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Skin Disease Scanner

Ms.Minnuja Shelly
Assistant Professor of Computer Science and Engineering
Universal Engineering College
Kerala, India
Sakthi1992@gmail.com

Unnimaya V.U
Department of Computer Science and Engineering
Universal Engineering College
Kerala, India
unnimayaunni592@gmail.com

Muhamed Muhzin V.I
Department of Computer Science and Engineering
Universal Engineering College
Kerala, India
Muhzin1113@gmail.com

Arun Gokul K
Department of Computer Science and Engineering
Universal Engineering College
Kerala, India
Arungokul36@gmail.com

Vaisaghan K.C
Department of Computer Science and Engineering
Universal Engineering College
Kerala, India
vaisaghan6@gmail.com

Abstract— ***This review explores the study of skin conditions using image scanners. Skin conditions can be brought on by viruses, germs, allergies, or fungi, among other things. In the discipline of dermatology, it is frequently necessary to do thorough tests in order to determine the patient's face's skin condition. This made it feasible to scan for skin conditions and rapidly and precisely diagnose them. This study uses skin photos to depict the effects of illness before pre-processing them. Following feature extraction and disease prediction of the picture using CNN based model, and presentation of the diagnosis report as a consequence. The user is then presented with the findings, which include the kind of ailment, its symptoms, its causes, and any medications or goods that include prescribed ingredients. Our suggested approach is meant to be easy to use and doesn't call for pricey technology beyond a camera or a cell phone.***

Keywords: Dermatology ;Image pre processing;CNN.

I. INTRODUCTION

Millions of individuals throughout the world suffer from common skin conditions. Dermatologists are specialists in identifying and treating skin conditions, but not everyone may have access to their services. This issue can be solved by creating a skin disease scanner, a device that examines photos of skin lesions and offers potential diagnosis using computer vision algorithms and machine learning methods.

Skin conditions tend to be persistent, contagious, and occasionally carcinogenic. To prevent the onset and spread of skin disorders, early diagnosis is therefore necessary. A skin condition requires more time for diagnosis and treatment, and the patient incurs both financial and physical costs. The majority of regular people often are not aware of the kind and stage of a skin illness. Some skin conditions don't manifest symptoms for several months, which allows the illness to grow and spread. This is a result of the general public's ignorance about medicine. Sometimes, a dermatologist (a physician who specializes in skin conditions) may also have trouble diagnosing the condition and may need pricey laboratory testing to accurately determine the kind and stage of the skin condition. The development of medical technology based on photonics and lasers has made it possible to identify skin illnesses considerably more rapidly and precisely. Nonetheless, the expense of such a diagnostic is still prohibitive and high. As a result, we suggest using image processing to identify skin problems. Even in the healthcare industry, artificial intelligence is replacing automation in all sectors of application. These illnesses have caused worry in recent years because of their abrupt onset and complexity, which has elevated life risks.

Our proposed approach is simple, fast and does no require expensive equipment's other than a camera and a computer. One of the most efficient and reasonably priced methods for identifying and categorizing skin problems is digital dermoscopy. Typically, an automated system for analyzing medical pictures goes through three stages: (1) Pre-processing

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of the image, (2) feature extraction and selection, and (3) Prediction. The right improvement is crucial since it impacts how precisely the succeeding procedures are carried out. It is quite simple to implement supervised enhancement by changing its settings to account for different lesion kinds, sizes, and colors as well as different skin types and textures. Skin disease types can be anticipated using the newest cutting-edge technology, such as deep learning and machine learning algorithms. Several different analyses and forecasts have been made. The findings' correctness is improvised. The skin conditions are forecasted using KNN, FCN, and Random Forest. The prediction's accuracy is skewed. The accuracy may or may not be correct at any given time. In this study, we review pertinent literature before summarizing our most current suggestion.

