malignant melanoma, are potentially lethal and their trouble is associated with the temporality that they carry.

People of almost 73% are affected with skin disorder do not seek medical advice. Chronic and several other incurable skin diseases, like psoriasis and eczema, are associated with significant sickness in the form of physical discomfort and impairment of patient's life; whereas malignant diseases like malignant melanoma, carry substantial temporality. With the wide range of health status and quality-of-life measures, the effects of most skin diseases on patients' lives can be measured efficiently. Along with some of the deep learning algorithms are used for detecting skin diseases in whole body.

The convolutional neural network (CNN) is a category of deep learning neural networks. CNN represents a huge advance in image recognition. They are used to analyse the visual images and image classification. A convolutional neural network (CNN) is used to extract features from images. This eliminates the need of manual feature work extraction. The features from the set of images are not trained they are learned while the network trains on a set of images. It makes extreme accuracy for the deep learning models. Documents in the training set involvement of the learned features. A particular amount dataset will be provided to detecting the skin diseases.

1. To build coding network i.e., CNN model which efficiently extract high level features.
2. To predict the melanoma and other skin diseases based on the trained model.
3. To do performance Analysis of the proposed system.

A. Proposed System

To classify and predict the dermoscopic images into benign and malignant a recently developed deep learning architecture called CNN is used. Classification of dermoscopic images are done automatically without applying lesion segmentation or complex image pre-processing. The proposed work involves analysing the performance of this architecture by applying CNN model. To identify a skin disease, a variety of visual clues may be used such as the individual lesion morphology, the body size distribution, colour, scaling and arrangement of lesions. By analysing the individual components separately, the complexity of the recognition process is quite increased and the human-engineered feature extraction method is not applicable for its classification. On the contrary, hand-crafted features are just devoted to a limited variety of skin diseases due to its diverse nature and are not suitable to be applied to classes and datasets. One way to solve this problem is to use feature learning which eliminates the need for feature engineering and allows the machine to decide which feature to use by itself. Though many classification systems that use feature-learning have been developed [1, 5], most of them are restricted to dermo copy or histopathology images . They are mainly used for detecting mitosis, which is a cancer indicator . For most of the cases, transfer learning can be utilized to train a deep Convolutional Neural Network (CNN). Also in transfer learning, instead of training the network from randomly initialized parameters, a pre-trained network can be used by fine-tuning its weights by continuing the back propagation. The reason is that the results of some of the initial layers of a well-trained network contain certain generic features like blobs, edges that are used in many tasks and such features can be applied directly to a new dataset. For the proposed skin diagnosis system, transfer learning is done by fine-tuning Image Net , which is a pre-trained model along with Caffe , which is a framework in deep learning that is used for efficient and expressive CNN training.

ii. Literature Survey

Skin disease recognition and observing is a major challenge looked by the medical industry. Because of expanding contamination and utilization of lousy nourishment, the tally of patients experiencing skin related issues is expanding at a quicker rate. Well-being isn't the main concern, however unfortunate skin hurts our certainty. Customary and appropriate skin checking is a significant advance towards early discovery of any destructive or starting changes in skin that may bring about skin disease. Machine learning methods can add to the improvement of capable frameworks which can order various classes of skin illnesses. To identify skin maladies, first, it is required to separate the skin and non-skin. In this paper, five diverse machine learning algorithms have been chosen and executed on skin infection data set to anticipate the exact class of skin disease. Out of a few machine learning algorithms, we have worked on Random forest, naive bayes, logistic regression, kernel SVM and CNN.

A similar examination dependent on confusion matrix parameters and training accuracy has been performed and delineated utilizing graphs. It is discovered that CNN is giving best training precision for the right expectation of skin diseases among all selected. Skin disease recognition and observing is a major challenge looked by the medical industry. Because of expanding contamination and utilization of lousy nourishment, the tally of patients experiencing skin related issues is expanding at a quicker rate. Well-being isn't the main concern, however unfortunate skin hurts our certainty. Customary and appropriate skin checking is a significant advance towards early discovery of any destructive or starting changes in skin that may bring about skin disease. Machine learning methods can add to the improvement of capable frameworks which can order various classes of skin illnesses. To identify skin maladies, first, it is required to separate the skin and non-skin. In this paper, five diverse machine learning algorithms have been chosen and executed on skin infection data set to anticipate the exact class of skin disease. Out of a few machine learning algorithms, we have worked on Random forest, naive bayes, logistic regression, kernel SVM and CNN.

