SKIN LESIONS ENCOUNTERING USING IMAGE ANALYSIS AND CONVOLUTIONAL NEURAL NETWORKS(CNN)

Submitted in partial fulfillment of the

requirements for the award of

Bachelor of Engineering degree in Computer Science and Engineering

By

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SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
Accredited with Grade “A”by NAAC | 12B Status by UGC| Approved by AICTE
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Y.L.Yochita(Reg.No - 39111122) and B.Mounisha (Reg.No - 39110185)** who carried out the Project Phase-2 entitled **"SKIN LESIONS ENCOUNTERING USING IMAGE ANALYSIS AND CONVOLUTIONAL NEURAL NETWORK(CNN)**under my supervision from January 2023 to April 2023.

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DECLARATION

I, **B.Mounisha(Reg.No-39110185),** hereby declare that the Project Phase-2 Report entitled**"SKIN LESIONS ENCOUNTERING USING IMAGE ANALYSIS AND CONVOLUTIONALNEURALNETWORK(CNN)"** done by me underthe guidance of **Dr. A.Yovan Felix, M.E.,Ph.D** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE: 20.4.2023

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PLACE: Chennai

SIGNATURE OF THECANDIDATE

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ABSTRACT

In this contemporary world, skin diseases are mostly found in humans, animals, and plants. Skin diseases are among the most common health problems worldwide. A skin disease is a particular kind of illness caused by bacteria or an infection. These diseases like psoriasis, ringworm, yeast infection, brown spot, allergies, eczema etc. have various dangerous effects on the skin and keep on spreading over time. It becomes important to identify these diseases at their initial stage to control it from spreading. These diseases are identified by using many advanced technologies such as image processing, data mining, convolutional neural networks (CNN) etc. Image processing has played a major role in this area of research and has widely used for the detection of skin diseases. Techniques like filtering, segmentation, feature extraction, image pre-processing and edge detection etc. are part of image processing and are used to identify the part affected by disease, the form of affected area, its affected area color etc. This project presents a survey of various skin disease diagnosis systems using image processing techniques in recent times. A comprehensive study of several skin disease diagnosis systems are done in this project, with different methodologies and their performances.

LIST OF FIGURES

CHAPTER 1

1 INTRODUCTION

1.1INTRODUCTION TO SKIN LESIONS.

Skin lesions are one of the most dangerous and common diseases that affect mankind very often. The two main types of skin lesions that affect humans are Melanoma, actinic keratosis, dermatofibroma, seborrheic keratosis, squamous cell carcinoma. However, Melanoma is the most affecting and dangerous type of skin cancer and has a high mortality rate with overall affecting cases of less than 5%. The World Health Organization also estimated high cases of Melanoma across the world. Skin self-examination and skin clinical examination are the conventional methods of skin lesionsdetection.

However, these methods of examination are very hectic and troublesome. This method requires a lot of physical visits of patient and are also very expensive. These examinations also require specialized tools such as micro spectroscopy and laser-based tools . It requires effort to operate and a lot of training.

The revolution brought by the smartphones allowed patients to share the image through phone for the skin lesions diagnosis. However, these images may be of not standard quality which may lead to inaccurate diagnosis also the privacy may be compromised by using internet for sharing. But with the AI evolution, the human and AI interaction have increased on a daily basis which may assist the decision making of the doctors.

Also, the use of AI will reduce the human error involved in the diagnosis. Despite the presence of such AI technology, the requirement of expert physician is mandatory. The aim of this research is on the use of deep learning and CNN for the early detection of skin lesions. Here, a model is trained based on the data available for the skin lesions and the accuracy of the model is improved with every training of data sets.

This does not use multilayer neural network instead it uses deep learning and deep multi-layered network which involve training of very large data sets for improving the accuracy of the system. These AI methods for detecting the skin cancer are very cheap, easy to use and accessible. Also, AI based technology has been superficial and offers a lot of liabilities and features than the conventional methods of skin cancer detection. The process of skin cancer detection using AI involves feeding the image to the model, segmenting it and processing it to classify the type of skin cancer. Deep learning has somewhere brought a revolution in the field of AI. The algorithms used in the deep learning are inspired by human brain. Deep learning [5] has improvised the results of machine learning and AI. This research performs the literature review of different classical deep learning methods used for the diagnosis of skin cancer and its methodology. In this paper a new model from scratch is made to get the more improved results using CNN. The superficial models Efficient Net B0 and inception V3 are used. The transfer learning is used to reuse a pre trained model for better accuracy. Thus, this model for skin cancer detection has made the diagnosis and detection easier than the conventional methods of detection.

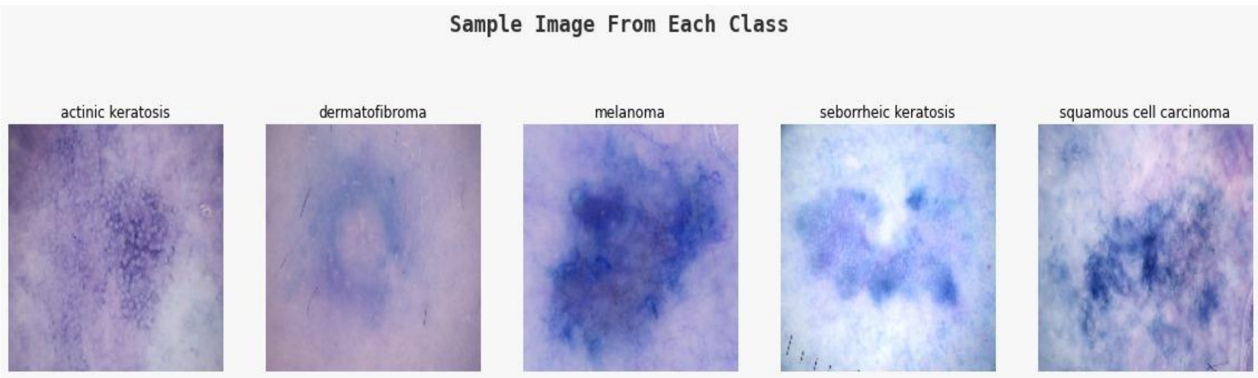


Fig-1.1-sample images of skin lesions

Melanoma can affect people of any skin tone. In people with darker skin tones, melanoma tends to occur on the palms or soles, or under the fingernails or toenails. Melanoma signs include:

- A large brownish spot with darker speckles
- A mole that changes in colour, size or feel or that bleeds
- A small lesion with an irregular border and portions that appear red, pink, white, blue.
- A painful lesion that itches or burns

- Dark lesions on your palms, soles, fingertips or toes, or on mucous membranes lining your mouth, nose, vagina or anus

Actinic keratoses vary in appearance. Signs and symptoms include:

- Rough, dry or scaly patch of skin, usually less than 1 inch (2.5 centimeters) in diameter
- Flat to slightly raised patch or bump on the top layer of skin
- In some cases, a hard, wartlike surface Color variation, including pink, red or brown
- Itching, burning, bleeding or crusting
- New patches or bumps on sun-exposed areas of the head, neck, hands and forearms

Dermatofibromas tend to grow slowly. The growths typically have some defining characteristics that can aid their identification.

Key markers of a dermatofibroma are:

- Appearance: A dermatofibroma presents as a round bump that is mostly under the skin.
- Size: The normal range is about 0.5-1.5 centimeters (cm), with most lesions being 0.7-1.0 cm in diameter. The size will usually remain stable.
- Color: The growths vary in color among individuals but will generally be pink, red, gray, brown, or black.
- Location: Dermatofibromas are most common on the legs, but they sometimes appear on the arms, trunk, and, less commonly, elsewhere on the body.
- Additional symptoms: Although they are usually harmless and painless, these growths may occasionally be itchy, tender, painful, or inflamed.

1.2 OVERVIEW OF DEEP LEARNING

Deep learning is a part of the broader family of machine learning wherein the learning can be supervised, unsupervised or semi supervised. Deep learning unlike machine learning uses a large dataset for the learning process and the number of classifiers used gets reduced substantially.6 The training time for the deep learning algorithm increases because of the usage of the very large dataset. Deep learning algorithm chooses its own features unlike the machine leaning making the prediction process easier for the end user as it does not use much of pre-processing.

Elaborately, a deep learning technique learn categories incrementally through it' s hidden layer architecture, defining low-level categories like letters first then little higher level categories like words and then higher level categories like sentences. In the example of image recognition, it means identifying light/dark areas beforecategorizing lines and then shapes to allow face recognition. Each neuron or node in the network represents one aspect of the whole and together they provide a full representation of the image. Each node or hidden layer is given a weight that represents the strength of its relationship with the output and as the model develops the weights are adjusted.

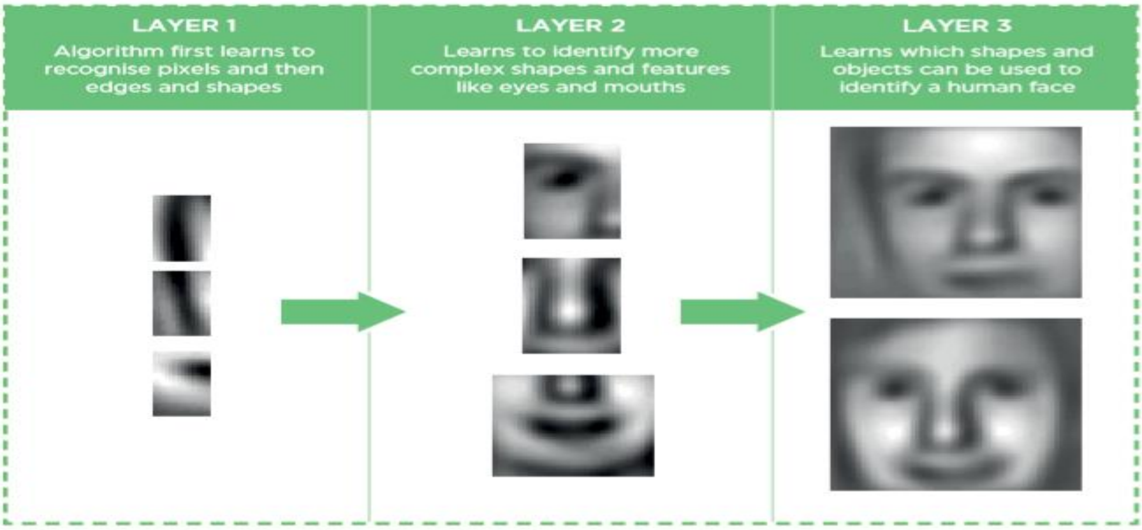


Fig-1.2.1-Layer representation

A big advantage with deep learning, and a key part in understanding why it' s becoming popular, is that it' s powered by massive amounts of data. The " Big Data Era" of technology will provide huge amounts of opportunities for new innovations in deep learning.

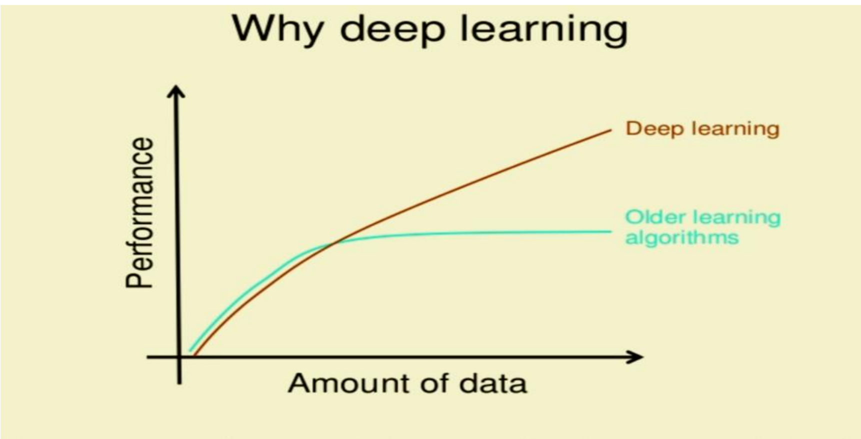


Fig-1.2.2-comparision graph

CHAPTER 2

LITERATURE SURVEY

With the advancement in the field of Artificial Intelligence, machine learningand deep learning the detection and diagnosis of skin lesions have made a great progress throughout the years. In the effort for improving the accuracy of the detection and diagnosis several researchers have employed different algorithms, models, and techniques.

