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Identifying Rosacea Skin Disease and Prescribing Medication to Treat

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ABSTRACT—

Rosacea is a common skin condition that causes blushing or flushing and visible blood vessels in your face. It may also produce small, pus-filled bumps. These signs and symptoms may flare up for weeks to months and then go away for a while. Rosacea can be mistaken for acne, other skin problems or natural ruddiness. This project proposes a skin disease detection method based on image processing techniques. This method is mobile based and hence very accessible even in remote areas and it is completely noninvasive to patient's skin. The patient provides an image of the infected area of the skin as an input to the prototype. Image processing techniques are performed on this image and the detected disease is displayed at the output. The proposed system is highly beneficial in rural areas where access to dermatologists is limited. The proposed solution in this project is a prototype with a database of six common skin diseases, using which a patient can self-diagnose and get some prior knowledge of their skin disease before consulting a dermatologist. This prototype can be used in mobile hospitals in rural areas. These days everybody is connected through mobile phones. Thus, this prototype can be accessed even in the most remote locations in the country. The proposed prototype provides a noninvasive method of skin disease detection where the patient provides a picture of the infected area as an input to the prototype and any further analysis is done on this input image. No pricking or prodding of the skin is required.

I. INTRODUCTION

Skin disease is an abnormal condition of the skin. Skin plays an important role in protecting the body from harmful bacterial, fungal and parasitic infections. Hence the correct diagnosis of skin disease is crucial. Various factors causing skin diseases and affecting skin disorder pattern are genetics, occupation, nutrition, habits, etc. Geographical factors like season and climate also affect. In developing countries, overcrowding and poor hygiene are responsible for spreading of skin diseases. The pattern of skin diseases varies from country to country. Moreover, remote areas are severely affected. The prevalence of skin diseases in a tertiary care center of Garhwali hills, North India was recorded in 2014 and it was found to vary from6.3% to 11.2%. Of the total population, 16.7% were affected by acne, 3.4% by psoriasis, 3.4% by urticaria, 3.6% by melasma and 3.3% by vitiligo. In this project, image processing is used to detect skin diseases in humans. This paper describes the current methods employed for detecting skin diseases, proposes a digital method to detect skin diseases and states the benefits of this method.

This paper includes a detailed description of the transforms used to implement the proposed method. The transforms implemented are compared on accuracy parameter.

II. EXISTING SYSTEM

There are various ways of diagnosing skin diseases through imaging. The three most common kinds of skin image data are: histopathological, dermoscopic, and clinical images. A few existing studies on skin disease diagnosis using traditional machine learning algorithms have been done using histopathological images for cancerous skin conditions. Most of the work on skin diseases has been done using dermoscopic images, primarily cancerous skin lesions. However, only a few studies have been done on clinical images of common and chronic skin conditions such as acne, rosacea, eczema, lupus, seborrheic dermatitis, and a few other conditions.

Below table 1 shows the list of accessible skin disease datasets where the dataset name along with the disease categories, imaging modality, volume, classes, rosacea images, accessibility and country.

Table 1: list of accessible skin disease

Index	Dataset Name	Disease Categories/ Names	Imaging modality	Volume	Classes	Rosacea images	Accessibility	Country/ Region
1	7-point criteria (aka derm7pt) [1] 2019	Melanoma and non-Melanoma skin le-sions	Clinical and Dermo- scopic	>2000	~20	0	Public	Canada, Italy
2	Asan and Hallym Dataset [2] 2018	12 types of Skin Can-cerous lesions	Dermoscopic	17.125	12	0	Partially	South Korea
3	Dermatology ATLAS [3] 1999	All kinds of skin diseases (including rosacea)	Clinical	~11,000	~550	38	Public	Brazil
4	DanDerm [4] 1995	All kinds of skin diseases (including rosacea)	Clinical	>3,000	~100	17	Public	Denmark
5	DermIS [5]	All kinds of skin diseases (including rosacea)	Clinical	~7,000	~700	49	Public	Germany
6	Dermnet Skin Disease Atlas [6]1998	All kinds of skin diseases (including rosacea)	Miscellaneous	~23,000	N/A	0	Public	United States
7	Dermofit Image Library (aka Edinburgh Dataset) [7]	Cancerous skin lesions	Dermoscopic	1,300	10	O	Under License Agreement	Scotland.UK
8	DermNetNZ [7] 2016	All kinds of skin diseases (including rosacea)	Clinical and Dermo- scopic	>25,000	>2,500	~50	Public	New Zealand
9	Dermatoweb. net [8] 2002	All kinds of skin diseases (including rosacea)	Clinical and Dermo- scopic	>7,300	O	45	Public	Spain
10	HAM10000 [9] 2018	Pigmented malignant and benign skin le-sions	Dermoscopic	10,015	7	0	Public	Austria
11	Hellenic Derma-tological Atlas [10] 2011	Common disease categories (including rosacea)	Miscellancous	2,663	N/A	9	Public	Greece
12	ISIC [11] 2016	Melanoma, seborrheic keratosis, benign nevi	Dermoscopic	>33,000	N/A	0	Public	Miscellaneou s
13	MED- NODE [12] 2015	Melanoma and be-nign nevi	Microscopic	170	2	0	Public	Netherlands
14	MoleMap [13] 2003	Malignant and benign lesions	Clinical and Dermo- scopic	>32,000	N/A	0	NA	New Zealand
15	PH2 Dataset [14] 2013	common nevi, atypical nevi, and melanomas	Dermoscopic	200 (80+80+40)	3	0	Public	Portugal