Various innovations are accessible for image and pattern-based discovery of different skin diseases. Machine learning is one of the areas which can play a massive role in operative and exact identification of different classes of skin diseases. Through image classification using machine learning, diseases may be classified. Image classification is a supervised learning issue in which a lot of objective classes is characterized and a model is trained to perceive the class. There exist many machine learning and deep learning algorithms which can distinguish and predict different categories of skin diseases based upon their classifications. This paper presents a comparative analysis of 5 different machine learning algorithms random forest, naive Bayes, logistic regression, kernel SVM and CNN. All these algorithms are implemented on three different types of skin diseases (acne, lichen planus and sjs ten) and perform classification based detection. Almost 3000 skin samples have been compiled for developing and validating the proposed framework. The training accuracy of these algorithms is compared and analyzed. The organization of our work is as follows. Section II explains a brief literature survey of skin problem and melanoma detection. Section III denotes overview of skin diseases and machine learning algorithms.

Ercal et al. [1] used an adaptive color metric from the RGB planes. It helps in discriminating the tumor and the background. Image segmentation is performed using a suitable coordinate transformation. Borders are drawn by extracting the tumor portion from the segmented image. This was an effective method to find tumors diagnosis. Demyanov et al. Machine Learning Algorithms based Skin Disease Detection Shuchi Bhadula, Sachin Sharma, Piyush Juyal, Chitransh Kulshrestha Machine Learning Algorithms based Skin Disease Detection 4045 Published By: Blue Eyes Intelligence Engineering & Sciences Publication Retrieval Number: B7686129219/2019©BEIESP DOI: 10.35940/ijitee.B7686.129219 used deep convolutional neural networks, image classification algorithms with data augmentation to successfully investigate automatic detection of dermoscopic patterns and skin lesion analysis.

Ganster et al. [3] developed a computer-based system for image analysis acquired through ELM. Basic segmentation algorithms with fusion strategy are used to get the binary mask of skin lesion. The malignancy of lesion is calculated based upon shape and radiometric features. The local and global parameters are also considered for better results. The system improves the early detection of malignant melanoma. Grana provided a novel mathematical approach to assess the lesion boundary. The approach considers luminance values along a direction normal to the contour at each point. Sigurdsson et al. classified skin lesion based on in vitro Raman spectroscopy. They used a nonlinear neural network classifier for their work. Unique bands in spectrum show explicit lipids and proteins which provides information to diagnose skin lesions. Aberg et al. uses electrical bio-impedance to assess skin cancers and lesions. Multi-frequency impedance spectra are used to separate skin cancer and benign nevi. Wong et al. proposed a novel iterative stochastic region-merging approach to segment skin lesion regions from the macroscopic images. In this approach initially, stochastic region merging is performed on a pixel level, and afterwards on a region level until convergence. Wighton et al. performed automated skin lesion diagnosis. A model based on supervised learning and MAP estimation are presented for the diagnosis.

iii. System design

a) System Architecture

Skin disease image databases for many diseases are available freely. However, some are fully or partially open source and others are commercially available. The input image can be of type dermoscopic or clinical based on the dataset used. Table I contains the information about the availability and details of various datasets. The widely used datasets are This dataset contains the training data

for the ISIC 2019 challenge, note that it already includes data from previous years (2018 and 2017).
The dataset for ISIC 2019 contains 25,331 images available for the classification of dermoscopic images among nine different diagnostic categories:

- Malignant Melanoma
- Melanocytic nevi
- Basal cell carcinoma
- Actinic keratosis
- Benign Melanoma
- Dermatofibroma
- Seborrhoeic keratosis

Image pre-processing is an important step and it is required because an image may contain many noises such as dermoscopic gel, air bubbles, and hairs. However, clinical images require more pre-processing as compared to dermoscopic because of parameters such as resolution, lightening condition, illumination, angle of image captured, size of skin area covered may vary and depends on the person who is capturing the image. These captured images could create problems in the subsequent stages. The skin hairs can be removed using different filters such as; median , average or Gaussian filter , morphological operations such as erosion and dilation, binary thresholding and software such as Dull Razor. For low contrast images; lesion or contrast enhancement algorithms are useful. The contrast enhancement with histogram equalization provides better visualization by uniform distribution of pixel intensity across the image and it is one of the most used techniques in literature. For salt and pepper kind of noise; a median or mean filter can give better noise removal results.