Alam et al. [1] automated the detection of eczema using image processing through a support vector machine which involves various phases that include segmentation of the acquired image, followed by feature selection using texture-based information for more accurate predictions, and finally making use of the Support Vector Machine (SVM) for evaluating the progress of eczema as presented by I. Immagulate. The Support Vector Machine model is not appropriate to handle the noisy image data; identifying the feature-based parameters is significant when working with SVM. It will underperform if the number of parameters at each feature vector is more significant than the number of training data samples.

Le Thu Thao and Nguyen Hong Quang [Thao2017][3]

Skin diseases are also classified through the necessary image processing approaches like morphological operations for skin detection. Morphological opening, closing, dilation, and erosion mostly rely on the binary image generated through the thresholding, and resultantly at most care must be taken to determine the optimal threshold value. The morphological-based operations may not be suitable in estimating the damaged regions growth based on the images texture. Genetic Algorithm (GA) established an approach for skin disease classification. The Genetic Algorithm does have challenges like too much time to converge towards the solution [26]. The model never grants the global best solution which would not result in a reasonable outcome.

In 2018, Jainesh Rathod et.al [4]

Artificial Neural Networks (ANN) is the most predominantly used techniques in identifying and diagnosing anomalies from radiological imaging technologies. The ANN-based model for earlier detection of breast cancer is through image processing; either of the neural network approaches methods need tremendous training data for the models considerable performance which requires a lot of computational effort [34]. The neural network models are more abstract, and we do not have the accessibility to customize the model. Moreover, in ANN, with the increase in image resolution, the number of trainable parameters increases significantly which results in tremendous efforts for training. The ANN model suffers with diminishing and exploding the gradient.

In 2019,Catarina Barata and Jorge S.Marques

The Fine-Tuned Neural Network-based skin disease classification model has achieved a reasonable accuracy of 89.90% for the validation set. However, it needs a significant effort to calibrate the network components to attain the desired accuracy. Back Propagation Neural Network is a supervisory learning model that works on the gradient descent principle that refines the weights based on the error rate. However, the model fails to work with noisy data. The other primary concern is that when the elements are fed with new weights, it forgets the previously associated weight, leading to a considerable impact on the previous associations

Yoonsik Kim, Insung Hwang and Nam Ik Cho [Kim2017][2]

Convolutional Neural Networks (CNN) [32] are the most predominantly used techniques in identifying and diagnosing anomalies from radiological imaging technologies. Skin diseases diagnosis using the CNN approach showed that the results are promising [33]. Yet, The neural network models are more abstract, and we do not have the accessibility to customize the model. CNN does not interpret the objects magnitude and size in its observation.

2.1 INFERENCES FROM LITERATURE SURVEY

- Making use of the Support Vector Machine (SVM) for evaluating the progress of lesions is not appropriate to handle the noisy image data and It will underperform if the no.of parameters if each feature vector is more significant than the no.of training data samples
- The Genetic Algorithm does have challenges like too much time to converge towards the solution. The model never grants the global best solution which would not result in a reasonable outcome.

- In ANN, with the increase in image resolution, the number of trainable parameters increases significantly which results in tremendous efforts for training. The ANN model suffers with diminishing and exploding the gradient.
- The other primary concern of back propagation neural network is that when the elements are fed with new weights, it forgets the previously associated weight, leading to a considerable impact on the previous associations.
- Using convolutional neural network In his work CNN haven'tProvided much accuracy and doesn't interpreted the object's size in its observation

2.2 EXISTINGSYSTEM

Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN)are the most predominantly used techniques in identifying and diagnosing anomalies from radiological imaging technologies. Skin diseases diagnosis using the CNN approach showed that the results are promising. Yet, the CNN models are not scaled and rotation invariant which is a challenging task to work with images captured using a mobile device or a digital camera. The ANN-based model for earlier detection of breast cancer is through image processing; either of the neural network approaches methods need tremendous training data for the models considerable performance which requires a lot of computational effort. The neural network models are more abstract, and we do not have the accessibility to customize the model. Moreover, in ANN, with the increase in image resolution, the number of trainable parameters increases significantly which results in tremendous efforts for training. The ANN model suffers with diminishing and exploding the gradient. CNN does not interpret the objects magnitude and size in its observations.

CHAPTER 3
REQUIREMENT ANALYSIS

3.1 FEASIBILITY STUDY

This study used a dataset consisting of five skin diseases:Melanoma, actinic keratosis, dermatofibroma, seborrheic keratosis, squamous cell carcinoma. This dataset contains more dermatoscopic images. A random (rand) function is applied to split the data into the training dataand testing data. The considered dataset is slightly imbalanced because some skin diseases are more, and some are less in number. To overcome such problems, we used data augmentation, and this technique balances the data and generates more images either by rotations or transformations from the existing data.

3.2 SOFTWARE REQUIREMENTS

- Anaconda Navigator
- Spyder
- Jupiter notebook
- HTML
- CSS
- Web Browser: Microsoft Internet Explorer, Mozilla, Google Chrome or later
- Operating System: Windows XP / Windows7/ Windows Vista

The model is designed using Jupyter Notebook in Anaconda software, which is an open-source distribution of the Python and the other programming languages for scientific computing. Deployment of application building is done using Flask which is a web-framework that provides tools, libraries and technologies that allow the developer to build a web application. This web application can be any website.

CHAPTER 4

DESCRIPTIONOF PROPOSED SYSTEM

4.1 SELECTED METHODOLOGY

Several researchers have proposed image processing-based techniques to detect the type of skin diseases. In, a system is proposed for the dissection of skin diseases using color images without the need for doctor intervention. The system consists of two stages, the first the detection of the infected skin by uses color image processing techniques, k-means clustering and color gradient techniques to identify the diseased skin and the second the classification of the disease type using convolutional neural networks.

Melanoma is type of skin cancer that can cause death, if not diagnose and treat in the early stages. The various segmentation techniques that could be applied to detect melanoma using image processing. Segmentation process is described that falls on the infected spot boundaries to extract more features. The development of a Melanoma diagnosis tool for dark skin using specialized algorithm databases including images from a variety of Melanoma resources. Similarly, classification of skin diseases such as Melanoma, Basal cell carcinoma (BCC), Nevus and Seborrheic keratosis(SK). It yields the best accuracy from a range of other techniques. Therefore, proposed a computer system that automatically detects skin disease and determines its severity. The system consists of three stages, the first effective segmentation by detecting the skin, the second extract a set of features, namely colour, texture, borders and third determine the severity of disease. An application is built where an user can upload an image from UI, then image will be sent to the trained model. The model analyze the image and detect the skin disease.

4.2 ARCHITECTURE

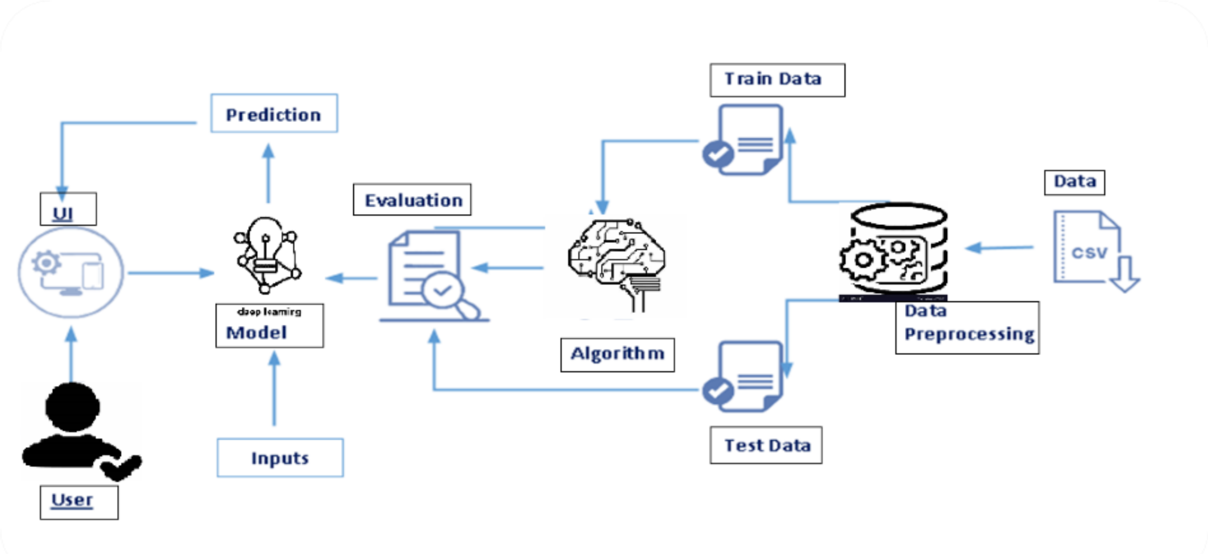
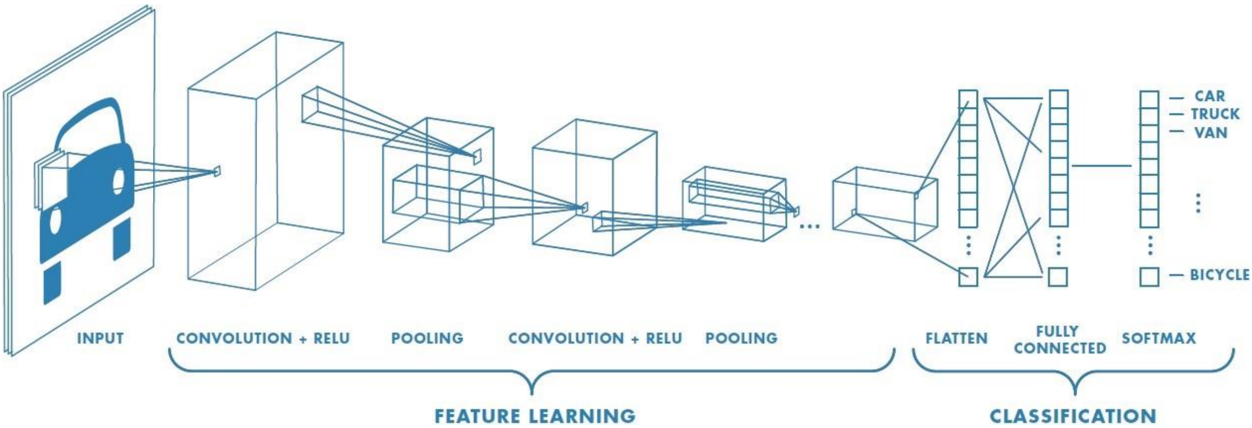


Fig-4.2.1-System Architecture

The objective is to create a portal to receive images and run it by an algorithm to identify the type of skin disease. The First step is collecting a large number of images for different types of skin diseases. After that research into the medical field to study these images and based on that developing and fine-tuning the algorithm to produce more and more accuracy. Developing a user-friendly portal where the user can upload images and get the result after processing.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING

The model is designed using Jupyter Notebook in Anaconda software, which is an open-source distribution of the Python and the other programming languages for scientific computing. Deployment of application building is done using Flask which is a web-framework that provides tools, libraries and technologies that allow the developer to build a web application. This web application can be any website.



4.2.2Standard architecture of a CNN

Convolutional Neural Networks are different from normal neural networks becausethey contain a special type of layer called a Convolutional Layer, which contains a filter that is able to understand certain types of patterns in the image. Apart from convolutional layers, CNN's contain a couple other layers, namely pooling and classification layers.

