



AI (CNN) project report on

Skin Disease Prediction

Submitted by:

Team - 3

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Acknowledgement

We sincerely thank Smart Bridge and IBM for providing us a platform to develop our skills in the domain of Artificial Intelligence and help us make the most of our time in the lock-down period. We convey our heartfelt thanks to Ms.D. Pradeepthi, our trainer for making every session interactive and interesting. We also thank the mentor, Mr. Ram Mohan for being patient and guiding us all through the program.

We thank our respective institutions for permitting us to attend this program which is sure to play a significant part in the interviews that we are to face soon.

Team - 3

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1. Introduction

Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. Based on a survey in 2010, skin diseases had the fourth leading cause of nonfatal disease burden in the world, and three of the world's most common diseases were skin diseases. Skin diseases have caused enormous economic burdens both in high-income and low-income countries. For each individual, skin problems can have adverse effects on all aspects of life, including interpersonal relationships, work, social functioning, physical activity and mental health.

The burden of skin disease is a multidimensional concept that encompasses psychological, social and financial consequences of the skin disease on the patients, their families and on society. Chronic and incurable skin diseases, such as psoriasis and eczema, are associated with significant morbidity in the form of physical discomfort and impairment of patients' quality of life; whereas malignant diseases, such as malignant melanoma, carry substantial mortality. With the availability of a wide range of health status and quality-of-life measures, the effects of most skin diseases on patients' lives can be measured efficiently.

1.1 Over view

The change in climatic conditions and increased pollution levels are leading to increase in the number of people are suffering from skin diseases. More than 125 million people suffering from Psoriasis also skin cancer rate is rapidly increasing over last few decades specially Melanoma is most diversifying skin cancer. If skin diseases are not treated at earlier stage, then it may lead to complications in the body including spreading of the infection from one individual to the other. The skin diseases can be prevented by investigating the infected region at an early stage. The characteristic of the skin images are diversified, so that it is challenging job to devise an efficient and robust algorithm for automatic detection of the skin disease and its severity. Skin tone and skin colour plays an important role in skin disease detection.

1.2 Purpose

To overcome the above problem we are building a model which is used for the prevention and early detection of Acne, Melanoma, psoriasis, Rosacea and vitiligo. An application is built where a person can upload an image from UI ,then image will be sent the trained model. The model analyse the image and detect the skin disease that person had. Our system will use a Convolution neural network to train the images of skin diseases.

In biomedical informatics field, research has been done on using image-based artificial intelligence diagnosis system to help early detection of certain diseases, especially skin diseases . For pattern recognition and classification of clinical image, deep neural networks have been widely used. Image processing techniques help to build automated screening system for dermatology at an initial stage.