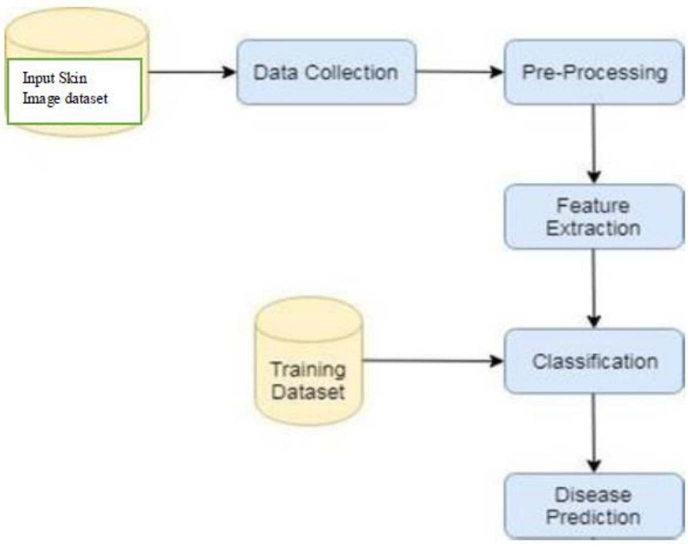

Fig. 1 Architecture of proposed Melanoma Prediction System

Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can take an input image, assign relevance (learnable weights and biases) to various aspects/objects in the image, and distinguish between them. When compared to other classification methods, the amount of pre-processing required by a ConvNet is significantly less. While basic approaches require hand-engineering of filters, ConvNets can learn these filters/characteristics with enough training.
The architecture of a ConvNet is inspired by the organization of the Visual Cortex and is akin to the connectivity pattern of Neurons in the Human Brain. Individual neurons can only respond to stimuli in a small area of the visual field called the Receptive Field. A number of similar fields can be stacked on top of each other to span the full visual field.

Working of CNN
A Convolutional Neural Network has three layers in general.
Input: If the image has 32 widths and 32 heights and three R, G, and B channels, it will retain the image's raw pixel([32x32x3]) values.
Convolution: It computes the output of those neurons that are related to input's local regions, such that each neuron calculates a dot product between weights and a small region in the input volume to which they are actually linked. If we opt to use 12 filters, for example, the volume will be [32x32x12].
Layer of ReLU: It's utilized to apply an elementwise activation function, such as max (0, x) thresholding at zero. It yields ([32x32x12]), which corresponds to a volume of the same size.
Pooling: This layer is used to perform a down-sampling operation along the spatial dimensions, resulting in a volume of [16x16x12].
Locally Connected: It is a normal neural network layer that accepts an input from the preceding layer, computes the class scores, and outputs a 1-Dimensional array with the same size as the number of classes. Next, we'll apply a Pooling layer to our Convolutional layer, so that we may construct a Pooled feature map from each feature map. The pooling layer's major goal is to ensure that our images exhibit spatial invariance. It also aids in reducing the size of our photos and preventing overfitting of our data. We'll then flatten all of our pooled photos into a single long vector or column containing all of these values, which we'll then feed into our artificial neural network. Finally, to get the final output, we'll feed it into the locally connected layer.

B. Dataflow Diagram

Figure 2 depicts DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system. Firstly we should define the process. Then we have created the list of all external entities i.e, Convolutional and Pooling Layers. And the skin disease is classified into malignant or benign.