Pooling layers are really important in making sure that it doesn't take forever to train your CNN. They do this by reducing the dimensions of the image. It works quite similarly to a convolutional layer, where a filter passes over the image, except now, the filter passes over the data, extracts the most important information, and puts it into a smaller sized matrix.

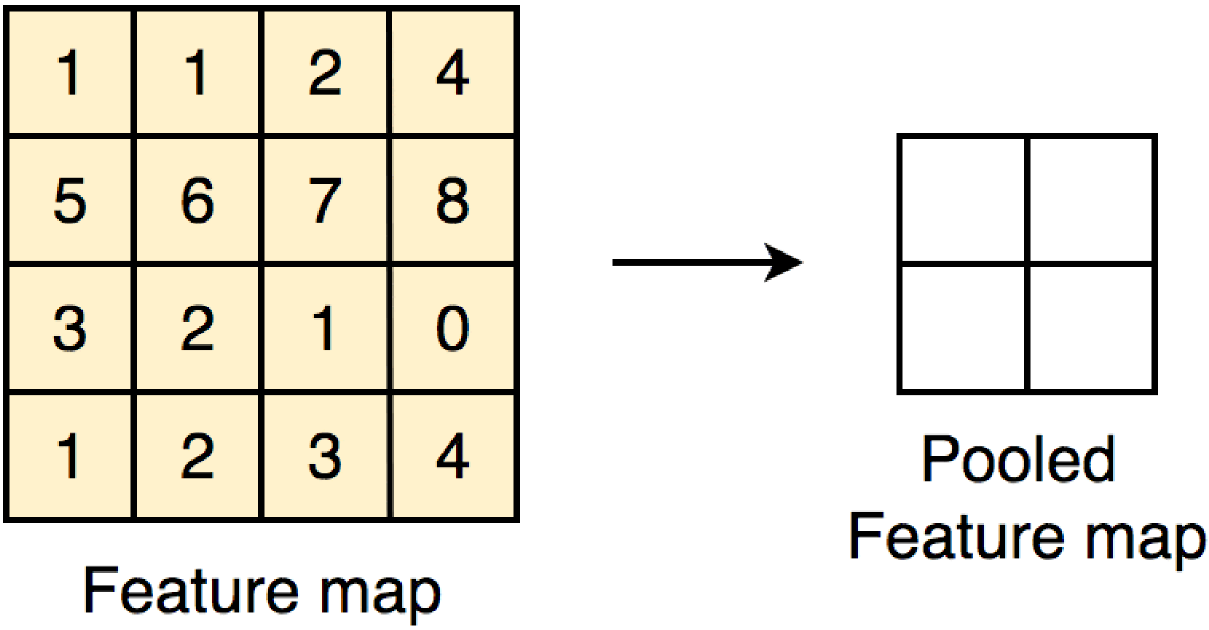


Fig-4.2.3- A graphical demonstration of a filter

A Pooling Layer reducing a feature map by taking the largest value.

All these layers are joined together at the end, into a softmax function(classification layer) which produces the final classification.

4.4 PROJECT MANAGEMENT PLAN

- The First step is collecting a large number of images for different types of skin diseases.
- After that research into the medical field to study these images and based on that developing and fine-tuning the algorithm to produce more and more accuracy.
- In construction of a ML system, selection of an appropriate ML algorithm is a crucial issue, because each algorithm has significant effect on the accuracy of the result.
- As each algorithm has its own advantages for a specific application, there is no algorithm which is suitable for all problems.
- Developing a user-friendly portal where the user can upload images and get the result after processing.

4.5 FINANCIALREPORT ON ESTIMATED COSTING

CHAPTER 5

IMPLEMENTATION DETAILS

5.1DEVELOPMENT AND DEPLOYMENT SETUP

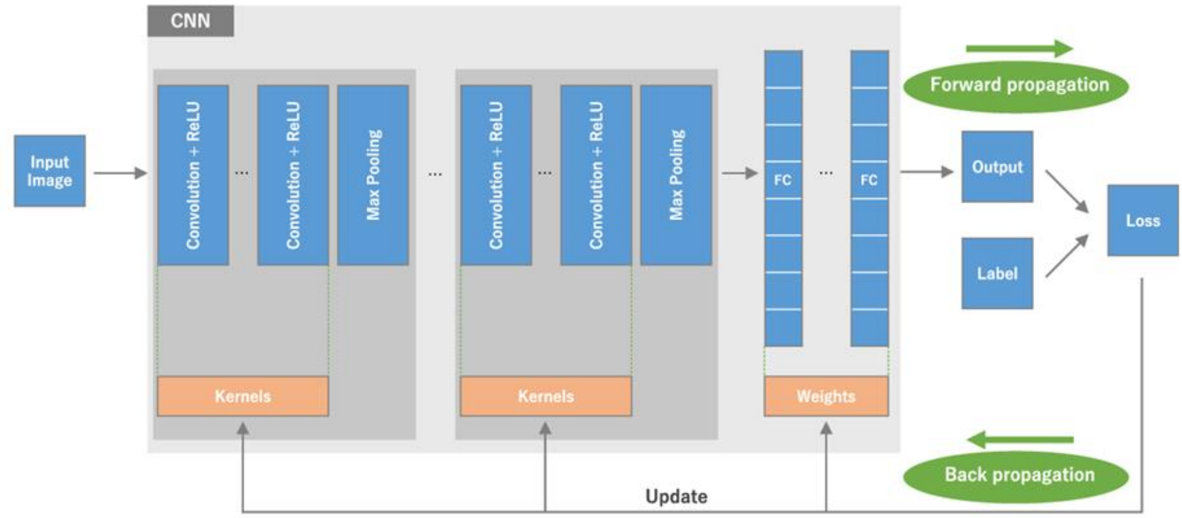
The model is designed using Jupyter Notebook in Anaconda software, which is an open-source distribution of the Python and the other programming languages for scientific computing. Deployment of application building is done using Flask which is a web-framework that provides tools, libraries like NumPy, pandas, os, matplotlib. pyplot, shutil, seaborn. The Matplotlib, pyplot, and Seaborn libraries are used for image operations and plotting, such as graphs, charts, and tables. The Shutil and os libraries offer path and directory operations on files and the collection of files. For model building such as classification report, ROC curve, and confusion matrix, we import the torchvision and seaborn libraries. The numpy and pandas are the most popularly used libraries for array processing and data analysis.Deployment of application building is done using different technologies that allow the developer to build a web application. This web application can be any website.

5.2 ALGORITHMS

In this study, a model is built from the ground up to produce superior outcomes when using Convolutional Neural Network (CNN). To reuse a previously trained model for greater accuracy, use transfer learning. In previous models they have used deep convolutional neural network models which may take days or even weeks to train on very large datasets. A way to short-cut this process is to re-use the model weights from pre-trained models that were developed for standard datasets, such as the ImageNet image recognition tasks. Top performing models can be downloaded and used directly, or integrated into a new model. Along with CNN we used the EfficientNetB0 model which will use the weights from the ImageNet dataset. Compared to traditional approaches of diagnosis, this model for skin lesions has made diagnosis and identification easier.

1.Convolution Neural Network Algorithm:

Convolutional layer consists of a filter capable of recognizing specific kinds of data and patterns in the image. Aside from convolutional layers, CNNs have two other layers: pooling and classification layers. CNN reduces the high dimensionality without losing its information. A small grid of parameters called kernel, an optimizable feature extractor, is applied at each image position, which makes CNNs highly efficient for image processing, since a feature may occur anywhere in the image. As one layer feeds its output into the next layer, extracted features can hierarchically and progressively become more complex. The process of optimizing parameters such as kernels is called training, which is performed so as to minimize the difference between outputs and ground truth labels through an optimization algorithm called backpropagation and gradient descent among all other techniques.



An overview of a convolutional neural network (CNN) architecture and the training process. A CNN is composed of a stacking of several building blocks: convolution layers, pooling layers (e.g., max pooling), and fully connected (FC) layers. A model's performance under particular kernels and weights is calculated with a loss function through forward propagation on a training dataset, and learnable parameters, i.e., kernels and weights, are updated according to the loss value through backpropagation with gradient descent optimization algorithm. ReLU, rectified linear unit.

The CNN architecture includes several building blocks, such as convolution layers, pooling layers, and fully connected layers. A typical architecture consists of repetitions of a stack of several convolution layers and a pooling layer, followed by one or more fully connected layers. The step where input data are transformed into output through these layers is called forward propagation.Although convolution and pooling operations described in this section are for 2D-CNN, similar operations can also be performed for three-dimensional (3D)-CNN.

Convolution layer:

A convolution layer is a fundamental component of the CNN architecture that performs feature extraction, which typically consists of a combination of linear and nonlinear operations, i.e., convolution operation and activation function.

Pooling layer:

A pooling layer provides a typical downsampling operation which reduces the in-plane dimensionality of the feature maps in order to introduce a translation invariance to small shifts and distortions, and decrease the number of subsequent learnable parameters. It is of note that there is no learnable parameter in any of the pooling layers, whereas filter size, stride, and padding are hyperparameters in pooling operations, similar to convolution operations.

Max pooling:

The most popular form of pooling operation is max pooling, which extracts patches from the input feature maps, outputs the maximum value in each patch, and discards all the other values.

2.Efficient B0 Algorithm:

Using more than a million photos from the ImageNet collection, the convolutional neural network EfficientNet-b0 was trained. In this research we are comparing custom CNN and Efficient b0 to get accurated model which predicts the effected skin area. The algorithm follows the following steps.

Data Collection

Artificial Intelligence is a data hunger technology,It is heavily reliant on data; without data, a machine cannot learn. It is the most important factor that allows algorithm training to take place. In Convolutional Neural Networks, as it deals with images, we need training and testing data set.

The initial step in making deep learning model is the collection of data to train the model. The accuracy of deep learning model predictions relies on the quality of the data used for training. We will be utilizing a downloadable dataset to train our neural network model and expand it to include real-time picture testing through Kaggle.

Data Processing

There are often incompatibilities and absence of certain behaviours or trends in raw data and images from the real world. They also contain mistakes. so, as soon the data collected it is pre-processed into a layout that can be used by machine learning algorithms.

Pre-processing contains many techniques to improve data accuracy and validity: Data cleaning, which can be done manually or with automated tools, removes incorrect information from the dataset. Data imputations, which are generally performed using machine learning algorithms, fill in missing values by randomly selecting one of several possible alternatives. Oversampling is used to correct for bias or imbalances in the data set by obtaining more observations with the methods like repetition and bootstrapping. Data integration refers to the process jointing different datasets in order to create a larger, more comprehensive body of data. This technique can overcome incompleteness within individual datasets and standardizes them. Data normalization is a process which reduces the size of datasets by reducing the magnitude and order of data. This decreases the amount of memory and processing need for training iterations. These are various steps takes place in data processing after data collection.

3.Model building

Many techniques are used in predictive modelling to create statistical models of future behaviour based on test data input. Model building includes the following main tasks Training and testing. In This Phase we will train the model using the dataset that we have pre-processed .The data set is divided into a training set and a testing set. 20% for testing and 80% for training. Once the data is fed into the model, it analyses the patterns ,it considers a portion of the image in respect to the background or surroundings; this process is crucial for any image classification, Obtained object or area with background gives feature extraction

$$\text{recognition rate} = \frac{\text{number of corrected detection}}{\text{number of given detection}} \times 100\%.$$

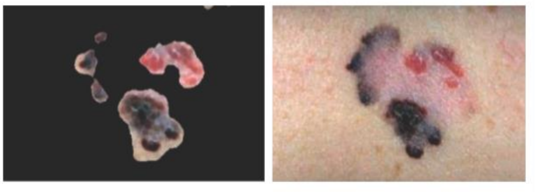


Fig -5.2.1-Lesion Identification

and make the decisions. The next task, evaluation of Model, high-level choices like the number, size, and kind of layers number of epochs are included in this. Every epoch displays the accuracy and loss for both the training and validation datasets. Save the model, After evaluating the model based on the accuracy obtained we have used Efficient b0 (89%) with more accuracy compared to custom CNN(75%), for predicting the output.