Below table 2 shows the studies that is based on the data data augmentation where skin disease name along with the dataset source, methodology and the best results and performance.

Table 2 : studies based on data augmentation and transfer learning

Author/ Index/ Year	Skin Disease Names	Dataset Name/ Source	Dataset volume in total/per class	Methodology	Best results and Perfor- mance measures
Esteva et al. [15]. 2017	2,032 skin diseases for Training the model and Tested for malignant melanomas benign nevi, malignant basal	ISIC Der- moscopic Archive, Edinburgh Dermofis Library and data from the Stanford Hospital	1,29,450 images 2,032 disease classes for Training and 7 types of cancerous lesion classes for Testing.	Pre-trained on ImageNet dataset Transfer Learning, Data Augmen-tation. InceptionNet-v3.	Accuracy -93.33% Confusion matrix Saliency Maps, Sensitivity specificity curves.
Binol et al. (Ros- Net) [16]. 2019	Rosacea lesions	Ohio State University (OSU) Division of Dermatol ogy (using DSLR camera)	41 facial images The size of each image is 4608x3072	Pre-trained on ImageNet DCNNs. Image classification problem for rosacea and non-rosacea	Dice co-efficient: 92.9% False positive rate. MAT-LAB
MAA [17]. 2019	Seven skin diseases Melanoma (1113), Melanocytic nevus (6705). Basal cell carcinoma (514).	ISIC 2018 Melanoma Detection Challenege and Dataset	Training set - 10015 skin lesion images dataset = 193 skin lesion images	Data Augmentation Representa- tion learning Pre-trained on Im-ageNet	Validation score: 76% (by PNASNet-5-Large)
W.Sae- Lim et al. (18). 2019	Seven skin diseases Can-cerous	Human Against Machine 10,000 (HAM10,000)	10,015 images	Pre-trained on ImageNet Modified Mobile-Net with Data Augmentation	Accuracy: 83.23% Speci- ficity: 87% Sensitivity: 85% FI score:82%
Kemal et al. [19]. 2020	Seven skin diseases: Can-cerous	HAM10,000	10,015 images	A CNN architecture + One verses all which 1,243,463 parameters in total Data Augmentation	Average precision: 92.90%
Hosny KM et al [20]. 2019	Melanoma skin lesions.	(i)2017 ISIC challenge dataset, (ii)MED. NODE. (iii)DermIS+ DermQuest	2000.170.206	Data Augmentation Pre-trained on ImageNet for transfer learning on AlexNet	Average Accuracy: 95.91% 96.68%.97.07%

A. Disadvantages of Existing System:

1. Accuracy is less than 90%.
2. Transfer learning and fine-tuning i.e. adapting a neural network model, which has beenpre-trained on another much larger dataset, to classify rosacea.
3. Generative Adversarial Networks (GANs) i.e. generating high quality synthetic faces with rosacea.
4. Meta-Learning and Few-Shot classification i.e. learning faster with fewer examples.

III. PROPOSED SYSTEM

In this project, image processing is used to detect skin diseases in humans. This project describes the current methods employed for detecting skin diseases, proposes a digital method to detect skin diseases and states the benefits of this method. This project also includes a detailed description of the transforms used to implement the proposed method. The transforms implemented are compared on accuracy parameter.

This model is can help to improve the detection performance and cover the limitations pointed out in the previous research. It will consume less time to train the model and prediction in real time. It supports with low features from data.