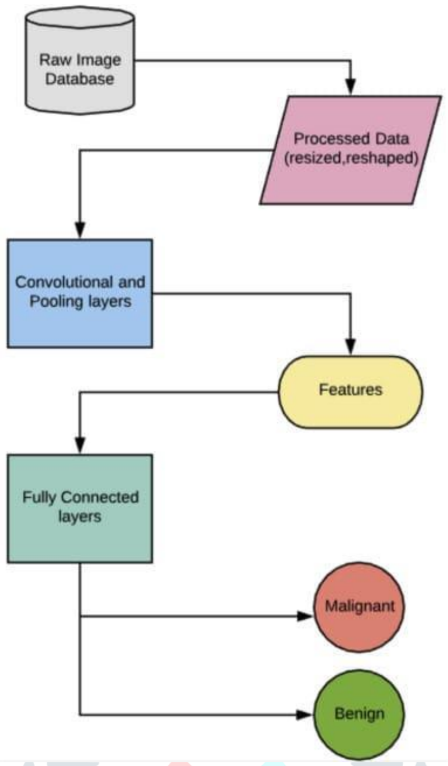

Fig. 2 Dataflow Diagram

A user uploads an image from dataset collection. The unwanted errors are removed from the dataset. Input data is split into train and test data. Then the skin cancer image is predicted as benign or malignant melanoma.

iv. RESULTS AND SCREENSHOTS

The figure 5 depicts the output screen of the proposed system. It is the home page in which we get login button. We use django framework for fron-end. Once we start the Flask server we get this page in our local host port.

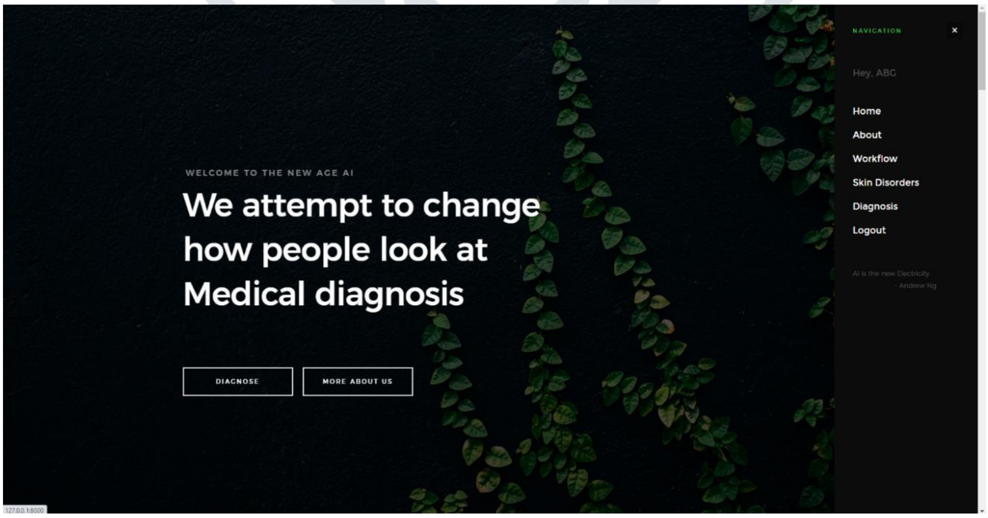

Fig. 5: Home Page

This is the home page. A user can enter the home page and see the list of options about the diagnosis. Home page is the main view for a user before his or her login.

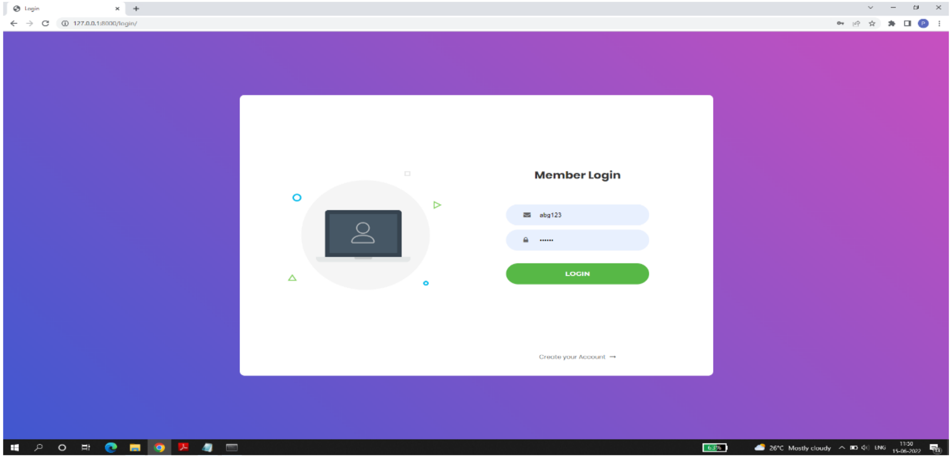

Fig. 6: Login Page

A user login to the system with his user name and password.A user is successfully logined only if his username and password matches.