4.App building

When the Efficient b0 model is created, we will be combining it to a web application so that users can also use it to predict the output without coding. In the web application, the user gives the input image and get the predictions. This section has the following tasks: Building HTML Pages, Building server-side script.

CHAPTER 6

RESULTS AND DISCUSSIONS

The last module of the system is a projection of the result. User interacts with the UI (User Interface) to enter Data. When the user clicks on the home button home page is displayed. Predict page is displayed when predict button is clicked. On predict page, upload the input image to predict the type of skin lesion. Finally, the prediction for the given input features is shown on the UI.

Lesion type 1:

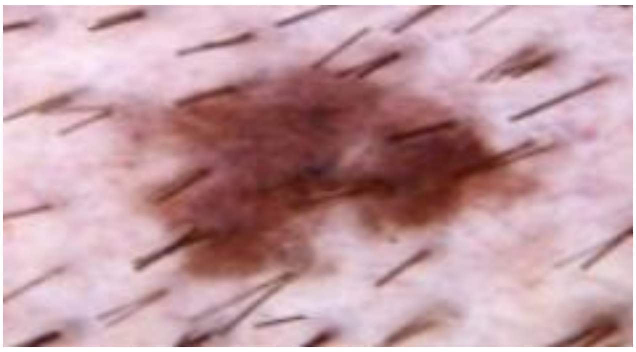


Fig:6.1- Actinic keratosis

The model analyses the affected area image and identify the skin lesion as Actinic Keratosis using Image Analysis.

Lesion type 2:

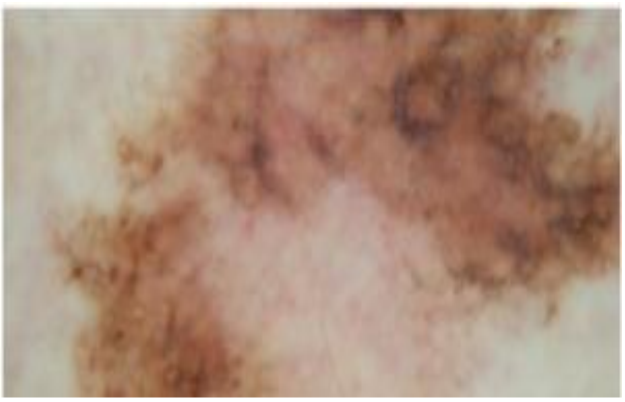


Fig :6.2 -Dermatofibrova

The model analyses the affected area image and identify the skin lesion as Dermatofibrovausing Image Analysis.

Lesion type 3:

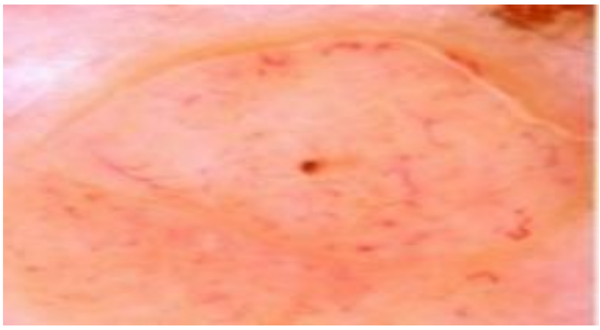


Fig:6.3 -squamous cell carcinoma

The model analyses the affected area image and identify the skin lesion as squamous cell carcinomausing Image Analysis.

Lesion type 4:

Fig:6.4 -Melanoma

The model analyses the affected area image and identify the skin lesion as melanoma using Image Analysis.

Lesion type 5:

Fig:6.5- Seborric keratosis

The model analyses the affected area image and identify the skin lesion as **Seborric keratosis** using Image Analysis.

CHAPTER-7

CONCLUSION

Convolutional neural networks (CNNs) have achievedamazing results across various areas like experimental medicine, computed tomography diagnostics and encountering different diseases. Although deep learning is considered as the predominant method in various difficult tasks such as classifying images and detecting objects, it is not a catholicon. It is essential to be aware of important concepts and benefits of CNN as well as the limits of deep learning are critical to take the advantage of them in diagnostic imaging research with the aim of improving its performance and better supervision of patients.

In model a pattern for detecting the skin lesions is done using image analysis and Convolutional Neural Networks. It is found that by using the Convolutional neural networks and Transfer learning we can reach a better precision value and we can also focus towards predicting a lot more lesions than with any other prior models made before. By applying a Transfer learning concept to CNN using efficient b0, we can predict up to five different skin lesions with a greater degree of precision level of 89%. This shows that deep learning algorithms have enormous potential in diagnosis the actual skin lesions. Even the high-quality system with a very large dataset can be used, so that the precision can be greatly enhanced and this pattern can be used for scientific trails because it includes dimensions.

This section displays accuracy results for theconstructed during this project. Neural network accuracy, while not good enough to confidently identify "the pictures in the skin diseases dataset, proved that the classification using a CNN is possible. The result provides a proper framed network, hidden layers, or larger input images, a convolution neural network constructed using six layers, has the capability of classification. There are various advantages like Easy model building with less formal statistical knowledge required, Capable of capturing interactions between predictors and Capable of capturing non-linearities between predictors and outcomes.

This study projects a method that uses techniques related to computer vision to distinguish different kinds of dermatological skin abnormalities. We have employed Deep learning algorithms for feature extraction and learning algorithm for training and testing purpose. Using the state-of-the-art architecture considerably increases the efficiency up to 88-93 percentage.

The methodology proposed in this work is more suitable for detecting and diagnosing skin problems than the existing methods. The proposed work helps extract the best features from the skin images, and then they are classified using the Softmax classifier, a highly accurate classifier. The attained accuracy of 0.87 suggests that this method is highly efficient in detecting and diagnosing skin problems. The results of this work can be helpful for students or researchers in the medical field

7.1 FUTURE SCOPE:

Detection of skin disease is one of the major problems in the medical industry and can be healed and retrieved if properly diagnosed at an early point. Literature study demonstrates that different skin disease observation techniques are being used. However, there is still a great need to classify skin diseases at an early point. Machine learning algorithms have the potential to have an impact on early detection of skin diseases. It can assist people make real-time adjustments to their skin. If embraced well, the techniques will certainly provide appropriate assistance and a unified approach to skin problems prevention. This will assist patients and physicians cure skin diseases in a timely manner. Research and execution of limited medical information are accessible. If more real-time data are available in the future, the detection of skin disease can be explored with recent advances in AI and the benefits of diagnosis assisted with AI.

7.2 RESEARCH ISSUES:

7.3IMPLEMENTATION ISSUES:

While implementing the algorithm there are few issues which may change the accuracy of the model. Some of the issues are:

- sharing an existing ANN model is difficult.
- Clinical interpretation model parameters can be black boxes.
- Prone to overfitting due the complexity of model structure

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APPENDIX

SOURCE CODE

1.CNN source code

```
from google.colab import drive
drive.mount('/content/drive')

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import cv2
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tqdm import tqdm
import os
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,
 TensorBoard, ModelCheckpoint
from sklearn.metrics import classification_report,confusion_matrix
import ipywidgets as widgets
import io
from PIL import Image
from IPython.display import display,clear_output
from warnings import filterwarnings

dir = '/content/drive/MyDrive/Projects /Proj -
 2 Skin Disease Identification Using Image Analysis/dataset (skin diseas
es)2'
for dirname, _, filenames in os.walk(dir):
    for filename in filenames:
        print(os.path.join(dirname, filename))

#data preparation
labels = ["actinic keratosis",
"dermatofibroma",
"melanoma",
"seborrheic keratosis",
"squamous cell carcinoma",
"Acne_and_rosacea",
"Eczema",
"Tinea_Ringworm"
]

X_train = []
y_train = []
image_size = 150
```

```
for i in labels:
    folderPath = os.path.join(dir,'Train',i)
    for j in tqdm(os.listdir(folderPath)):
        img = cv2.imread(os.path.join(folderPath,j))
        img = cv2.resize(img,(image_size, image_size))
        X_train.append(img)
        y_train.append(i)

for i in labels:
    folderPath = os.path.join(dir,'Test',i)
    for j in tqdm(os.listdir(folderPath)):
        img = cv2.imread(os.path.join(folderPath,j))
        img = cv2.resize(img,(image_size,image_size))
        X_train.append(img)
        y_train.append(i)

X_train = np.array(X_train)
y_train = np.array(y_train)

k=0
fig, ax = plt.subplots(1,8,figsize=(20,20))
fig.text(s='Sample Image From Each Class ',size=18,fontweight='bold',
             fontname='monospace',y=0.62,x=0.4,alpha=0.8)
for i in labels:
    j=0
    while True :
        if y_train[j]==i:
            ax[k].imshow(X_train[j])
            ax[k].set_title(y_train[j])
            ax[k].axis('off')
            k+=1
            break
        j+=1

X_train, y_train = shuffle(X_train,y_train, random_state=101)

X_train.shape

X_train,X_test,y_train,y_test = train_test_split(X_train,y_train, test_s
ize=0.1,random_state=101)

y_train_new = []
for i in y_train:
    y_train_new.append(labels.index(i))
y_train = y_train_new
y_train = tf.keras.utils.to_categorical(y_train)


y_test_new = []
for i in y_test:
```

```
    y_test_new.append(labels.index(i))
y_test = y_test_new
y_test = tf.keras.utils.to_categorical(y_test)

train_labels = []
test_labels = []

img_size= 300

for i in os.listdir(dir+'/Train/'):
    for j in os.listdir(dir+"/Train/"+i):
       train_labels.append(i)

for i in os.listdir(dir+'/Test/'):
    for j in os.listdir(dir+"/Test/"+i):
        test_labels.append(i)

plt.figure(figsize = (17,8));
lis = ['Train', 'Test']
for i,j in enumerate([train_labels, test_labels]):
    plt.subplot(1,2, i+1);
    sns.countplot(x = j);
    plt.xlabel(lis[i])

from keras.models import Sequential
from keras.layers import Activation, Dropout, Flatten, Dense, Conv2D, Ma
xPool2D, BatchNormalization
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator

import numpy as np
from glob import glob
import matplotlib.pyplot as plt
from keras.models import load_model

# Start training freshly
tf.keras.backend.clear_session()

model = Sequential()
model.add(Conv2D(filters=32,kernel_size=(3,3),input_shape=(image_size,im
age_size,3),activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool2D(pool_size=(2,2)))

model.add(Conv2D(filters=64,kernel_size=(3,3),activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.5))

model.add(Conv2D(filters=128,kernel_size=(3,3),activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
```

```python
model.add(Dropout(0.5))

model.add(Flatten())

# model.add(Dense(64))
# model.add(Activation('relu'))
# model.add(Dropout(0.5))

model.add(Dense(8))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',optimizer='adam',metrics=[
'accuracy'])

model.summary()

tensorboard = TensorBoard(log_dir = 'logs')
checkpoint = ModelCheckpoint("skin-
snehit.h5",monitor="val_accuracy",save_best_only=True,mode="auto",verbos
e=1)
reduce_lr = ReduceLROnPlateau(monitor = 'val_accuracy', factor = 0.3, pa
tience = 2, min_delta = 0.001,
                              mode='auto',verbose=1)

history = model.fit(X_train,y_train,validation_split=0.1, epochs =30, ve
rbose=1, batch_size=16,
                   callbacks=[tensorboard,checkpoint,reduce_lr])

#Visualize Training
def plot_graphs(history, string):
    sns.set_style("whitegrid")
    plt.plot(history.history[string])
    plt.plot(history.history["val_"+string])
    plt.xlabel("Epochs")
    plt.ylabel(string)
    plt.title("Skin Disease Model Epochs")
    plt.legend([string,"val_"+string])
    plt.show()
plot_graphs(history,'accuracy')
plot_graphs(history,'loss')

pred = model.predict(X_test)
pred = np.argmax(pred,axis=1)
y_test_new = np.argmax(y_test,axis=1)
print(classification_report(y_test_new,pred))

fig,ax=plt.subplots(1,1,figsize=(14,7))
sns.heatmap(confusion_matrix(y_test_new,pred),ax=ax,xticklabels=labels,y
ticklabels=labels,annot=True)
```

```
fig.text(s='Heatmap of the Confusion Matrix',size=12,y=0.92,x=0.28,alpha
=0.8)

plt.show()
```