IV. SYSTEM ARCHITECTURE

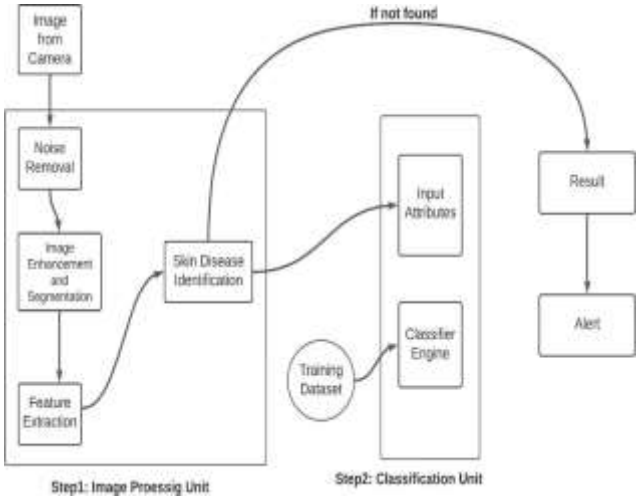


Fig 1: System Architecture

In this system Architecture we are creating application with two stages, First stage is image processing unit and second stage is classification unit. In the first unit we are capturing the image using camera and passing to our system, System will remove noise, segment the image and extract the features using DCT and passed to second step, In second step we are building the mobilenet model to classify the type of skin disease. The architecture of the system shown in Fig.1 reflects the way it is thought about in terms of its structure, functions, and relationships.

V. METHODOLOGY

The project "Identifying Rosacea Skin disease and prescribing medication to treat" aims to develop a methodology for identifying the skin disease and prescribing the medication for the treatment. The methodology involves several key steps. Firstly, a literature review is conducted to gather existing knowledge and identify research gaps. Next, a suitable dataset of skin disease is acquired and preprocessed to remove noise and normalize intensities. Relevant features associated with skin disease are then extracted from the preprocessed images, and image data generator technique is applied to select the most informative features. A predictive model, such as a machine learning or deep learning algorithm, is developed and trained using the extracted features. The model's performance is evaluated using appropriate metrics and validated on independent datasets. The results are interpreted, visualized, and ethical considerations are considered throughout the project. Overall, this methodology provides a way to identify the various skin diseases and the predict the name of the disease along with its medication.

VI. IMPLEMENTATION

To implement the model used python 3.6 with built in packages CNN MobileNet in Windows platform. The specification of processor Intel i5, 2.4 GHz and 8GB RAM.

CNN

Below fig 2 shows flow diagram of CNN model where we upload dataset along with the label. Then the image pre Processing is done where features are extracted using the CNN Mobile Net. Now, train the CNN model and input the test images. Then, classify the test images and finally show the output result.

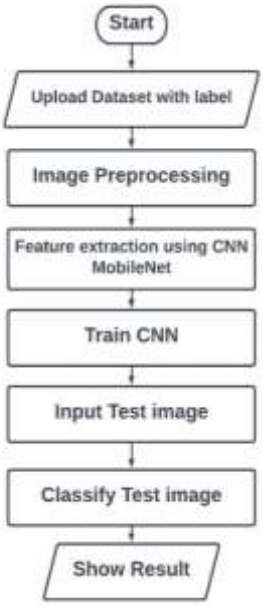
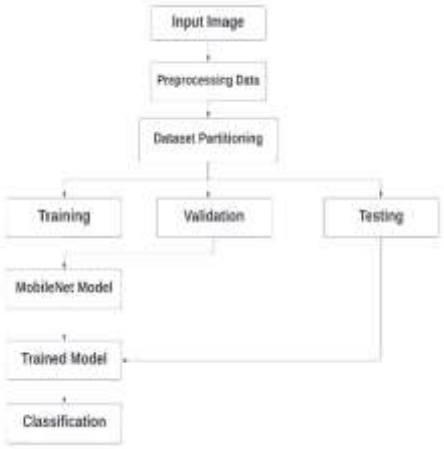


Fig 2: Flowchart of CNN

PREPROCESSING

Below fig 3 shows the flowchart diagram for the preprocessing of the image. First, input the image and preprocess the data. Then, the dataset is partitioned into three models i.e. training, testing and validation. For the training and validation model we use the MobileNet model. The testing is done from the trained model and finally classification is done for the image.

Fig 3: Flowchart of Preprocessing



Pseudo Code for the MOBILENET

// Input: Trained model and input images

// Output: Disease detection

Begin

Step 1: Define the input shape of the image

Step 2: Initiate the mobile net architecture using **tf.keras.applications.mobilenet.MobileNet()** function.

Step 3: Add a new classification layer to the top of the model using the **tf.keras.layers** API.

Step4: Compile the model using the **tf.keras.Model.compile()** function

Step 5: Train the model on a dataset of images using the **tf.keras.Model.fit()** function

Step 6: Evaluate the performance of the model on a test dataset using the **tf.keras.Model.evaluate()** function

Step 7: Use the model to make predictions on new images using the **tf.keras.Model.predict()** function

Return detected disease/no disease

VII. RESULTS AND DISCUSSION

The Analysis Phase is where you break down the deliverables in the high-level Project Charter into the more detailed business requirements. The Analysis Phase is also the part of the project where you identify the overall direction that the project will take through the creation of the project strategy documents. Gathering requirements is the main attraction of the Analysis Phase. The process of gathering requirements is usually more than simply asking the users what they need and writing their answers down.