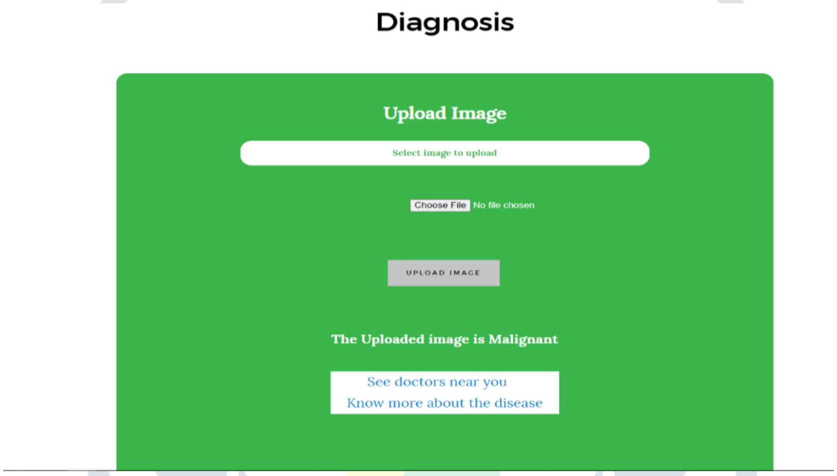

Fig. 7: Predicted result of the uploaded data image.

Figure 7 shows the Diagnosis page. Here we can see that the system displays the type of disease identified and also suggests the nearest doctors and depicts about the disease.

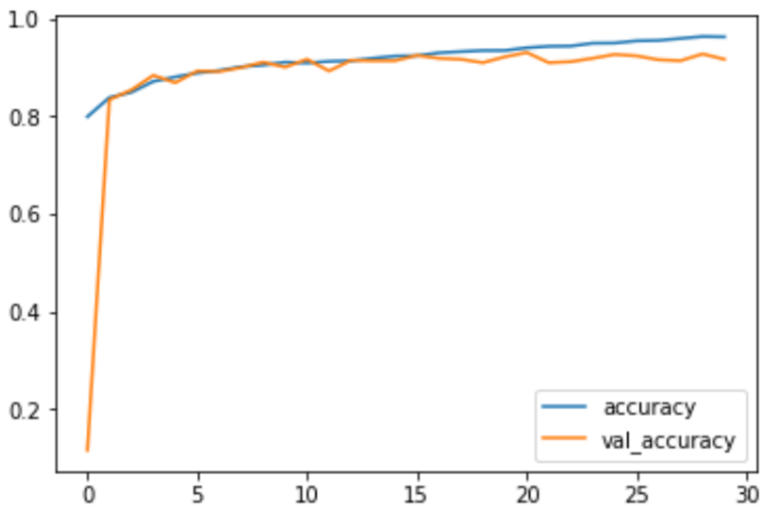

Fig. 8: Model Accuracy

Our model gives the training accuracy up to 92% and validation accuracy up to 90.5%.

V. CONCLUSION

This work performed experiments using CNN structure for the skin image diagnosis of three common skin diseases and had constructed a dataset consisting mainly of skin disease images. The results demonstrates that CNNs have the ability to recognize and classify skin diseases. Further, our experiments also showed that a reasonable network structure could improve the performance of the model. The performance of the current network structure is used for classification in some diseases, but the overall performance is yet to be improved. As a result, if people want to actually use this technique to check their skin health in their daily life, specialized improvements should be done. In our opinion, with the increasing amount of image data of various skin diseases and the continuous improvement of the network structure, CNN-based skin disease diagnosis algorithms will continue to improve in performance. Apart from CNN and Alex Net, other architecture may also be implemented to improve the accuracy of classification. The threshold for the confidence score of CNN was set to 0.5 in this analysis. However, the threshold can be adjusted based on user preference. For example, if it is more important to not miss cancerous legions than it is to misidentify benign legions as malignant, then the user must reduce the threshold to improve sensitivity at the expense of specificity. This means moving the red point on the curve towards the left. The proposed approach can be deployed in computer-aided detection systems to assist dermatologists to identify skin cancer. Moreover, it can be implemented in smartphones to be applied on skin lesion photographs taken by patients. This allows for early detection of cancer, especially for those without access to doctors. Early diagnosis can significantly facilitate the treatment and improve the survival chance.

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