2.EfficientNet B0 source code

```
tf.keras.backend.clear_session()

model = effnet.output
model = tf.keras.layers.GlobalAveragePooling2D()(model)
model = tf.keras.layers.Dropout(rate=0.5)(model)
model = tf.keras.layers.Dense(8,activation='softmax')(model)
model = tf.keras.models.Model(inputs=effnet.input, outputs = model)

model.compile(loss='categorical_crossentropy',optimizer = 'Adam', metric
s= ['accuracy'])

tensorboard = TensorBoard(log_dir = 'logs')
checkpoint = ModelCheckpoint("skin-
snehit.h5",monitor="val_accuracy",save_best_only=True,mode="auto",verbos
e=1)
reduce_lr = ReduceLROnPlateau(monitor = 'val_accuracy', factor = 0.3, pa
tience = 2, min_delta = 0.001,mode='auto',verbose=1)

history = model.fit(X_train,y_train,validation_split=0.1, epochs =30, ve
rbose=1, batch_size=16,
                   callbacks=[tensorboard,checkpoint,reduce_lr])

pred = model.predict(X_test)
pred = np.argmax(pred,axis=1)
y_test_new = np.argmax(y_test,axis=1)
print(classification_report(y_test_new,pred))


fig,ax=plt.subplots(1,1,figsize=(14,7))
sns.heatmap(confusion_matrix(y_test_new,pred),ax=ax,xticklabels=labels,y
ticklabels=labels,annot=True)
fig.text(s='Heatmap of the Confusion Matrix',size=12,y=0.92,x=0.28,alpha
=0.8)

plt.show()


model.save('lesion-skin.h5')
```

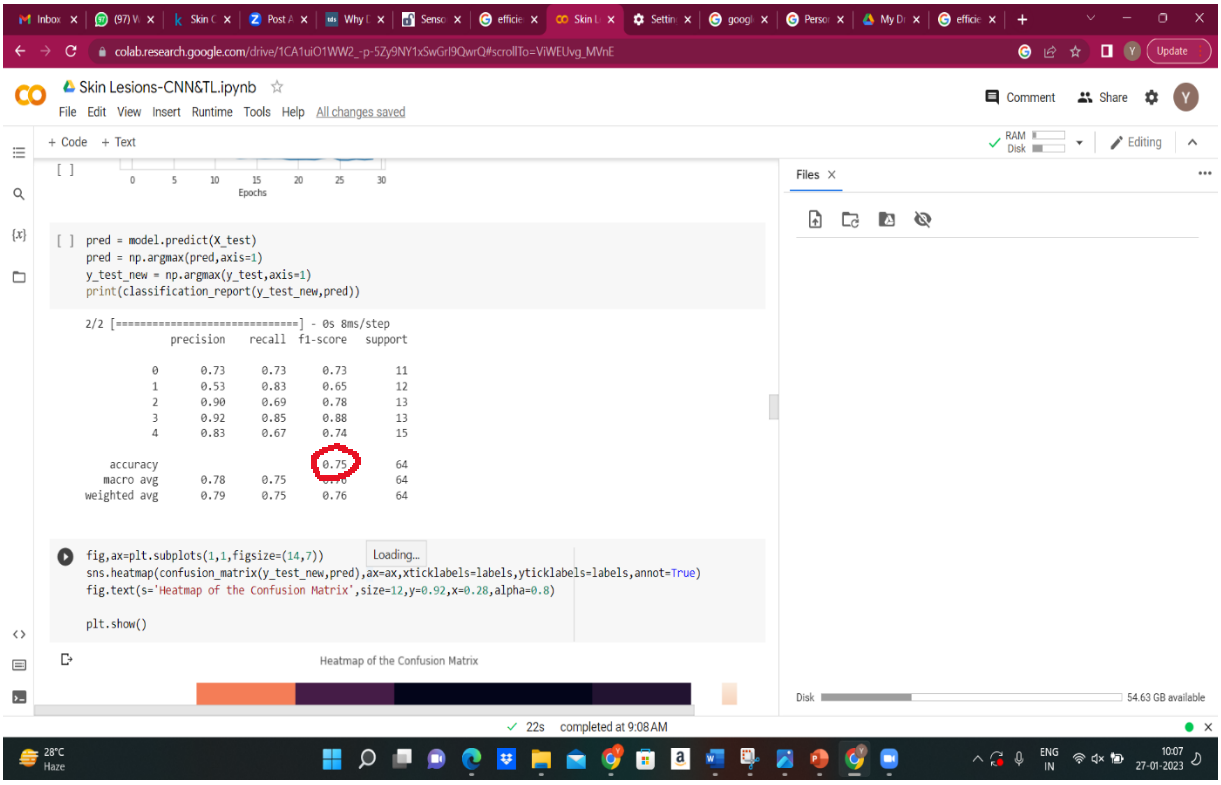
3.app.py source code

```
import numpy as np
import os, cv2
from PIL import Image
from keras.models import load_model
from keras.preprocessing import image
import tensorflow as tf
global graph
graph = tf.compat.v1.get_default_graph()
from flask import Flask , request, render_template
##from werkzeug.utils import secure_filename
from gevent.pywsgi import WSGIServer

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

app = Flask(__name__)
model = load_model("skin-snehit.h5")

@app.route('/')
def index():
    return render_template('UIndex.html')

@app.route('/predict',methods = ['GET','POST'])
def upload():
    if request.method == 'POST':
        f = request.files['image']
        print("current path")
        basepath = os.path.dirname(__file__)
        print("current path", basepath)
        filepath = os.path.join(basepath,'uploads',f.filename)
        print("upload folder is ", filepath)
        f.save(filepath)

##        img = image.load_img(filepath,target_size = (64,64))
##        x = image.img_to_array(img)
##        x = np.expand_dims(x,axis =0)

        img = Image.open(filepath)
        opencvImage = cv2.cvtColor(np.array(img), cv2.COLOR_RGB2BGR)
        img = cv2.resize(opencvImage,(64,64))
        img = img.reshape(1,64,64,3)
        x = img

        preds = np.argmax(model.predict(x), axis=-1)
        print(preds)
        index = ['Actinic Keratosis - Must undergo Cryotherapy.',
                 'Dermatofibroma - It is Harmless ,but need to be removed surgically.',
                 'Melanoma - It is a serious form of skin cancer,must be treated
immediately.',
```

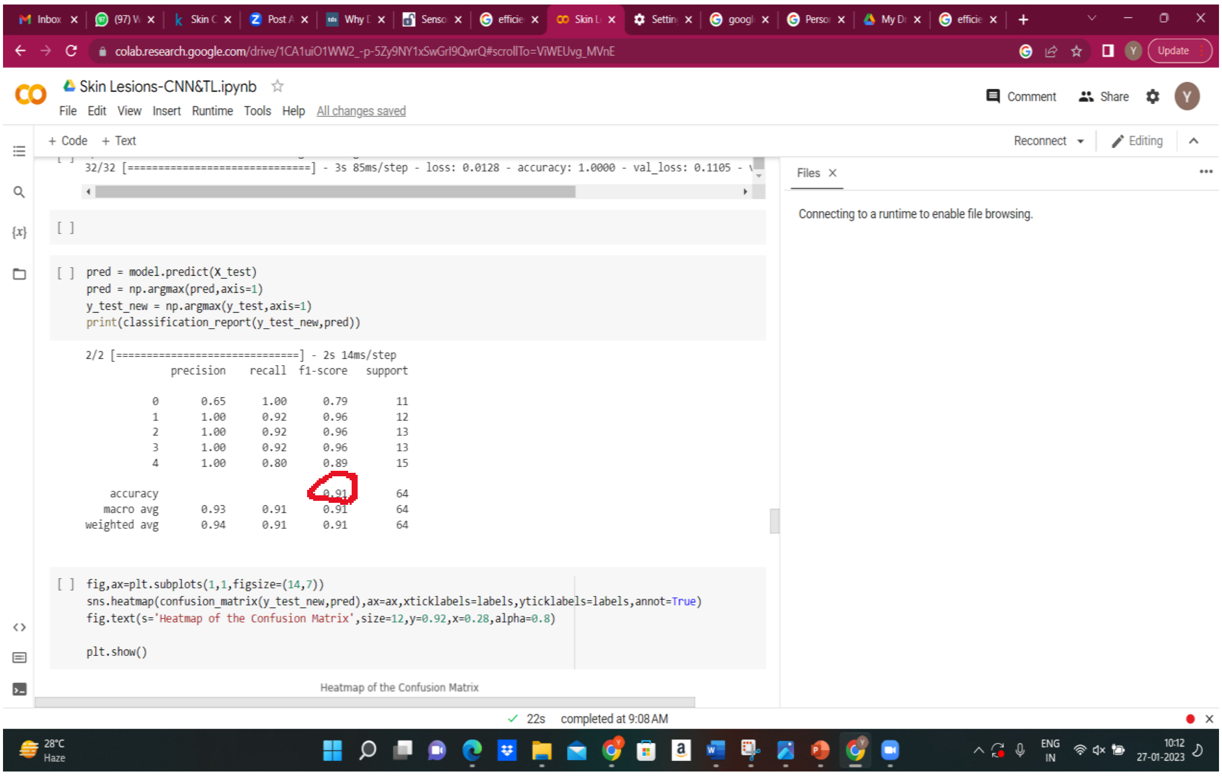
```
                'Seborrheic Keratosis - It is a type of skin growth which is harmless.',
                'Squamous Cell Carcinoma - It is a common type of skin cancer and can be treated by a Laser Surgery.'
                ]

        print("-------------------------------------\n")
        print("\nprediction -> ",index[preds[0]])
        print("\n-------------------------------------")

        text = "The predicted Disease is " + str(index[preds[0]])

    return text
if __name__ == '__main__':
    app.run(debug = True, threaded = False)
```