2. LITERATURE SURVEY

2.1 Existing Problem

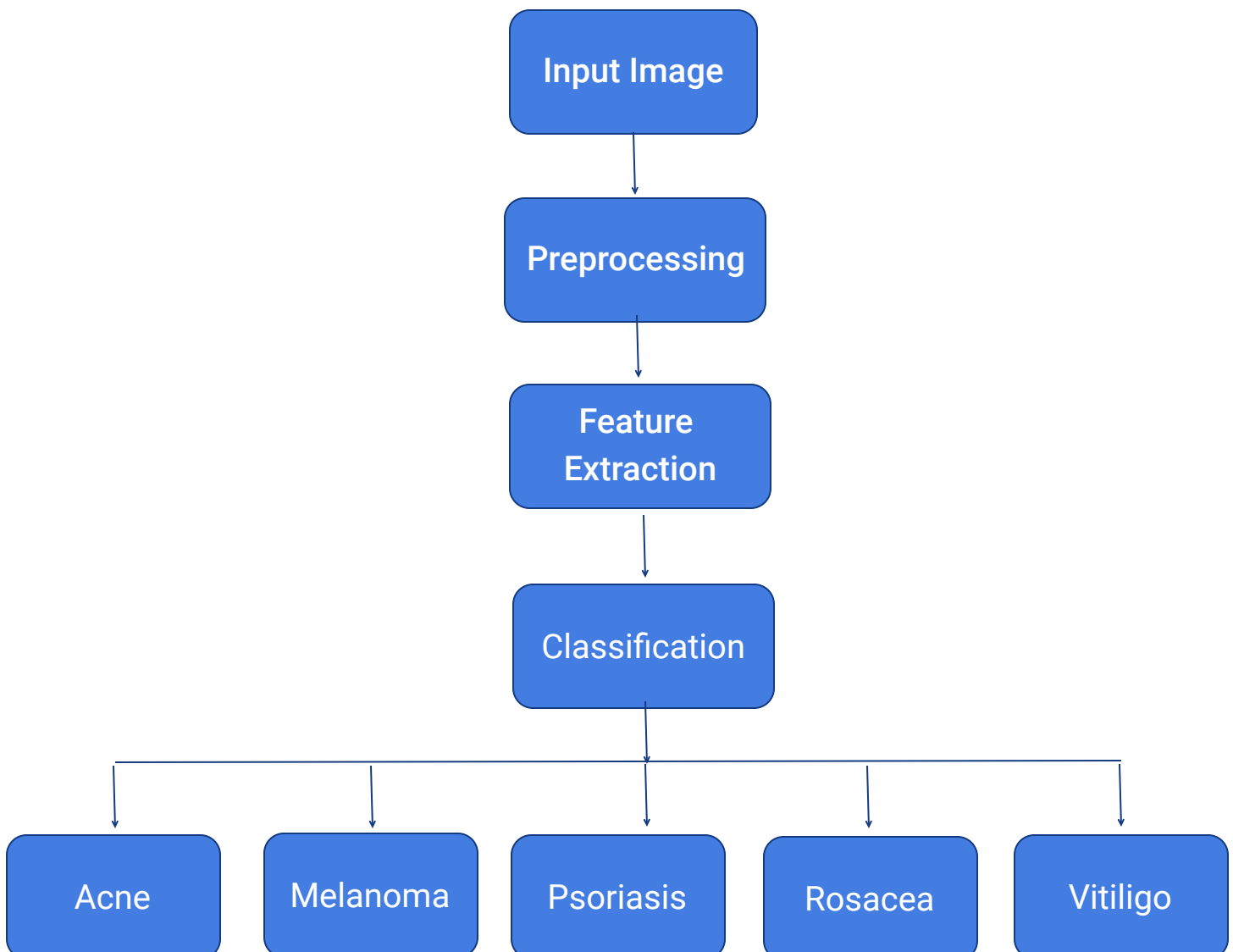
The characteristic of the skin images are diversified, so that it is challenging job to devise an efficient and robust algorithm for automatic detection of the skin disease and its severity. Skin tone and skin colour plays an important role in skin disease detection.

2.2 Proposed Solution

The present project aim at building a CNN model that can read in an image and further classify it into Acne, Melanoma, psoriasis, Rosacea and vitiligo. Also it can be extended to integrating a camera to the system that can read in the input at real time insances and further the built model can processes the image to classify the image into the specified classes.

3. Theoretical Analysis

3.1 Block Diagram



3.2 Hardware / Software designing

HARDWARE:

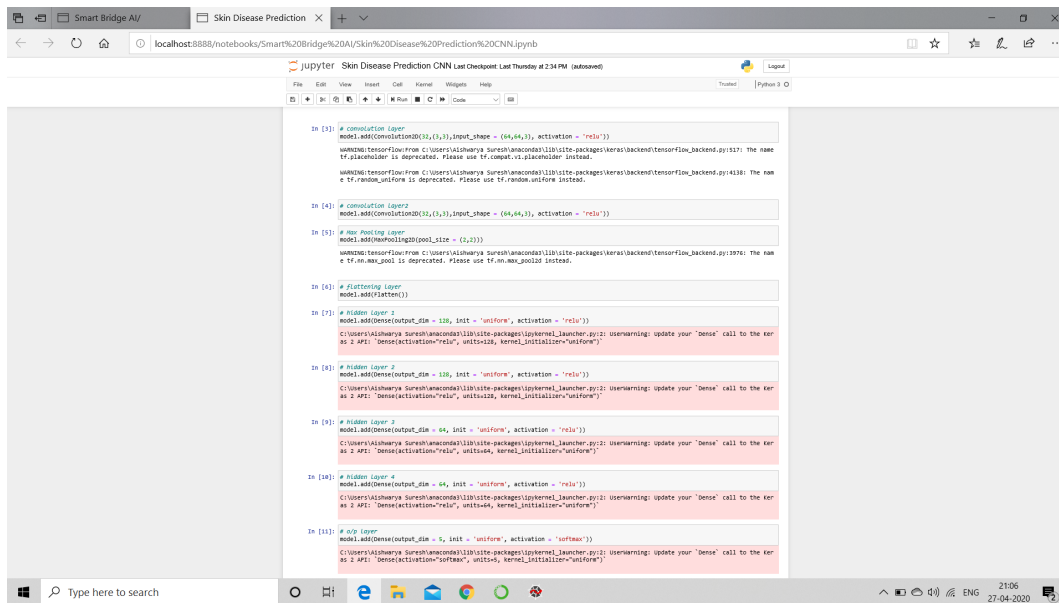
- COMPUTER
- CAMERA – USED IN REAL TIME ENVIRONMENT FOR TAKING THE PICTURES OF SKIN DISEASES AND PREDICTING THEM

