SKIN DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING ALGORITHMS

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Abstract: Melanoma is the most serious type of skin cancer, with a very low chance of survival, out of the three primary types: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma. Melanoma early identification may increase survival rates. The four fundamental parts of skin cancer detection technology are, in general, image preprocessing, which includes hair removal, de-noise, sharpening, and resizing of the skin picture, segmentation, which is used to segment out the region of interest from the given image, and resizing. Segmentation can be done in a variety of ways. K-means, threshold in histograms, etc., as well as feature extraction from the segmented picture and classification of the image from the features set retrieved from segmented image, are some examples of segmentation techniques that are frequently employed. For this, a variety of classification techniques can be applied. Recent advances in skin cancer detection technology classify data using machine learning and deep learning-based algorithms. Support vector machine (SVM), feed forward artificial neural network, and deep convolutional neural network are the most widely used classification techniques. This essay offers research and analysis on skin cancer detection, including a thorough review of the literature on the subject and a precise comparison of cutting-edge algorithms.

Index Terms: - : Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), And Melanoma

I Introduction

Nowadays, skin cancer is quite common. According to the American Cancer Society, Inc.'s Surveillance Research, there will be 100,350 new instances of melanoma skin cancer in 2020, with 60,350 of those cases being male and 43,070 being female According to estimates, 6,850 people will die from skin cancer this year, 3,450 of whom will be female and 8,030 men [1]. Typically, there are three forms of skin cancer Basal Cell Carcinoma (BCC): It develops from the base of the epidermis in areas exposed to sunlight over an extended period of time. Skin cancer grows slowly, making diagnosis fairly simple. Visualize a basal cell carcinoma as a small, shiny, smooth, waxy or light mass that is red and covered in rough, dry, or scaly areas. (2). The skin cancer squamous cell carcinoma (SCC) is another kind. It similarly grows at the skin's outer layer as a basal cell carcinoma. Early on, it spread to other parts of the skin. The fundamental distinction between BCC and SCC is this. Small, smooth lumps that are genuine or brown can be visualised as Squamous Cell Carcinoma. Malignant melanoma (MM) is the third and most serious kind of skin cancer. The melanocytes are where it occurs. The shape, borders, and colour of melanoma skin cancer are obviously asymmetrical and odd.

2.Releated work

Manual diagnosis of skin diseases by visiting and consulting dermatologists is time consuming. Most rural areas do not have this option. These rural people need to travel to a nearby city for advice and diagnosis. This takes a lot of human effort. Not to mention, it costs a lot just to see your doctor. This also includes human contact, which is an unnecessary evil in this pandemic crisis. Few diseases are contagious. In the existing system, body contact is unavoidable. The existing computer-aided diagnosis involves identifying burns and injuries as skin diseases. The accuracy of these methods is not as good as needed. Thus, there is a need to develop a computer-aided system that automatically diagnoses the skin disease problem and differentiates skin diseaseswith other skin issues. Quan Gan et.al [3] used image colour and Texture feature for the recognition of skin disease. Median filtering was used to pre-process the images. Denoise images are rotated to get the segments of the images. GLCM tool was used to extract text features and finally used SVM for classification of skin diseases herpes, dermatitis, and psoriasis. Md Nafiul Alam et al [4]., "Automatic Detection and Severity Measurement of Eczema Using Image Processing", suggested an automatic eczema detection and severity measurement model using image processing and computer algorithm. The system identified and determine the severity of eczema by allowing patients to input an image of the affected skin area. This system used image segmentation, feature extraction, and statistical classification to recognize and differentiate between mild and severe eczema. Once the eczema type was identified, a severity index was assigned to that image. Later Researches used Deep learning techniques for classifying the skin diseases. Parvathaneni Naga Srinivasu et.al [5] used deep learning based MobileNet V2 and Long Short Term Memory for classifying skin diseases. A grey level co-occurrence matrix was used to estimate the progress of disease growth. The system has achieved an accuracy of 85% on the HAM10000 skin disease dataset. S.Malliga et.al [6], used the CNN algorithm for training and classifying all kind of clinical images. They have taken three types of skin diseases. They are Melanoma, Nevus, Seborrheic keratosis and achieved an accuracy of 71%.Nazia Hameed et.al [7] designed, implemented and tested to classify skin lesion image into one of five categories, i.e. healthy, acne, eczema, benign, or malignant melanoma using AlexNET, a pre-trained CNN model to extract the features. SVM classifier was used for classification and the overall accuracy achieved is 86.21%.