SCREENSHOTS

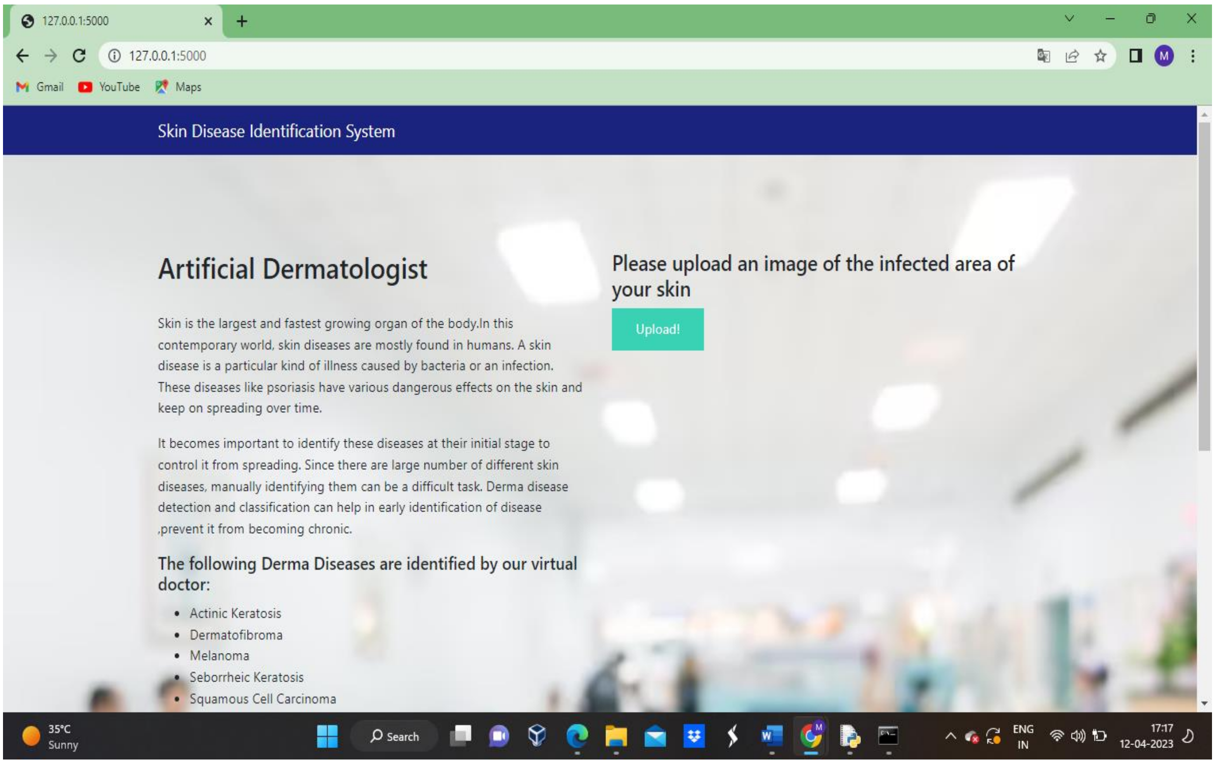
Accuracy obtained for CNN - 75%

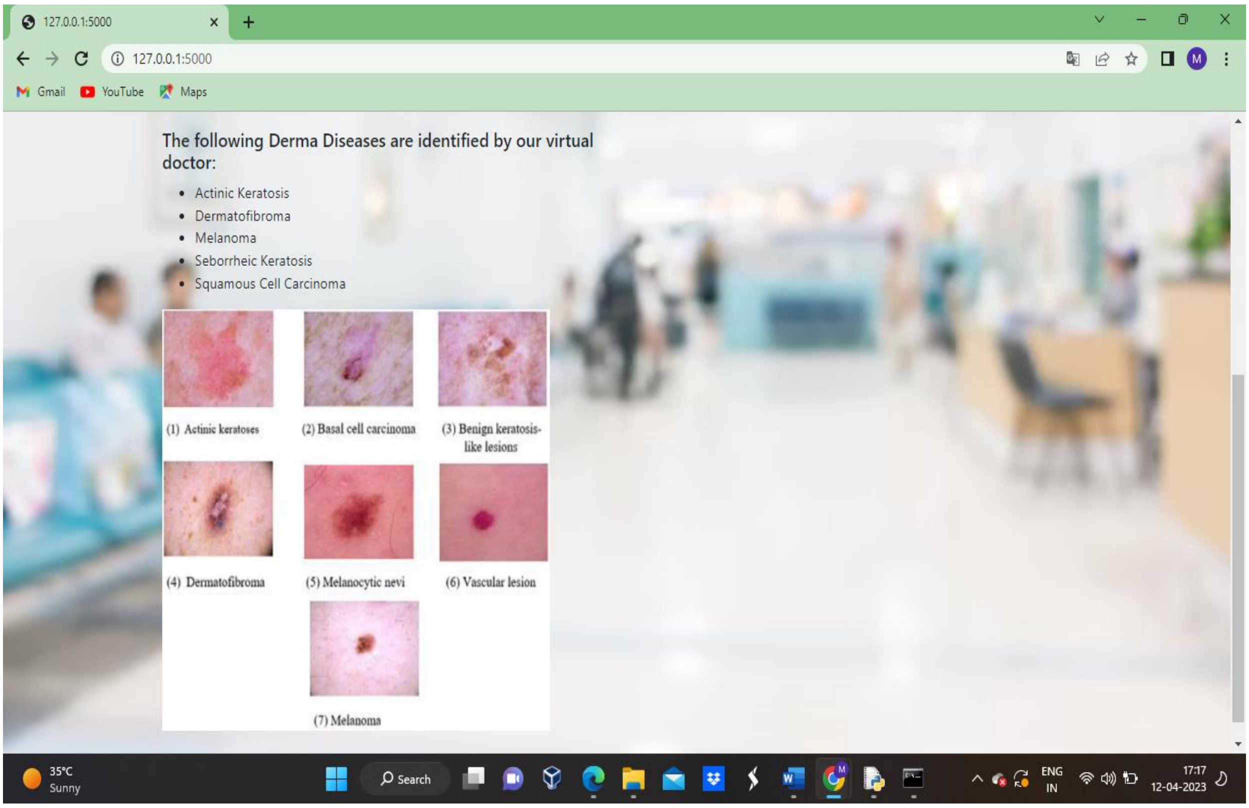


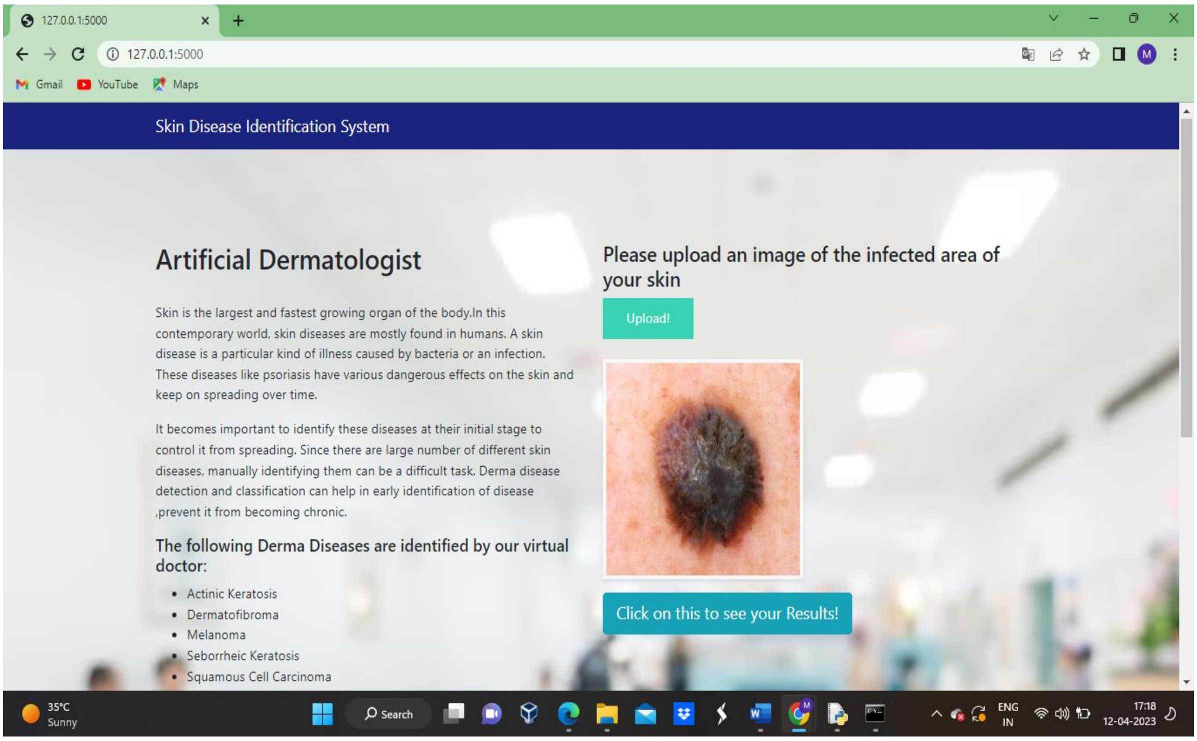
Accuracy Obtained for Efficient B0 – 91%