The below fig 4 shows the line graph for epochs versus loss prediction for the graph for training and validation loss.

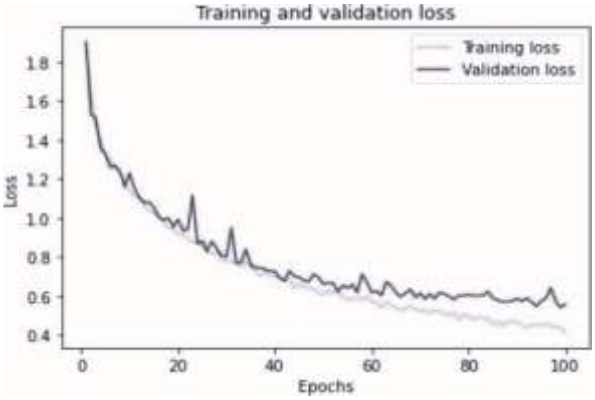


Fig 4: Training and validation loss

Below Fig 5 shows the graph for the evaluation metrics and the values along with the category accuracy1, category accuracy 2, top 2 aauracy and top 3 accuracy.

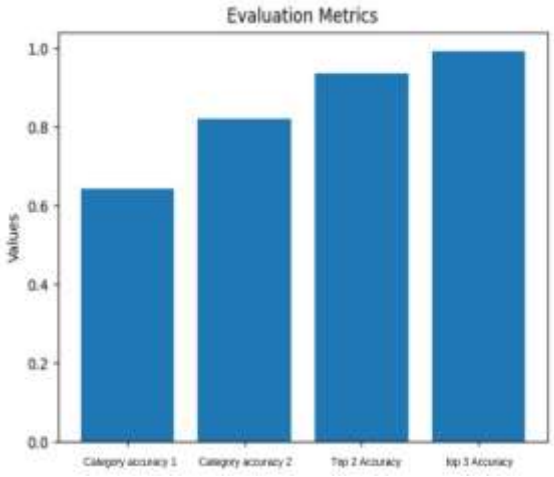


Fig 5: Graph for the evaluation metrics

Below Fig 6 shows the home page where all the buttons for importing the image, displaying and predicting the disease is shown.

Fig 6: Home page of the system

Below Fig 7 shows the popup window for selecting the images from the trained images or through mobile & we train the model with real pic of web.

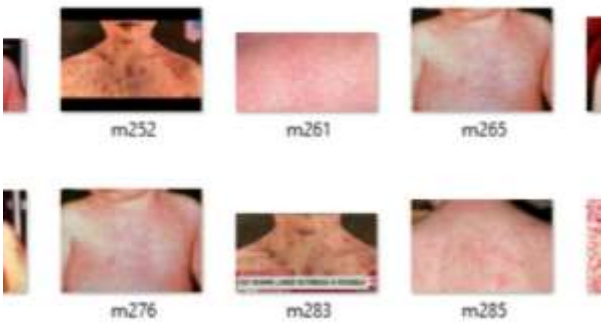


Fig: 7 Trained datasets

Below Fig. 8 shows the skin disease selected from the trained dataset and to build the models.

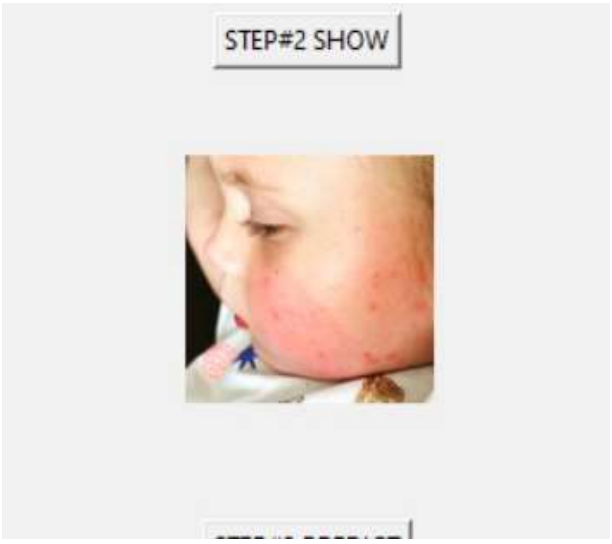


Fig 8: Display the image select

Below Fig.9 shows the test case of model. The final output with the predicted skin disease and its medication for the treatment.

Fig 9: Final output

Below Fig.10 shows the final output when the skin disease is not found in the trained dataset so it displays the result as no disease.

Fig 10: Final output

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