3 Implementation Study

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3.1 Proposed Methodology

integrating the LSTM with the MobileNet V2 is explained with an architecture diagram. MobileNet V2 is used in classifying the type of skin disease, and LSTM is used to enhance the performance of the model by maintaining the state information of the features that it comes across in the previous generation of the image classification. MobileNet [68] architecture is equally efficient with a minimum number of features, such as Palmprint Recognition [17]. The architecture of MobileNet is depth-wise [69]. The fundamental structure is based on different abstraction layers, a component of different convolutions that appear to be the quantized configuration that assesses a regular problem complexity in-depth. The complexity of 1 × 1 is called point-wise complexity. Platforms to make in-depth are designed to have abstraction layers with structures in-depth and point through a standard, rectified linear unit (ReLU). The resolution multiplier variable ω is added to minimize the dimensionality of the input image and each layer’s internal representation with the same variable.

3.2 Proposed Model

The MobileNet V2 architecture comprises the residual layer with a stride of 1 and the downsizing layer with a stride of 2 alongside the ReLu component. Both residual and downsizing layer encompass 3 sub-layers each.

- The 1 × 1 convolution with the ReLu6 is the first layer.
- Depth-Wise Convolution is the second layer in the architecture. The Depth-Wise layer adds a single convolutional layer that performs a lightweight filtering process.
- 1 × 1 convolution layer without non-linearity is the third layer in the proposed architecture. In the third layer, the ReLu6 component is used in the output domain.
- ReLu6 is used to ensure the robustness used in low-precision situations and improvise the randomness of the model.
- All the layers have the same quantity of output channels within that overall sequence.
- The filter of size 3 × 3 is common for contemporary architecture models, and dropout and batch normalization are used during the training phase.
- There is a residual component to support the gradient flow across the network through batch processing and ReLu6 as the activation component.

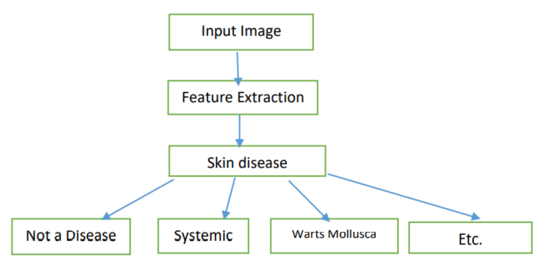

Fig1: System Architecture

4. Methodology

MODULES:

1. dataset

A dataset of seven skin diseases was used in this study that includes Warts Mollusca, Systemic Disease, Seborrheic Keratosis, Nevus, Bullous, Actinic Keratosis, Acne and Rosacea. This dataset has over 7000 dermatoscopic images. The Dataset was expanded by adding new images (750), indicating skin burns and skin cuts. Existing systems have identified skin burns and skin cuts also as skin diseases. To Overcome this problem, the images representing cuts and burns were collected and added to the dataset. A random (rand) function is applied to split the data into the training data (5900) and validation data (1930).

2. Train Model

In this Module we train the data with cnnn and mobile v2 net with 97% accuracy

3. prediction

Proposed system is a web application that acts as a preliminary step for the diagnosis of a disease where a person uploads the image of the affected area of the skin and then gets to know the type of the disease and few suggestions are given regarding the disease using this application.The proposed framework involves a deep learning-based method to detect skin diseases. This system will utilize computational techniques to analyse, process, and relegate the image data predicated on various features of the images.The Architecture of skin disease detection and classification system