SOFTWARE:

- PYTHON - Python is the language most commonly used today to build and train neural networks and in particular, convolutional neural networks.
- There are many Python frameworks and libraries available for machine and deep learning, including NumPy, scikit-learn, as well as the “big three” deep learning frameworks.
- All major deep learning frameworks support Python. Of these, the most popular and powerful platforms are TensorFlow, Keras (which is typically used as a front-end wrapper for TensorFlow), and PyTorch.
- Python is suitable for collaborative coding and implementation, because its code is readable and easy to convey to others.
- HTML ,CSS – USER INTERFACE OF WEB APPLICATION FOR PREDICTION OF SKIN DISEASES.
- FLASK- WEB APPLICATION FRAMEWORK FOR INTEGRATING THE TRAINED MODEL , UI AND RENDERING THE WEB PAGE ONTO BROWSER.

4. Experimental Analysis

- Number of hidden layers used: 4
- Number of convolution layers used: 2
- Accuracy attained: 75%



```
In [1]: # convolution layer
model.add(Convolution2D(32,(3,3),input_shape=(64,64,3), activation='relu'))

In [2]: # convolution layer
model.add(Convolution2D(32,(3,3),input_shape=(64,64,3), activation='relu'))

In [3]: # Max Pooling Layer
model.add(MaxPooling2D(pool_size=(2,2)))

In [4]: # flattening Layer
model.add(Flatten())

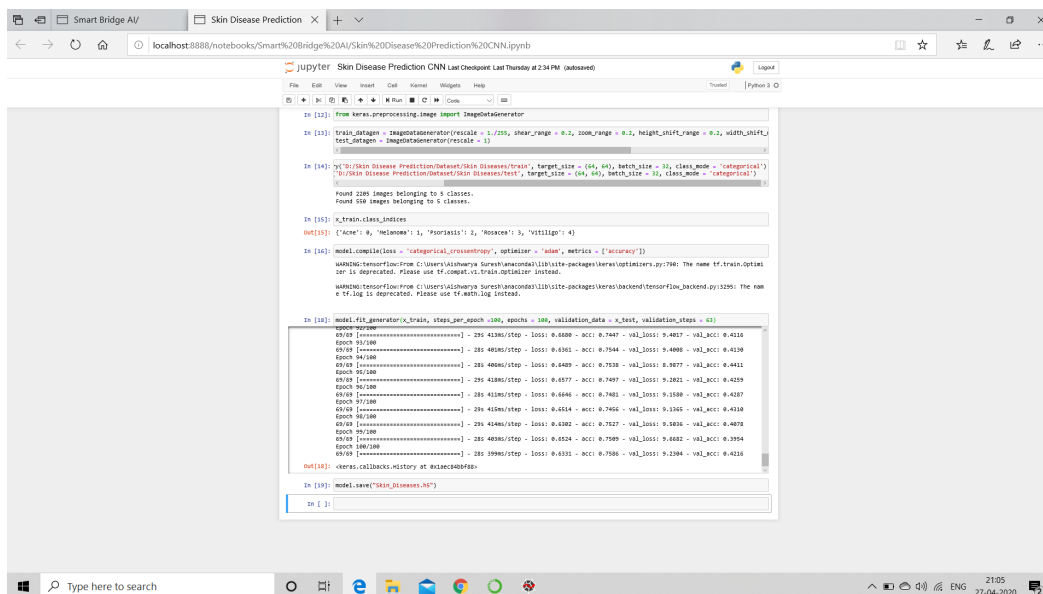
In [5]: # Hidden Layer 1
model.add(Dense(output_dim=128, init='uniform', activation='relu'))

In [6]: # Hidden Layer 2
model.add(Dense(output_dim=128, init='uniform', activation='relu'))

In [7]: # Hidden Layer 3
model.add(Dense(output_dim=64, init='uniform', activation='relu'))

In [8]: # Hidden Layer 4
model.add(Dense(output_dim=64, init='uniform', activation='relu'))

In [9]: # Soft Layer
model.add(Dense(output_dim=5, init='uniform', activation='softmax'))
```



```
In [10]: from keras.preprocessing.image import ImageDataGenerator