II. PREVIOUS WORK

Implementation of The Introduction of skin Disease Based on Augment reality[1] In this application is for introducing and informing various types of skin disease with the Convolutional Neural Network(CNN) algorithm and implementation for introducing the skin disease using augmented reality. This application is created using java programming language and is implemented on smart phones with the Android Operating System. The Convolutional Neural Network is used as deep artificial neural network that is often used to classify images. CNN working by reducing image. Smaller size so that it is easily processed and carried out to next stage where average value of the filter taken from previous are carried out to next stage where average value of the filter is taken from previous convolution process and continued with the convolutional process again to produce a fully connected layer on the output. Advantage :as the model itself provide information about each skin disease by showing information in the form of writing contained can detect skin disease.The main limitation of this model is ,had least accuracy. Light intensity of camera distance from the object may effect the accuracy of disease .only few disease were tested.

Skin Lesion Segmentation Based on Deep Learning[2]This paper proposed the method in deep learning Mask R-CNN to segment skin disease and introduced K-means Clustering algorithm in the preprocessing of the data set. This method can ensure accurate labeling of the data set itself, while accurately segmentation the skin pathology area. Our frame work is based on Mask R-CNN includes a two stage procedure with one process Network(RPN).The second stage is made up of fast R-CNN classifier and binary mask prediction branch. The process head is used to preprocess head is used to preprocess data set. In the Section we introduce our proposed segmentation framework. Then we will introduce the clustering algorithm K-means to process the data set. Preprocess stage use K-means to preprocess the data set to make label images. Proposal generate stage input image to the data set to make label image, the image will processed by RPN and get many candidate boxes. Final select stage. The candidate frame is screened by NMS and then process by remaining mask R-CNN to obtain the result nap. Its Advantage is Development of method for automated diagnosis of skin lesion could be for the humanity and could provide low cost medical help. Disadvantage of this system is the accuracy of Melanoma skin disease will be lower. The reason for this problem is that the position of the candidate frame for the region is not very accurate resulting in a slightly lower segmentation accuracy.

Deep Semantic Segmentation and Multiclass Skin Lesion Classification Based on Convolutional Neural Network[3]In this article this method is proposed for segmentation and classification of skin lesion at an early stage. The proposed method contain three phases. In phase 1 different types of the skin lesions are classified using YOLOv2 model in which Open Neural Network (ONN)and squeeze net model are used as backbone. In phase 2 13 layer 3D semantic segmentation modes in proposed segmentation model, pixel classification layer is used for the computing the overlap region between the segmented and grounded through the image. Later in phase 3 extract deep feature using Renet-18 modulated optimized feature are selected using an colony optimization (ACO)method. The methodology is proposed deep learning approach for skin lesion data set where ONNA and Squeeze Net Model are used for skin lesion data set YOLOv1 model to localize the skin lesion more accurately. The semantic segmentation model is trained based on the grounded truth annotation to perform pixel classification. Later deep feature are extra using Resnet mode. The optimized feature are select using ACO which passed to the O-SVM and O-NB classifier. Advantage is Hybrid classification approach provides good classification results compared to react existing work. Disadvantage is difficult and expensive to implemented these classifier.

Studies on Different CNN Algorithm for Face Skin Disease Classification Based on Clinical Images[4],This paper studied different CNN algorithm for face skin disease classification based on the clinical images, here performed studies using an independent data set of the same disease types, but for other body parts to perform transfer learning our models .Comparing the performance the model that used transfer learning our models. The model that used transfer learning a higher avg performs and recall for almost all structure. A CNN is a type of neural network.IT generally consist of an input layer, many hidden convolutional layer and an output layer using the structure the model can include a layer no of parameters and obtain some usable properties, for a image related tasks. Advantage, CNN model has the ability to recognize facial skin disease Disadvantage, for this technique to check their face skin health their daily, specialized

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improvement should be developed on order to improve performance.

An Enhanced Model for Skin Disease Detection Using Dragon fly optimization based Deep Neural Network[5]In this paper performed an efficient skin disease identification approach using enhanced dep neural network model. The data base image are segment using enhanced level set approach based segmentation, Feature extraction is carried out for all image to retrieve the feature vector using GICM .Finally, dragonfly optimization based deep neural network is utilized for the classification of skin disease. The proposed method is used to quality of the segmentation result. It has much accuracy in classifying images it can be only implemented on platform using MATLAB.