5 Results and Evolution Metrices

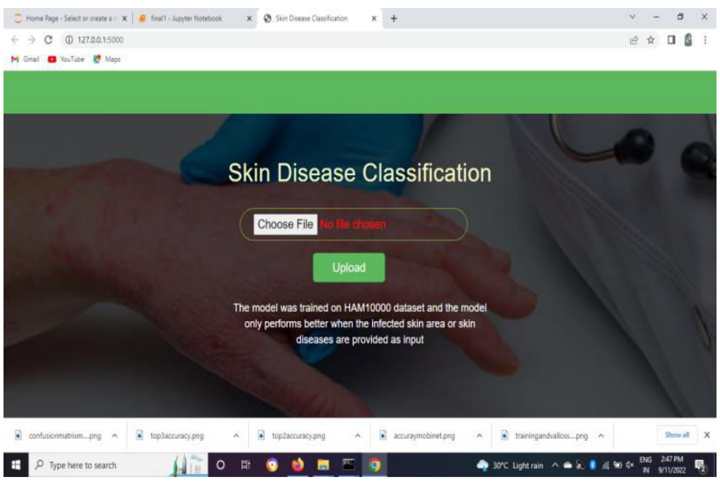

Fig 2: Home Page

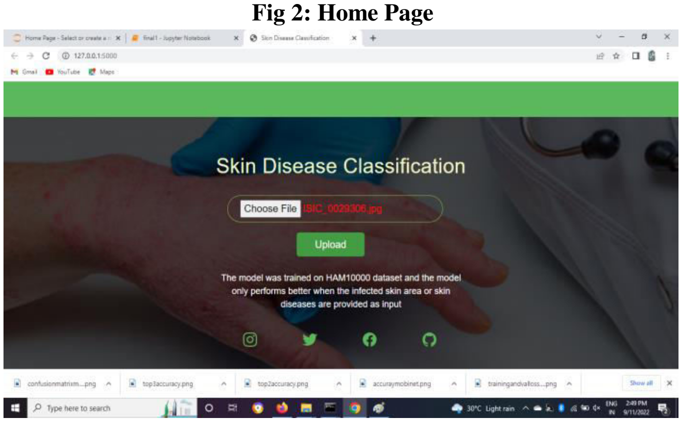

Fig 3: upload Page

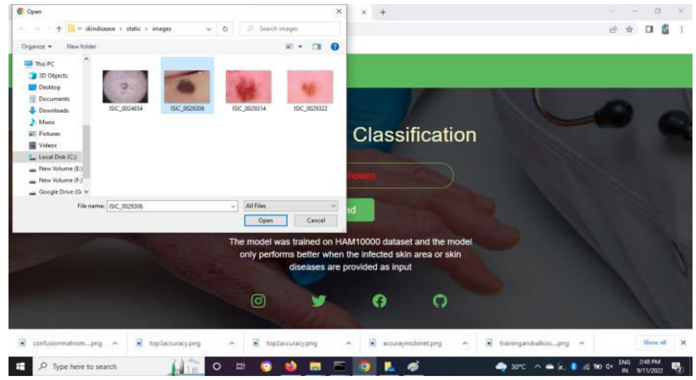

Fig 4: Input image

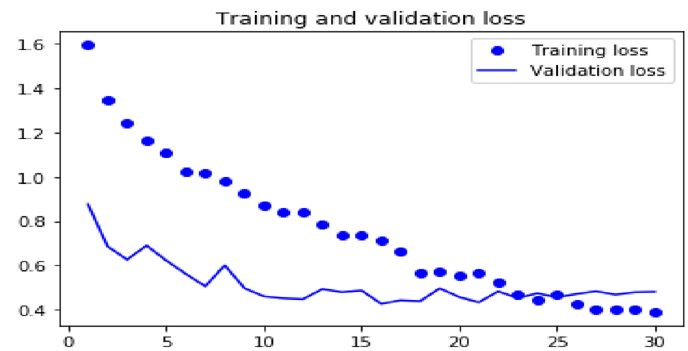

Fig 5: tranning and validation loss using proposed system

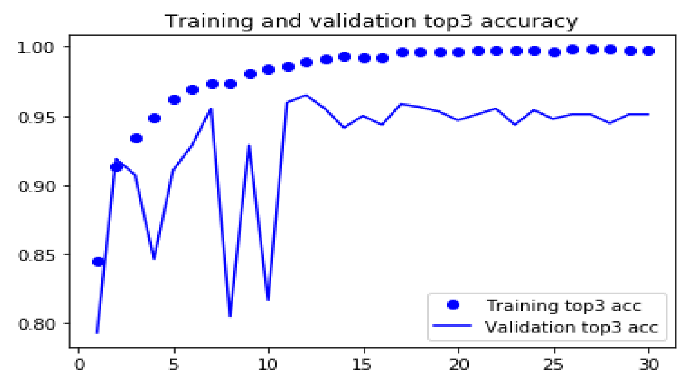

Fig 6:tranning and validation accuracy using top 3

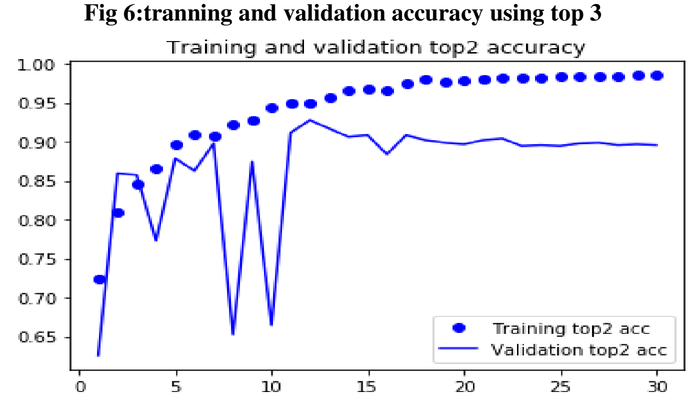

Fig 7: tranning and validation accuracy using top 2

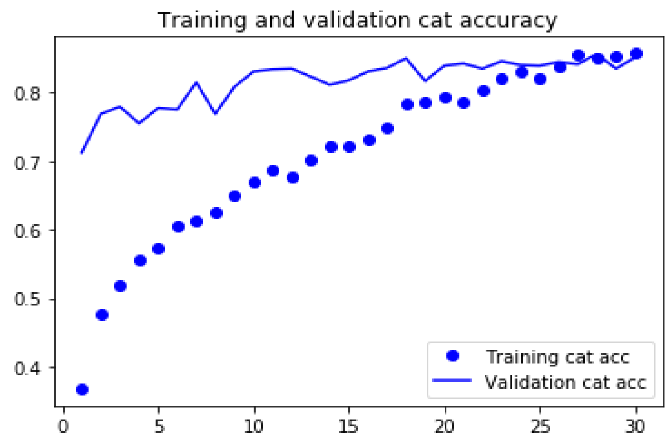

Fig 7: tranning and validation accuracy using cat model

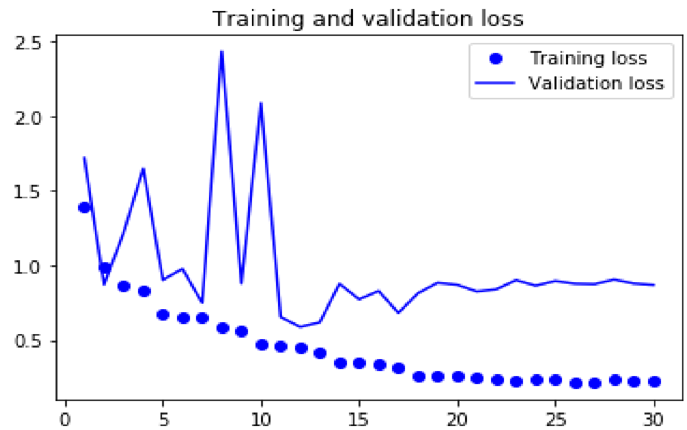

Fig 8: tranning and validation loss using cat model