In [11]: train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, height_shift_range=0.2, width_shift_range=0.2)
test_datagen = ImageDataGenerator(rescale=1./255)

In [12]: train_generator = train_datagen.flow_from_directory('D:/Skin Disease Prediction/Dataset/Skin Diseases/train', target_size=(64, 64), batch_size=32, class_mode='categorical')
test_generator = test_datagen.flow_from_directory('D:/Skin Disease Prediction/Dataset/Skin Diseases/test', target_size=(64, 64), batch_size=32, class_mode='categorical')

In [13]: train_class_indices = {}
for i in range(5):
    train_class_indices[i] = 'Acne' if i == 0 else 'Melanoma' if i == 1 else 'Rosacea' if i == 2 else 'Vittigo' if i == 3 else 'Eczema' if i == 4

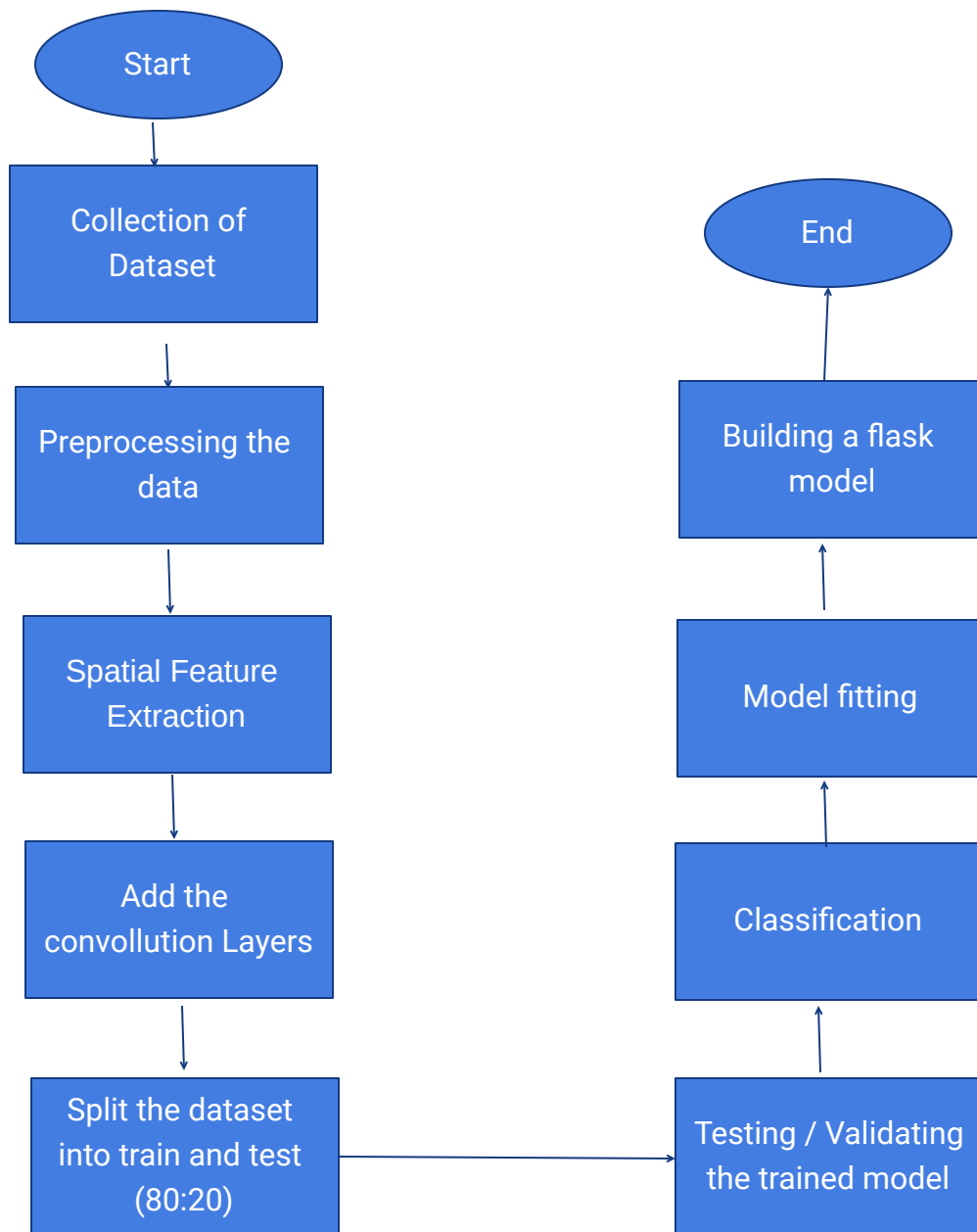
In [14]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

In [15]: model.fit_generator(train_generator, steps_per_epoch=100, epochs=100, validation_data=test_generator, validation_steps=10)

Out[15]:
Epoch 01/100: 295/41360 Step - Loss: 0.6000 - acc: 0.7447 - val_loss: 0.4067 - val_acc: 0.4210
Epoch 02/100: 295/41360 Step - Loss: 0.6300 - acc: 0.7544 - val_loss: 0.4000 - val_acc: 0.4210
Epoch 03/100: 295/41360 Step - Loss: 0.6400 - acc: 0.7554 - val_loss: 0.3877 - val_acc: 0.4411
Epoch 04/100: 295/41360 Step - Loss: 0.6500 - acc: 0.7607 - val_loss: 0.3802 - val_acc: 0.4209
Epoch 05/100: 295/41360 Step - Loss: 0.6600 - acc: 0.7681 - val_loss: 0.3580 - val_acc: 0.4207
Epoch 06/100: 295/41360 Step - Loss: 0.6514 - acc: 0.7662 - val_loss: 0.3361 - val_acc: 0.4310
Epoch 07/100: 295/41360 Step - Loss: 0.6302 - acc: 0.7827 - val_loss: 0.3004 - val_acc: 0.4070
Epoch 08/100: 295/41360 Step - Loss: 0.6524 - acc: 0.7580 - val_loss: 0.6682 - val_acc: 0.3954
Epoch 09/100: 295/41360 Step - Loss: 0.6331 - acc: 0.7586 - val_loss: 0.2394 - val_acc: 0.4210
Out[15]: <keras.callbacks.History at 0x1ac240b0a0>

In [16]: model.save('Skin_Diseases.h5')
```