An Ensemble of Fine-Tuned Convolutional Neural Network for Medical Image Classification[6]In this paper we introduce a new method for classification method images that uses an ensemble of different convolutional neural network architecture. CNNs are a state of the art image classification technique that learns the optical image feature for given classification task our method develop a new feature extract by fine turing CNN that have been initial a large data set of images. The fine taken process leverage the generic images and optimize them for variety of medical images. Then feature are used to train numerous multiclass classifier whose posterior probabilities are used to predict the unseen images. Advantage is in top I accuracy method was 1.737 was accurate than best baseline method Disadvantage of this method was 0.127 lower than the best performing method.

Dual Stream Network With Selective Optimization for Skin Disease Recognition in Consumer Grade Images[7]Here Consumer grade images refer to the image taken using available imaging devices such as mobile care or a handed held digital camera. A weakly supervised segmentation algorithm is first employed to extract Region of interest from the image the RO1 and the original image from the two input stream of the proposed architecture. Each stream of architecture learns high level and between level feature from the original image and the RO1 Advantage of this model will have capability to high the skin lesion in the image and generate differential diagnosis out of the large number dermatology conditions. Disadvantage is RO1 segmentation phase and dual stream are separate increasing the time. Only the most performing skin region is consider for patch stream so local cars from the images with muti-class such as region will be less representative.

Improving skin disease classification based on customized loss function combined with balanced minibatch logic real-time image augmentation[8]In this study we have proposed a new approach for multiple skin-disease classification by proposing a hybrid method, which combines designing new loss function with a data level method of balanced mini-batch logic followed by a real-time image augmentation. The major results of this research are, our proposed hybrid method, which combines the algorithm level method of new designed loss function and the data level method of balanced mini-batch logic integrated with the real-time image augmentation, is effective in handling class effectiveness of networks optimization on the imbalanced dataset because it helps the networks learn the minority classes faster.

A Method Of Skin Disease Detection Using Image Processing And Machine Learning[9], here In this section, the methodology of the proposed system for detection, extraction and classification of skin diseases images is described. The system will help significantly in the detection of melanoma, Eczema and Psoriasis. The whole architecture can be divided into several modules comprising of preprocessing, feature extraction, and classification. In this research the method of detection was designed by using pretrained convolutional neural network (AlexNet) and SVM. In conclusion, we must not forget that this research has an effective role in the detection of skin diseases in Saudi Arabia because it has a very hot weather for the presence of deserts; this indicates that skin diseases are widespread. This research supports medical efficiency in Saudi Arabia.

FCN-Based Dense Net Framework for Automated Detection and Classification of Skin Lesions in Dermoscopy Images [10] The proposed framework consists of two stages: the first stage leverages on an encoder-decoder Fully Convolutional Network (FCN) to learn the complex and inhomogeneous skin lesion features with the encoder stage learning the coarse appearance and the decoder learning the lesion borders details. Our FCN is designed with the sub-networks connected through a series of skip pathways that incorporate long skip and short-cut connections unlike, the only long skip connections commonly used in the traditional FCN, for residual learning strategy and effective training. The network also integrates the Conditional Random Field (CRF) module which employs a linear combination of Gaussian kernels for its pairwise edge potentials for contour refinement and lesion boundaries localization. The second stage proposes a novel FCN-based DenseNet framework that is composed of dense blocks that are merged and connected via the concatenation strategy and transition layer. The system also employs hyper-parameters optimization techniques to reduce network complexity and improve computing efficiency. This approach encourages feature reuse and thus requires a small number of parameters and effective with limited data. The proposed system has been able to overcome the challenges of dealing with the complex features of skin lesion images and heavy parameter tuning of the traditional CNN.

Digital Diagnosis of Hand, Foot, and Mouth Disease Using Hybrid Deep Neural Networks , In this paper[11] we proposed a lightweight and efficient Hybrid Deep Neural Networks to detect or diagnose HFMD using clinical symptoms and image data. The proposed Hybrid Deep Neural Networks architecture has two input branches1) Multi-Layer

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Perceptron and 2) modified pre-trained CNN model to integrate the features learnt from clinical symptoms and image data. The performance of our proposed multi-branch Hybrid Deep Neural Networks for diagnosing HFMD was compared with the image classification model and clinical symptom-based HFMD classification model (MLP). The image classification models: MobileNet, NasNetMobile and RestNet50, classified the skin lesions with an accuracy of 88%, 85% and 91.2%, respectively; however, this approach has some limitations of misdiagnosing similar appearing skin lesions.