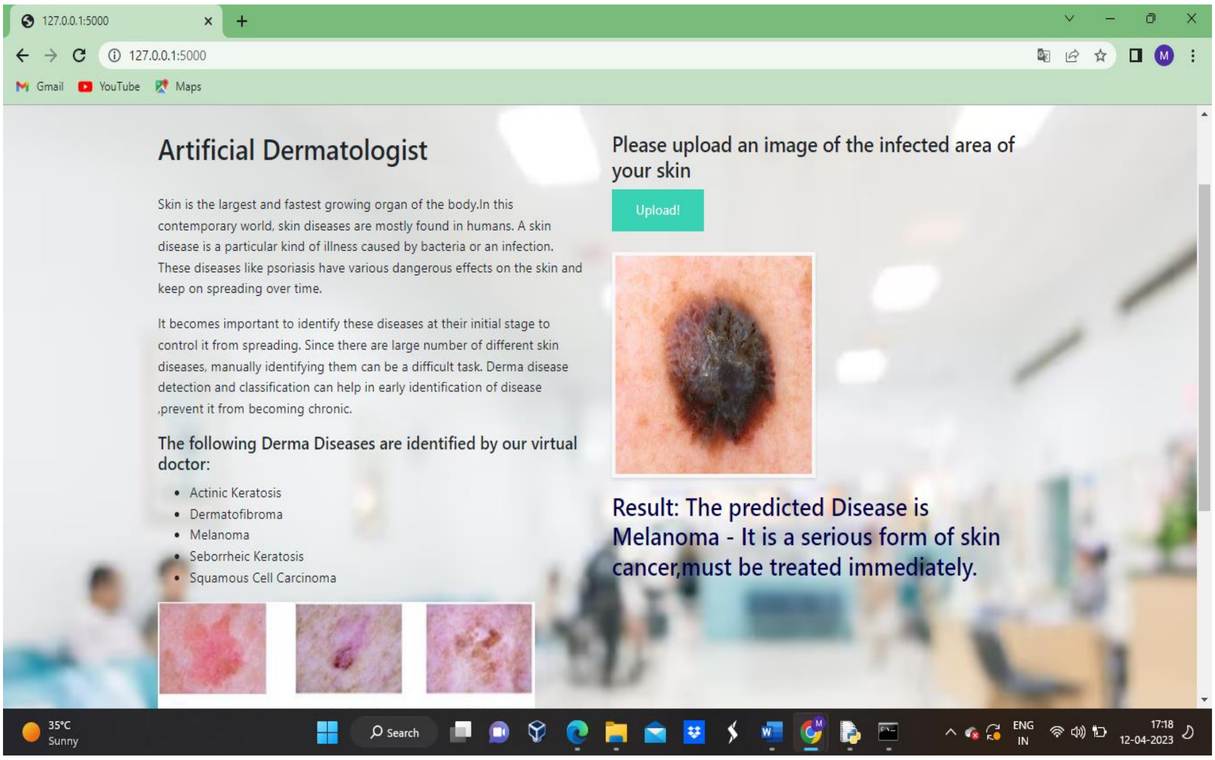


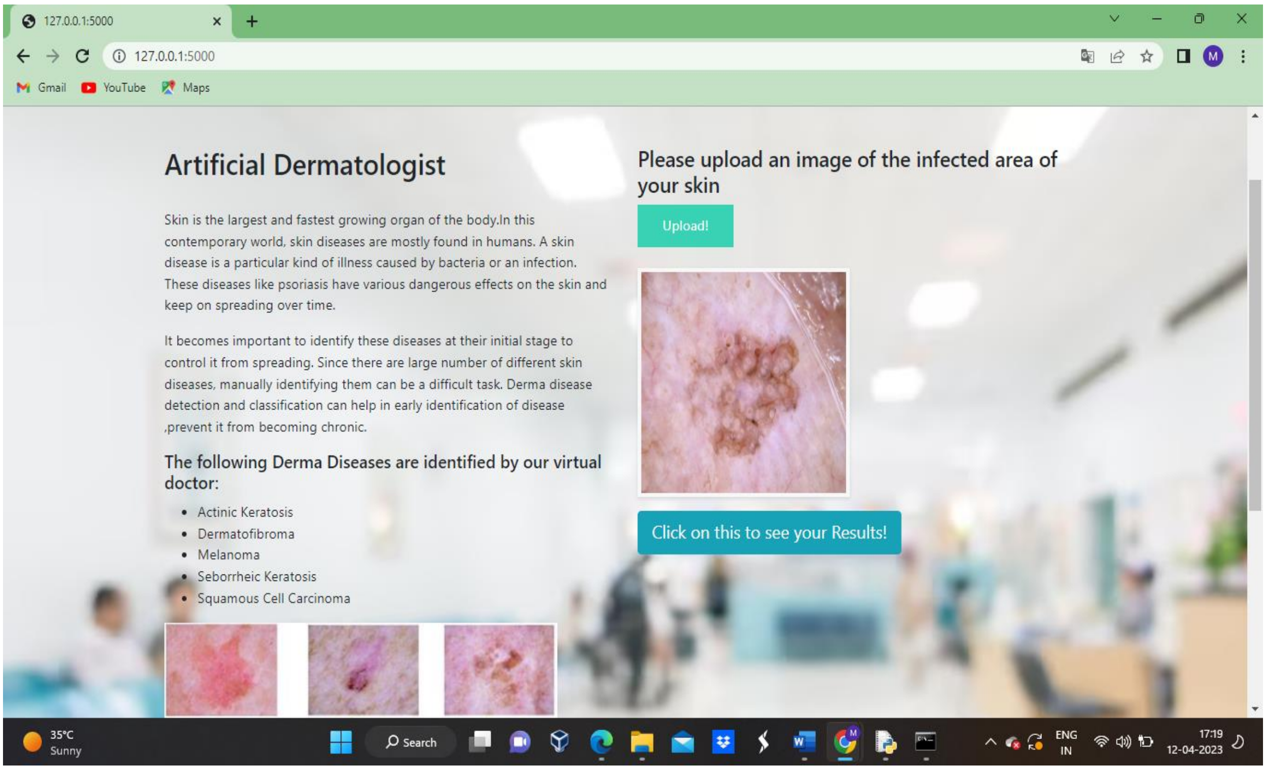
Front Page of Web application:

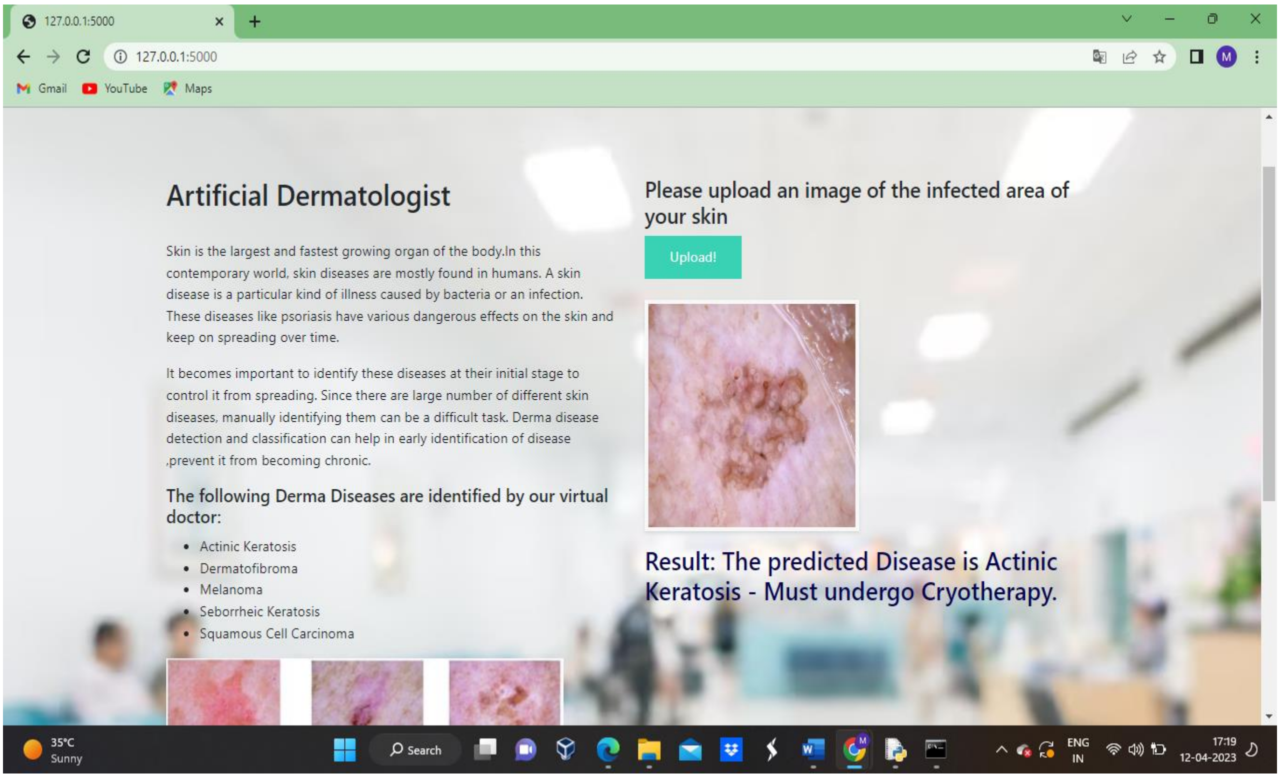





127.0.0.1:5000
Gmail
YouTube
Maps
Skin Disease Identification System
Artificial Dermatologist
Skin is the largest and fastest growing organ of the body.In this contemporary world, skin diseases are mostly found in humans. A skin disease is a particular kind of illness caused by bacteria or an infection. These diseases like psoriasis have various dangerous effects on the skin and keep on spreading over time.
It becomes important to identify these diseases at their initial stage to control it from spreading. Since there are large number of different skin diseases, manually identifying them can be a difficult task. Derma disease detection and classification can help in early identification of disease ,prevent it from becoming chronic.
The following Derma Diseases are identified by our virtual doctor:
Actinic Keratosis
Dermatofibroma
Melanoma
Seborrheic Keratosis
Squamous Cell Carcinoma
Please upload an image of the infected area of your skin
Upload!
Click on this to see your Results!
35°C
Sunny
Search
ENG
IN
17:18
12-04-2023


127.0.0.1:5000
Gmail
YouTube
Maps
Artificial Dermatologist
Skin is the largest and fastest growing organ of the body.In this contemporary world, skin diseases are mostly found in humans. A skin disease is a particular kind of illness caused by bacteria or an infection. These diseases like psoriasis have various dangerous effects on the skin and keep on spreading over time.
It becomes important to identify these diseases at their initial stage to control it from spreading. Since there are large number of different skin diseases, manually identifying them can be a difficult task. Derma disease detection and classification can help in early identification of disease ,prevent it from becoming chronic.
The following Derma Diseases are identified by our virtual doctor:
Actinic Keratosis
Dermatofibroma
Melanoma
Seborrheic Keratosis
Squamous Cell Carcinoma
Please upload an image of the infected area of your skin
Upload!
Result: The predicted Disease is Melanoma - It is a serious form of skin cancer,must be treated immediately.
35°C
Sunny
Search
ENG
IN
17:18
12-04-2023





Research paper

SKIN LESIONS ENCOUNTERING USING IMAGE ANALYSIS AND CONVOLUTIONAL NEURAL NETWORK

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Abstract—
In today's world, skin lesions are mostly found in humans, animals, and plants. Skin lesions are one of the most common health concerns in the world. A skin lesion is a specific disease caused by a bacteria or infection. These diseases like actinic Keratosis, Dermatofibrova,squamous cell carcinoma, melanoma, brown spot, allergies, eczema etc. have different dangerous effectson the skin and keep on spreading over time. Identifying these diseases in their early stage becomes crucial in controlling their spread. These lesions are identified by using numerous advanced technologies such as image processing, data mining, convolutional neural networks (CNN) etc. For the diagnosis of skin lesions, image processing has been extensively applied in this field of study.To identify the section of the body afflicted by disease, the form of the affected area, its affected area tone, etc., image processing techniques such as filtering, segmentation, feature extraction, image pre-processing, and edge detection, among several others, are used.This study provides an overview of recent image processing-based approaches for diagnosing various skin lesions.In this research, a thorough analysis of various skin lesions diagnosis systems is carried out, with varied approaches and their results.
Keywords*— Skin Lesion, convolutional neural network, Efficient B0, Deep learning*

I.INTRODUCTION

This article guides about Skin lesions. Skin lesions among the most hazardous and widespread illnesses that frequently harm people. The main types of skin lesions that affect humans are Melanoma, actinic keratosis,dermatofibroma,seborrheickeratosis,squamous cell carcinoma. However, Melanoma has a high mortality rate with an overall impacting case of less than 5% and is the most deadly and debilitating type of skin lesions. The World Health Organization also predicted that melanoma cases were widespread. The traditional approaches for identifying skin lesions include skin self-examination and skin clinical examination. However, these examination techniques are exceedingly time-consuming and complex. This approach is quite expensive and involves frequent patient visits. Additionally, these tests require specialist equipment including laser-based and micro-spectroscopy techniques. Managing it involves work and extensive training.The smartphone revolution made it possible for patients to share images for the diagnosis of skin lesions through phone. However, these images might not be of standard quality, which could result in an incorrect diagnosis. Besides, using the internet for sharing could risk privacy. But as AI has evolved, daily interactions between humans and AI have expanded, which could help doctors make better decisions. Also, the usage of AI will lessen diagnostic human mistake. Despite the existence of such AI technologies, a skilled physician is still necessary. The purpose of this study is to investigate the application of CNN and deep learning to the early diagnosis of skin lesions. Here, a model is developed using the data available for the skin lesions, and with each training set of data, the model's accuracy is improved. Instead of using a multilayer neural network, this uses deep learning and a deep multi-layered network, which require training on enormous amounts of data to increase the system's accuracy. These AI techniques for diagnosing skin lesions are relatively accessible, user-friendly, and inexpensive. Also, AI-based technology is simplistic and provides many more obligations and characteristics than traditional methods of treating skin lesions. The process of encountering skin lesions with AI involves feeding the image to the model, segregating it, and handling it to classify the kind of lesions encountered. Deep learning has ushered in a shift in the field of artificial intelligence. The outcomes of AI and machine learning have been enhanced through deep learning. This study conducts a review of the literature on various traditional deep learning techniques used for skin lesion diagnosis. In this study, a model is built from the ground up to produce superior outcomes when using Convolutional Neural Network (CNN). To reuse a previously trained model for greater accuracy, use transfer learning. In previous works they have used deep convolutional neural network models which may take days or even weeks to train on very large datasets. A way to short-cut this process is to re-use the model weights from pre-trained models that were developed for standard datasets, such as the ImageNet image recognition tasks. Top performing models can be downloaded and used directly, or integrated into a new model.

In this research we used the **EfficientNetB0** model which will use the weights from the **ImageNet** dataset. Compared to traditional approaches of diagnosis, this model for skin lesions has made diagnosis and identification easier.