5. Flow Chart



6. Result

To the dataset that has been created CNN modelling has been applied with two convolutional layers and four hidden layers. The model predicts the entered image to be that of a person suffering from Acne, Melanoma, psoriasis, Rosacea or vitiligo. The predictions some times vary as the initial stages of a few diseases look like others, also skin disease prediction largely depends on the skin tone of the patient. The model has an accuracy of 75.8%

A flask application has also been built for the model to provide it with a front-end. The HTML page acts as a bridge for the user to launch the model through the local host on his / her machine and receive predictions.

7. Advantages and Disadvantages

7.1 Advantages

- Acute prediction of diseases available first on hand to every citizen who uses this application
- Disease Analysis possible right from home, sparing the need to visit Hospitals, Nursing homes or health centers.
- Awareness, Suggestions and first aid tips for every disease for quick user reference. Diseases, when identified quicker can be averted or cured much easier.

7.2 Disadvantages

- Artificial intelligence presents a whole new set of challenges around data privacy and security - challenges that are compounded by the fact that most algorithms need access to massive datasets for training and validation.
- Shuffling gigabytes of data between disparate systems is uncharted territory for most healthcare organizations, and stakeholders are no longer underestimating the financial and reputational perils of a high-profile data breach.
- The characteristic of the skin images are diversified, so that it is challenging job to devise an efficient and robust algorithm for automatic detection of the skin disease and its severity. Skin tone and skin colour plays an important role in skin disease detection.