Targeted Ensemble Machine Classification Approach for Supporting IoT Enabled Skin Disease Detection[12] In the paper presented a research work that firstly discussed a dynamic AI-model configuration and secured IoT-Fog-Cloud architecture for remote disease diagnosis, especially it related to skin diseases detection. Secondly, we provided a new classification process to produce better classification results in skin disease detection. To achieve it, we evaluated the existed machine learning models in a controlled and standard testing environment. Different from the other evaluation work, our evaluating environment applies to a well-known and widely used HAM10000 dataset rather than the customized dataset. Besides, the evaluation uses only Keras GPU APIs to test on different combinations of three pre-processing methods working on the condition images, which are colour featuring, model transfer and data balancing. Moreover, we did not only evaluate the training-test accuracy but did cross-validation analysis. In the end, the evaluation outcomes enhanced our research hypothesis of having a two-phase classification process can produce a better result than only using one specific CNN model. Limitation of this model is Evaluating the proposed two-phase classification process as a base of transfer model for wider skin-related disease classification problem such as rash, allergy or bone-related diseases.

Classification of Skin Disease Using Deep Learning Neural Networks with MobileNetV2 and LSTM[13]The proposed model based on the MobileNet V2 and LSTM approach proved efficient for skin disease classification and detection with minimal computational power and effort. The outcome is promising, with an accuracy of 85.34% when experimented with and compared with other methods over the real-time images acquired from Kaggle. The MobileNet V2 architecture is designed to work with a portable device with a stride2 mechanism. The model is computationally effective, and the use of the LSTM module with the MobileNet V2 would enhance the prediction accuracy by maintaining the previous timestamp data. The information related to the current state through weights optimizations would make the model robust. It is also compared against various other conventional models like CNN,FTNN, and HARIS. It is observed that the proposed model has outperformed in classification and analyzing the progress of the tumor growth based on the textured based information as presented in the Results and Discussion section. The bidirectional LSTM may further improvise the performance of the model. In the practical implementation of the proposed model, an association of the front end designed through the android studio/SSDLite/DeepLabv3+ and the business model built over Kaggle has taken tremendous efforts in integrating either of the models. However, at the present point, there is a range of shortcomings that must be resolved in future work. The model's precision is dramatically decreased to just below 80 percent when checked on a series of photographs captured in poor illumination conditions distinct from those used during testing. Eventually, the proposed approach is not designed to replace but rather to supplement existing disease-diagnostic solutions. Laboratory test results are always more trustworthy than diagnoses based solely on visual symptoms, and visual inspection alone often challenges early diagnosis.

A new preprocessing approach to improve the performance of CNN-based skin lesion classification[14]Skin lesion is one of the severe diseases which in many cases endanger the lives of patients on a worldwide extent. Early detection of disease in dermoscopy images can significantly increase the survival rate. However, the accurate detection of disease is highly challenging due to the following reasons: e.g., visual similarity between different classes of disease (e.g., melanoma and non-melanoma lesions), low contrast between lesions and skin, background noise, and artifacts. Machine learning models based on convolutional neural networks (CNN) have been widely used for automatic recognition of lesion diseases with high accuracy in comparison to conventional machine learning methods. In this research, we proposed a new preprocessing technique in order to extract the region of interest (RoI) of skin lesion dataset. We compare the performance of the most state-of-the-art CNN classifiers with two datasets which contain (1) raw, and (2) RoI extracted images. Our experiment results show that training CNN models by RoI extracted dataset can improve the accuracy of the prediction (e.g., InceptionResNetV2, 2.18% improvement). Moreover, it significantly decreases the evaluation (inference) and training time of classifiers as well.