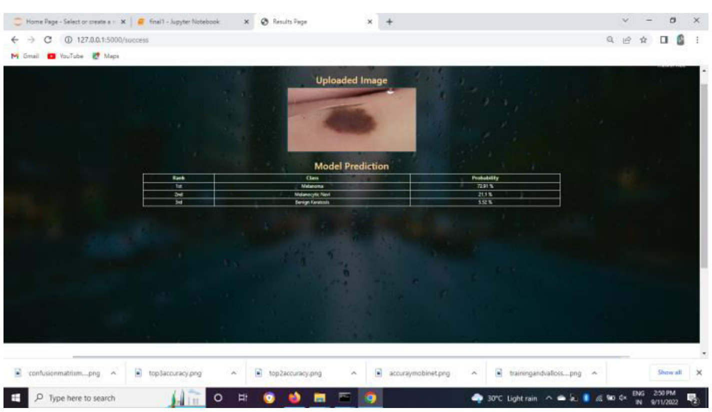

Fig 9:predecited diseases with ratio

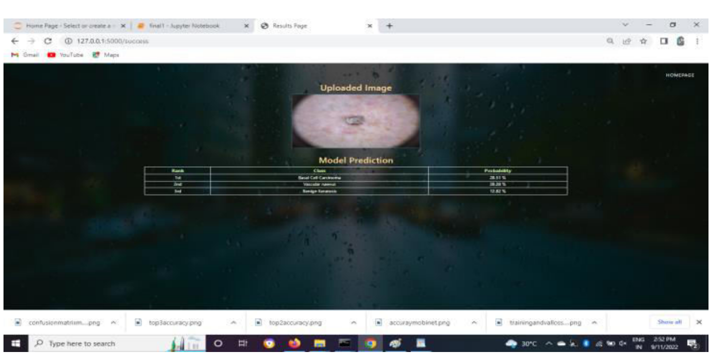

Fig 10:predecited disease with ratio

6 Conclusion

Early detection of melanoma skin cancer accelerates the time of dermatologists and improves diagnosis performance. This paper is mainly focused on the current and traditional technologies of melanoma skin cancer detection in an early stage. From the study of literature, it is concluded that various methods are employed for detecting melanoma skin cancer are image pre-processing, post-processing, image segmentation, Feature extraction, and classification algorithms

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