8. Applications

In this work a model for prediction of skin diseases is done using deep learning algorithms. It is found that by using the ensembling features and deep learning we can achieve a higher accuracy rate and also we can go for the prediction of many more diseases than with any other previous models done before. A maximum of five skin diseases with a maximum accuracy level of 75%. This proves that deep learning algorithms have a huge potential in the real world skin disease diagnosis. If even a better system with high end system hardware and software with a very large dataset is used the accuracy can be increased considerably and the model can be used for clinical experimentation as it does have any invasive measures. Future work can be extended to make this model a standard procedure for preliminary skin disease diagnosis method as it will reduce the treatment and diagnosis time.

9. Conclusion

This study projects a method that uses techniques related to computer vision to distinguish different kinds of dermatological skin abnormalities. We have employed various types of 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 75 percentage. For enhanced performance and selecting the optimum architecture for the application, we have used logistic regression technique.

The feasibility of building a skin disease classification system has been investigated using deep CNN. Better accuracy can be obtained by providing a training set with more variance and also by increasing its size. Also, note that the images retrieved by the networks are closely related to the ground truth. We may need to design a hierarchical classification algorithm using the retrieved images to improve the accuracy. Thus by using ensemble features as well as deep learning, predictions can be achieved with a higher rate than previous models. It is also found that Convolution Neural Networks performs well compared to Residual Neural Network in the diagnosis of skin diseases.

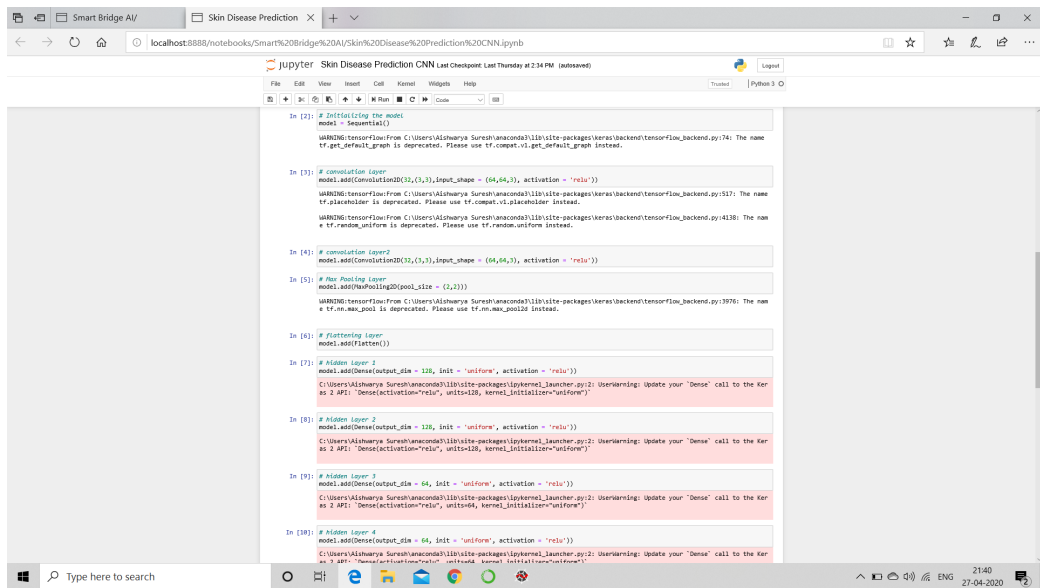
10. Future scope

The present model can be improvised by integrating more data and training it. It can be used further to identify skin problems at an early stage and help the patient seek the right the treatment and get cured. The idea can also be commertilized. It is sure to get good returns as the increasing pollution levels are leading to more and more skin problems. Also we now live in a world where appearance plays a major role. Hence it can be strongly said that the product will have a good scope.