A machine learning model for skin disease classification using convolution neural network[15] The incidence of melanoma is at its highest level ever recorded in both Australia and New Zealand. The survival rate can significantly increase if melanoma is identified in dermos copy images at an earlier stage. On the other hand, the detection of melanomas is an incredibly challenging task. Consequently, the detection and recognition of skin cancer are of tremendous assistance to the accuracy of pathologists. In this research, a deep learning technique is shown for reliably diagnosing the type of melanoma present at a preliminary phase. The proposed model makes a distinction among lesion maligna, superficial spreading, and nodular melanoma. This permits the early diagnosis of the virus and the quick isolation and therapy necessary to stop the transmission of infection further. Deep

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learning (DL) and the standard non-parametric machine learning method are exemplified in the deep layer topologies of the convolutional neural network (CNN), which are neural network algorithms. The outcomes of the experiments show that the proposed method is superior in terms of diagnostic accuracy compared to the methodologies that are currently considered state of the art. Within the scope of this study, a Convolutional Neural Network (CNN) model for the diagnosis of skin cancer was created, constructed, and evaluated using a well-known melanoma dataset. Our proposed method, which is a two stage learning platform, has great-predicted accuracy at each stage, as demonstrated by its overall accuracy of 88.83 percent. This is true not only for classification algorithms such as DT, RF, GBT. The strategy that has been suggested is based on CNN, and it is possible to think of it as an effective method of multiclass categorization. In terms of melanoma classification accuracy, the modular and hierarchical structure of our CNN classifier not only beats state-of-the-art machine learning techniques, but it significantly minimizes the amount of computational effort that is required. The fact that this strategy is only tested on a single dataset is one of the method's drawbacks.

Comparison of Psoriasis Disease Detection and Classification Through Various Image Processing Techniques- A review[16] Skin disease is the major problem that we facing today. There are many reasons for skin diseases such as food, water, environmental conditions and so on. Among such diseases, Psoriasis is one of them. Psoriasis could be a skin contamination that causes reddish, aggravated flaky patches, most normally on the knees, elbows, trunk and scalp. Psoriasis could be a typical, long haul contamination (tenacious) with no cure. It tends to go through cycles, which means it occurs continuously for weeks or months. Skin illnesses such as psoriasis has lower affect on death rate but have more prominent affect on the quality of life. There are various types of image processing techniques for the psoriasis disease identification and classification. In this paper we compare the different techniques used in past for preprocessing, segmentation, feature extraction and classification. After comparing different techniques we make a new model approach for the psoriasis disease detection and classification having high efficiency and accuracy.

Recognition of Type of Skin Disease Using CNN, According to a study conducted by National Centre for Biotechnology Information (NIH)[17] the cost associated with lost productivity and treatment among those who sought medical care for skin cancer exceeded 1.2 billion dollars and also more than 5.1 million people got serious effects like infections, hair loss, itches, burns of skin cancer. The study also concludes that most of those cases can be decremented by early detection of the cancer. The diseases like basal cell carcinoma, melanoma, pyogenic granulomas, are cancerous diseases and non-cancerous diseases like dermatofibroma, melanocytic nevi, have a variety of harmful impacts on the skin and continue to spread overtime, if treatment of skin disease at early stage is not done then it leads to complication in the body and including spreading of the infection from one another. To overcome this an early detection of skin disease plays a very major impact in today's world. Now a days image processing has become widely used in developing a solution to this type of problems. Developing a high accurate methodology can be used to decrement the count of skin infections and their huge loses. This paper presents a seven types of skin disease detection using CNN. The dataset used is HAM10000.We obtain high accuracy by making the dataset ordered by adding duplication. The input image undergoes different layers such as maxpool2d, conv2d, batch normalization, flatten, dense, Softmax etc, As this classification is among seven different types of skin diseases out of which four are cancerous and other three are non-cancerous, the output is one among these seven.