II. LITERATURE SURVEY

The detection and diagnosis of skin lesions have advanced significantlyover time thanks to developments in artificial intelligence, machine learning, and deep learning. To improve the precision of identification and diagnosis, numerous researchers have employed various algorithms, models, and techniques.Deep learning enhances skin lesion encountering. Deep learning enhanced ML and CV. Deep learning surpasses machine learning. Deep learning can identify skin lesions in photos to reduce losses. The advantages are: Technology enhances the accuracy of skin lesion identification and may help doctors to identify various forms of skin lesions. Automated eczema identification using image processing via a support vector machine, which includes segmentation of the obtained image, feature selection using texture-based knowledge for better accurate predictions, and finally evaluating using the Support Vector Machine (SVM). eczema development as witnessed by a researcher. Finding feature-based parameters is critical when collaborating with SVM since the Support Vector Machine model cannot handle noisy image data. If there are more parameters at each feature vector than there are training data samples, it will perform poorly[1].The requisite image processing methods, like morphological procedures for skin lesion analysis, are employed to identify skin lesions.Because morphological opening, closure, contraction, and depletion are primarily determined by the binary image produced by thresholding, the ideal threshold value must be chosen with the utmost care.The morphological-based techniques might not be appropriate for calculating the expansion of affected regions based on the texture of the images [2].The approach for categorising skin issues was developed by the Genetic Algorithm (GA).The Genetic Algorithm does face difficulties, such as taking too long to settle on the answer. The model never offers the optimal global answer because that would not produce a fair result [3]. The most widely utilised methods for locating and diagnosing anomalies in radiological imaging technology are artificial neural networks (ANN). The ANN-based model for breast cancer prior detection is image-based; both neural network approaches necessitate a massive proportion of training data for the model to accomplish well, which necessitates a meaningful amount of computational effort.The neural network approaches are very conceptual, and we are unable to customise the model. Furthermore, in ANN, as image resolution increases, so does the number of trainable parameters, resulting in massive training efforts. The ANN model suffers with declining and exploding the gradient[4]. The validation set accuracy for the Fine-Tuned Neural Network-based skin lesions classification model was a respectable 79.90%.However, in order to achieve the desired accuracy, the system components must be scaled. Back Propagation Neural Network (BPNN) is a supervisory learning model that fine-tunes weights focusing on error rate. However, the model does not work with noisy data. Another significant disadvantage is that when fresh weights are assigned to the components, they ignore the previously assigned weight, which has a huge impact on the earlier associations [5].Convolutional Neural Networks (CNN) are the frequently used methods for classifying as well as sensing radiological imaging errors.The CNN approach to skin lesions diagnosis yielded promising results. However, neural network models are very conceptual, and we lack the ability to customise the model. CNN does not really define the magnitude and size of the object in its analysis [6]. A DenseNet121 model trained on simulated and real pictures classifies skin lesions images into 3 disease groups. The suggested model was trained and tested using skin lesion data. The suggested approach classified skin lesions accurately into 3 classes. The suggested methodology trump's current methods. The advantages are. A DenseNet121 model gives better diagnosis methodology and the disadvantages are accuracy is missing because of class segregation [7]. In this study, we suggest a deep learning-based method for Skinlesion prediction that uses Convolutional neural network to generate synthetic images of skin diseases. The photos of skin diseases are then classified into five kinds of diseases using custom CNN model that has been trained on both fake and genuine images using transfer learning. The publicly accessible skin lesiondataset has been used for extensive training and testing of the proposed model. The accuracy of the suggested method for classifying skin lesions images into 5 classes. The proposed strategy demonstrates how it is better than the current approaches. Apart from the sample dataset, the benefits are exceedingly accurate, but the drawbacks are accuracy will be questioned [8]. Skin diseases pose a severe threat to humans. Therefore, it is essential to recognize and diagnose such illnesses as soon as possible. The quantity and calibre of labelled training data determines how accurate deep learning models will be, however ongoing advancements in deep learning have greatly benefited.

III. SYSTEM ARCHITECTURE

Many of the experimenters have suggested image processing-based methods to identify the class of the skin lesions. The objective is to create a portal to receive images and run it by an algorithm to predict the type of skin lesion. The First step is collecting a large number of images for different types of skin diseases. After that research into the medical field to study these images and based on that developing and fine-tuning the algorithm to produce more and more accuracy. Developing a user-friendly portal where the user can upload images and get the result after processing.

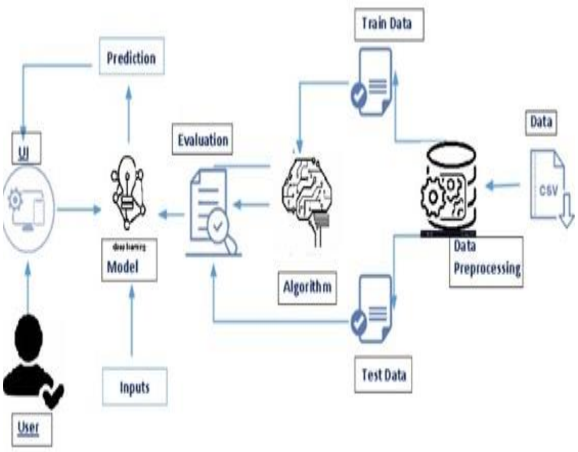

Fig 1 Architecture Diagram

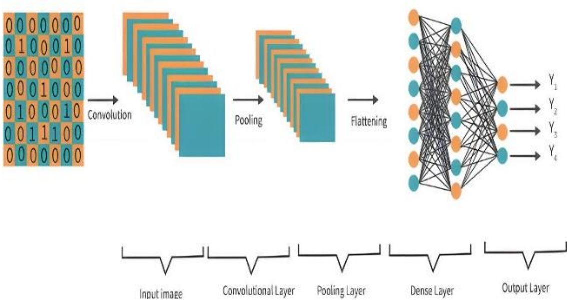

Fig 2 Convolutional neural network

Convolutional Neural Networks contains convolution layer which makes CNN different from Traditional neural networks. Convolutional layer consists of a filter capable of recognizing specific kinds of data and patterns in the image. Aside from convolutional layers, CNNs have two other layers: pooling and classification layers. CNN reduces the high dimensionality without losing its information.

Using more than a million photos from the ImageNet collection, the convolutional neural network EfficientNet-b0 was trained. In this research we are comparing custom CNN and Efficient b0 to get accurated model which predicts the effected skin area.

IV. PROPOSED METHODOLOGY

4.1 Data Collection

Artificial Intelligence is a data hunger technology,It is heavily reliant on data; without data, a machine cannot learn. It is the most important factor that allows algorithm training to take place.In Convolutional Neural Networks, as it deals with images, we need training and testing data set.

The initial step in making deep learning model is the collection of data to train the model. The accuracy of deep learning model predictions relies on the quality of the data used for training.We will be utilizing a downloadable dataset to train our neural network model and expand it to include real-time picture testing through Kaggle.

4.1.1 Data Processing

There are often incompatibilities and absence of certain behaviours or trends in raw data and images from the real world. They also contain mistakes. so, as soon the data collected it is pre-processed into a layout that can be used by machine learning algorithms.

Pre-processing contains many techniques to improve data accuracy and validity: Data cleaning, which can be done manually or with automated tools, removes incorrect information from the dataset. Data imputations, which are generally performed using machine learning algorithms, fill in missing values by randomly selecting one of several possible alternatives. Oversampling is used to correct for bias or imbalances in the data set by obtaining more observations with the methods like repetition and bootstrapping. Data integration refers to the process jointing different datasets in order to create a larger, more comprehensive body of data. This technique can overcome incompleteness within individual datasets and standardizes them. Data normalization is a process which reduces the size of datasets by reducing the magnitude and order of data. This decreases the amount of memory and processing need for training iterations. These are various steps takes place in data processing after data collection.

4.2 Model building

Many techniques are used in predictive modelling to create statistical models of future behaviour based on test data input. Model building includes the following main tasks Training and testing.In This Phase we will train the model using the dataset that we have pre-processed .The data set is divided into a training set and a testing set. 20% for testing and 80% for training. Once the data is fed into the model, it analyses the patterns ,it considers a portion of the image in respect to the background or surroundings; this process is crucial for any image classification, Obtained object or area with background gives feature extraction

$$\text{recognition rate} = \frac{\text{number of corrected detection}}{\text{number of given detection}} \times 100\%.$$

Fig -4.2.1-Lesion Identification

and make the decisions. The next task, evaluation of Model, high-level choices like the number, size, and kind of layers number of epochs are included in this.Every epoch displays the accuracy and loss for both the training and validation datasets. Save the model, After evaluating the model based on the accuracy obtained we have used Efficient b0 (89%) with more accuracy compared to custom cnn(75%),for predicting the output.

4.3 App building

When the Efficient b0 model is created, we will be combining it to a web application so that users can also use it to predict the output without coding. In the web application, the user gives the input image and get the predictions.This section has the following tasks: Building HTML Pages, Building server-side script

V. RESULTS AND DISCUSSIONS

The last module of the system is a projection of the result. User interacts with the UI (User Interface) to enter Data. When the user clicks on the home button home page is displayed. Predict page is displayed when predict button is clicked. On predict page, upload the input image to predict the type of skin lesion. Finally, the prediction for the given input features is shown on the UI.

Lesion type 1:

Fig 3 Actinic keratosis

The model analyses theaffected area image and identify the skin lesion as Actinic Keratosis using Image Analysis.

Lesion type 2:

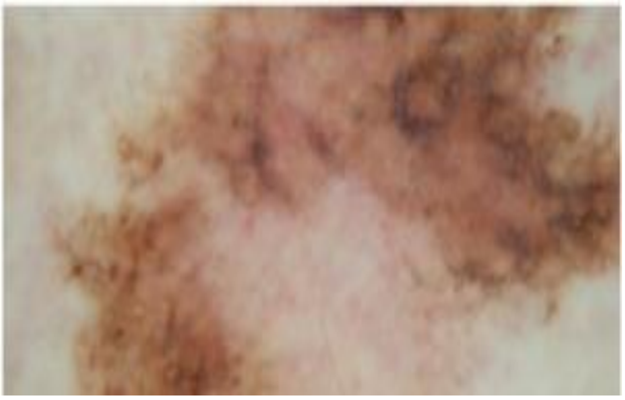

Fig 4 -Dermatofibrova

The model analyses theaffected area image and identify the skin lesion as Dermatofibrovausing Image Analysis.

Lesion type 3:

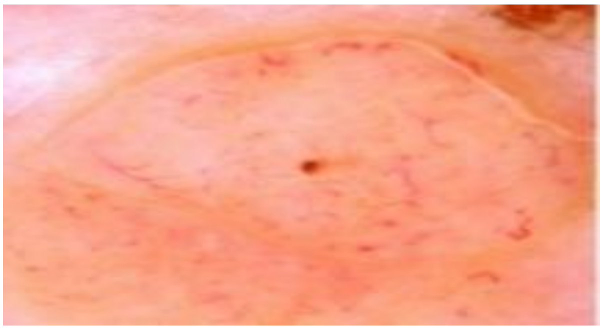

Fig 5 squamous cell carcinoma

The model analyses theaffected area image and identify the skin lesion as squamous cell carcinomausing Image Analysis.

Lesion type 4:

Fig 6 Melanoma

The model analyses theaffected area image and identify the skin lesion as melanoma using Image Analysis.

Lesion type 5:

Fig 7 Seborric keratosis

The model analyses theaffected area image and identify the skin lesion as**Seborric keratosis**using Image Analysis

VI. CONCLUSION

Convolutional neural networks (CNNs) have achieved amazing results across various areas like experimental medicine, computed tomography diagnostics and encountering different diseases. Although deep learning is considered as the predominant method in various difficult tasks such as classifying images and detecting objects, it is not a catholicon. It is essential to be aware of important concepts and benefits of CNN as well as the limits of deep learning are critical to take the advantage of them in diagnostic imaging research with the aim of improving its performance and better supervision of patients.

In this article a pattern for detecting the skin lesions is done using image analysis and Convolutional Neural Networks. It is found that by using the Convolutional neural networks and Transfer learning we can reach a better precision value and we can also focus towards predicting a lot more lesions than with any other prior models made before. By applying a Transfer learning concept to CNN using efficient b0, we can predict up to five different skin lesions with a greater degree of precision level of 89%. This shows that deep learning algorithms have enormous potential in diagnosis the actual skin lesions. Even the high-quality system with a very large dataset can be used, so that the precision can be greatly enhanced and this pattern can be used for scientific trails because it includes dimensions.

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