III. PROPOSED SYSTEM

Given that the skin is the largest organ in the body, maintaining healthy skin is crucial. One of the most prevalent illnesses in people is skin disease, and its prevalence is sharply rising. Numerous technical improvements have been made in the contemporary era that have greatly improved our quality of life. The medical industries are undergoing several technological developments. Even in the healthcare industry, artificial intelligence is replacing automation in all sectors of application. These diseases have caused worry in recent years because of their abrupt onset and complexity, which has elevated life risks. These skin abnormalities are highly contagious and must be treated early to stop them from spreading. Unprotected exposure to excessive ultraviolet radiation (UR) is a primary contributor to disease. This technique uses image analysis to determine the type of disease by taking a digital photograph of the affected skin area. The most prevalent kind of illnesses are skin conditions. Skin conditions come in a variety of forms. Some are brought on by allergies, while others by long-term illnesses. The process of diagnosing and treating the correct skin illness is laborious. Different diseases have different symptoms. Skin cancer and other disorders might develop as a result of improper skin disease treatment. Every illness could follow a pattern. Therefore, the only method to determine the type of sickness is to comprehend the disease pattern. Typically, a dermatologist finds it difficult to comprehend the patterns. Several Direct or indirect skin-related variables can result in disorders that can be treated with particular medications while others need a doctor's consultation. Through picture analysis, information extraction, and image categorization based on the type of skin condition, this study will assist readers in understanding the steps necessary for treating various skin diseases. The prototype receives as input from the patient a picture of the skin area that is diseased. This photograph is

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processed using image processing techniques, and the output shows the disease that was found. This paper will help people to know what are the required procedures for treatment of skin disease by analysing the image and extract useful information that help to show the infected skin area and classification of image based on the kind of skin disease. 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.

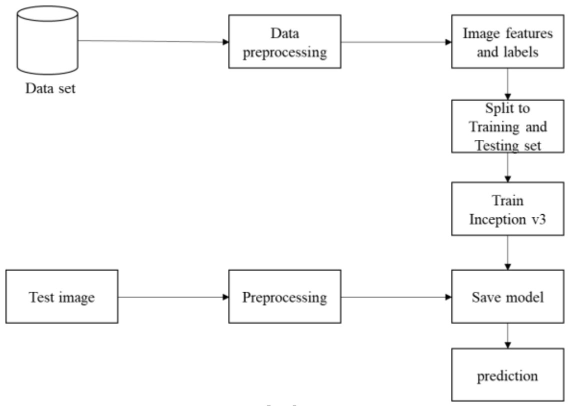

Fig 3 Block Diagram

IV. DESIGN

A. *DFD – Level 0*

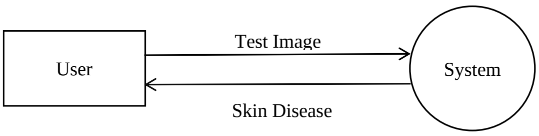

Fig 4.1 Data Flow Diagram Level 0

In this level, a simple representation of system and which all data is transmitted from one module/operation to other module/operation. It is clear that client interacts with the python based android application. The input can be touch feedback or image captured using the smartphone camera. The output is visual feedback stating the result of classification in all the cases.

B. DFD – Level 1

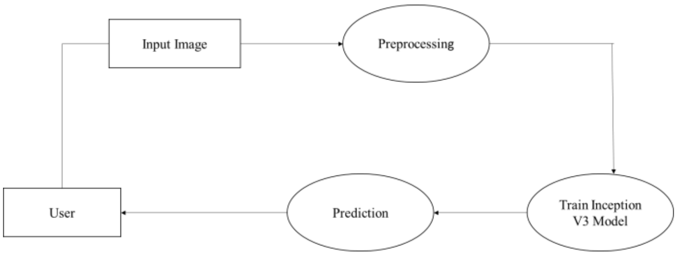

Fig 4.2 Data Flow Diagram Level 1

In here the application is broken into sub processes. The application contains image pre processing, training inception v3 to show the result inception v3 .Start with giving an input image by capturing an real time image using mobile camera. Input image undergoes image pre processing to improve picture data by enhancing certain image features that are important for subsequent processing and analysis. After classification of disease from database result sent back to the client.

B. *DFD – Level 2*

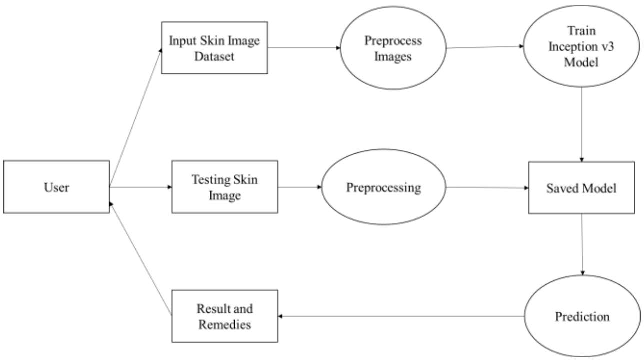

Fig 4.3 Data Flow Diagram Level 2

After pre processing, we use Inception v3 to train the model. Encrypt the model. The skin condition was discovered using a CNN-based model. The client receives the classification results in a new page that includes information on the diseases and their treatments. The programme will respond with the message "disease not detected" if no disease is found.

V. METHODOLOGY

The prototype that is suggested as a solution in this research has a database of various skin illnesses, allowing patients to learn more about their condition before seeing a dermatologist. In remote places, mobile hospitals can make use of this concept. Thus, even the most isolated parts of the country can access this prototype. A picture of the affected area taken by the patient serves as the input prototype for the suggested prototype, which offers a simple and practical way to diagnose skin diseases. Any further analysis is then performed on this input image. The primary goal of the proposed system is to identify skin illnesses utilising feature extraction techniques that take shape, color, and texture into account. We use different OpenCv for Image Pre processing and For Feature extraction and Image Classification Inceptionv3 is used. The details are given

A.OPENCV

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A computer vision and machine learning software library called OpenCV is available for free use. In order to speed the use of machine perception in the production of commercial goods, OpenCV was created in order to provide a standard framework for computer vision applications. These algorithms can be used to find and identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models from objects, create 3D point clouds from stereo cameras, stitch together images to create high-resolution images of entire scenes, find and remove red eyes from images taken with ash, follow eye movements, and identify scenery and establish markers to overlay it with information.

Machines observe and process everything using numbers, including text and image, including reading, writing, and displaying images. Image to numeric conversion: Two words: pixel values, the pixel intensity for each number corresponds to that specific position. In the image above, I've displayed the pixel values for a grayscale picture, where each dot represents the intensity of the black colour in that spot. It should be noted that each pixel in colour photographs will have numerous values. For RGB photos, for example, these values represent the intensity of the relevant Red, Green, and Blue channels. Every project using computer vision needs to be able to read and write images. Additionally, the OpenCV package greatly simplifies this function.

Now, let's see how to import an image into our machine using OpenCV:After importing cv2 module using import cv2, Use the imread() method of the cv2 module to read the image now. Include the path to the image in the arguments, and then save the image in a variable .The OpenCV resize() method can be used to resize an image. Numpy is then used to transform it into an array format. With values saved in image for the rows and columns, the picture is now handled as a matrix. Actually, if you verify the image's type, you'll get an outcome. It's an array in Numpy. That explains why using OpenCV to process images is so simple. You are constantly utilising a Numpy array. You can either specify the image's height and width values in the reshape method. Color Spaces That Change A methodology for representing colours in a form that facilitates easy replication is known as a colour space. We are aware that while colour photos have three values for each pixel, grayscale images only have one value per pixel (the intensity of the Red, Green, and Blue channels).RGB images are processed in the majority of computer vision use cases. Hue-Saturation-Value, or HSV, colour spaces are crucial for some applications, such as video compression and device-independent storage. By default, OpenCV reads BGR-formatted images. Therefore, while reading images with OpenCV, you must switch the colour space from BGR to RGB. We also use imgtoarray, imgpath,etc in OpenCv in order to image pre processing. The category that corresponds to the image supplied to the data field is passed to the label fields.

B.INCEPTION V3

A neural network that has already been trained is used in the machine learning technique of transfer learning. The Inception-v3 image recognition model presented here is divided into two sections: component of the convolutional neural network used for feature extraction. Classification section with softmax and fully-connected layers. Convolutional neural network model Inception-v3 has 48 layers and was pre-trained. It is a network that has been trained using a variant of the ImageNet database's more than a million photos. It is the third iteration of Google's Inception CNN model, which was first developed for the ImageNet Recognition Challenge. This pre-trained network can categorise photos into 1000 different object categories.

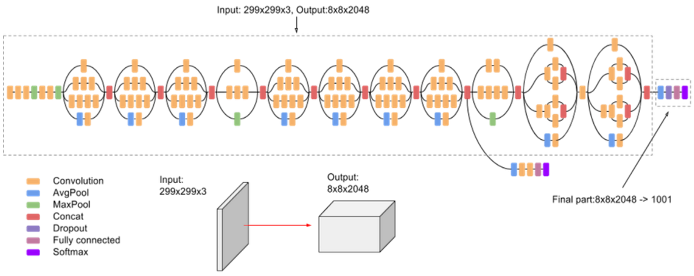

Fig 5 Schematic diagram of Inception v3

Inception v3 is a widely-used image recognition model. Here Inceptionv3 is used to build a model to extract features and image classification .Inceptionv3 is loaded using tensorflow. The model is the culmination of many ideas introduced by multiple researchers over the past years. Inception-v3 adopts convolutional kernels of different sizes, which enables it to own receptive fields of different areas. To reduce the design space of the network, it adopts a modular system followed by final joining, thereby realizing the fusion of features of varying scales.First, the input image is delivered to this model for feature categorization. The input image size for this model is (299,299,3) The pictures have to be jpg files. The larger photos are converted into this format. The features are initially retrieved from an input image.

In Inception-v3, a batch normalization (BN) layer is inserted as a regularizer between the auxiliary classifier and the fully connected (FC) layer. In the BN model, the batch gradient descent method can be employed to accelerate the training speed and model convergence of the deep neural network.

Furthermore, in Inception-v3, large convolution kernels are divided into small convolution kernels in series, convolution and pooling are connected in parallel, and Label Switching Router(LSR) labels are added for regularization based on the smoothing criteria. In addition, considering the distribution inconsistency between inputs and outputs in a traditional deep neural network, which creates great obstacles

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for feature extraction, BN is introduced into Inception-v3. By normalizing the input into each layer, the learning effect is optimized.

VI. EXPERIMENTAL RESULT

Our suggested system is a Skin Disease Detection System. This technique evaluates skin images taken with a camera to identify the disease, The recommended system uses techniques for image processing and machine learning. The initial phase of the process involves pre processing of an input image, reading it, and resizing it. The image is scaled and converted to a numpy array format. Using the Inception v3 initialization, the image is delivered to the appropriate fields, where it is used as input for features and labels. Later, train the model with labels and features. Then save the model. After pre processing test images and load models for testing, the system will forecast the associated disease.

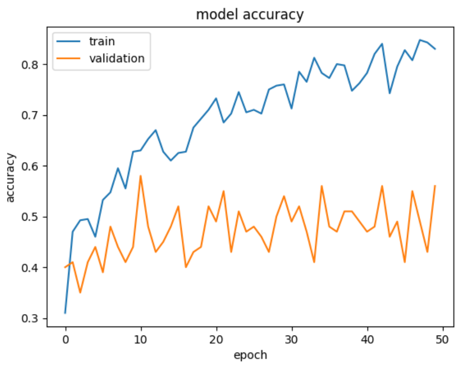

Fig 6.1 Model Accuracy Curve

After each update during training, the model can be tested on the training dataset and a hold-out validation dataset, and graphs of the measured performance can be made to display learning curves shown in Fig 6.1

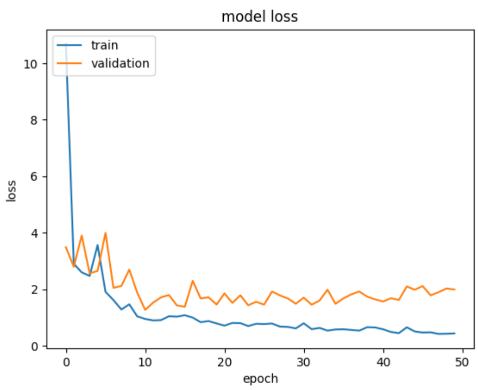

Fig 6.2 Loss Curve

Data for training and testing are split 80/20. According loss curve is displayed in Fig. 6.2.

VII. CONCLUSION

In many different methods, we are able to recognise skin issues and offer treatments. Each has benefits and disadvantages. The simplest and least expensive way is visual analysis, but it is also the least reliable and effective. The most frequently cited aspect of image processing technology is its incredibly high accuracy and short time investment. Applications for Convolutional Neural Networks (CNN)layers have been created for the classification of skin diseases. The primary objective of the offered method is to accurately and effectively identify the condition. Additionally, we offer suggestions for the elements of products or medications that patients should use to treat particular illnesses.

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