11. Bibilography

1. <https://www.kaggle.com/datasets>
2. <https://www.quora.com/>
3. <http://www.google scholar.com/>
4. <https://www.journals.elsevier.com/artificial-intelligence/>
5. <https://www.healthline.com/health/skin-disorders>

Code:



```
Smart Bridge AI/ Skin Disease Prediction x + -
localhost:8888/notebooks/Smart%20Bridge%20AI/Skin%20Disease%20Prediction%20CNN.ipynb

jupyter Skin Disease Prediction CNN Last checkpoint: Last Thursday at 2:34 PM (autosaved)
Python 3.8

In [11]: # @ipynb
model.add(Dense(output_dim = 5, init = 'uniform', activation = 'softmax'))

C:\Users\Aishwarya Suresh\anaconda3\lib\site-packages\ipykernel_launcher.py:2: UserWarning: Update your 'Dense' call to the Keras 2 API: 'Dense(activation='softmax', init='uniform', kernel_initializer='uniform')'

In [12]: from keras.preprocessing.image import ImageDataGenerator

In [13]: train_datagen = ImageDataGenerator(rescale = 1./255, shear_range = 0.2, zoom_range = 0.2, height_shift_range = 0.2, width_shift_range = 0.2)
test_datagen = ImageDataGenerator(rescale = 1)

In [14]: y_train = SkinDiseasePredictionDataset(SkinDisease/train, target_size = (64, 64), batch_size = 32, class_mode = 'categorical')
y_test = SkinDiseasePredictionDataset(SkinDisease/test, target_size = (64, 64), batch_size = 32, class_mode = 'categorical')

Found 2285 Images belonging to 5 classes.
Found 558 Images belonging to 5 classes.

In [15]: x_train_class_indices
Out[15]: ('Acne': 0, 'Melanoma': 1, 'Psoriasis': 2, 'Rosacea': 3, 'Vitiligo': 4)

In [16]: model.compile(loss = 'categorical_crossentropy', optimizer = 'adam', metrics = ['accuracy'])

WARNING:tensorflow:From C:\Users\Aishwarya Suresh\anaconda3\lib\site-packages\keras\optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From C:\Users\Aishwarya Suresh\anaconda3\lib\site-packages\keras\backend\tensorflow_backend.py:3295: The name tf.nn.conv2d is deprecated. Please use tf.nn.conv2d instead.

In [18]: model.fit_generator(x_train, steps_per_epoch = 100, epochs = 100, validation_data = x_test, validation_steps = 43)

Epoch 01/100
00:00 [=====] - 20s 425ms/step - loss: 0.6252 - acc: 0.7623 - val_loss: 0.3348 - val_acc: 0.4397
Epoch 02/100
00:00 [=====] - 20s 413ms/step - loss: 0.6090 - acc: 0.7647 - val_loss: 0.4017 - val_acc: 0.4316
Epoch 03/100
00:00 [=====] - 20s 408ms/step - loss: 0.6361 - acc: 0.7564 - val_loss: 0.4080 - val_acc: 0.4319
Epoch 04/100
00:00 [=====] - 20s 408ms/step - loss: 0.6489 - acc: 0.7538 - val_loss: 0.3977 - val_acc: 0.4411
Epoch 05/100
00:00 [=====] - 20s 413ms/step - loss: 0.6377 - acc: 0.7697 - val_loss: 0.3921 - val_acc: 0.4259
Epoch 06/100
00:00 [=====] - 20s 413ms/step - loss: 0.6646 - acc: 0.7481 - val_loss: 0.3190 - val_acc: 0.4287
Epoch 07/100
00:00 [=====] - 20s 413ms/step - loss: 0.6514 - acc: 0.7456 - val_loss: 0.3195 - val_acc: 0.4319
Epoch 08/100
00:00 [=====] - 20s 414ms/step - loss: 0.6392 - acc: 0.7527 - val_loss: 0.3036 - val_acc: 0.4078
Epoch 09/100
00:00 [=====] - 20s 409ms/step - loss: 0.6524 - acc: 0.7599 - val_loss: 0.6682 - val_acc: 0.3954
Epoch 10/100
00:00 [=====] - 20s 399ms/step - loss: 0.6331 - acc: 0.7586 - val_loss: 0.2384 - val_acc: 0.4216

Out[18]: <keras.callbacks.History at 0x1a0c040e08>

In [19]: model.save("Skin_Disease.h5")

In [ ]:
```

```
Smart Bridge AI/ Skin Disease Prediction x + -
localhost:8888/notebooks/Smart%20Bridge%20AI/Skin%20Disease%20Prediction%20CNN.ipynb

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y_test = SkinDiseasePredictionDataset(SkinDisease/test, target_size = (64, 64), batch_size = 32, class_mode = 'categorical')

Found 2285 Images belonging to 5 classes.
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In [15]: x_train_class_indices
Out[15]: ('Acne': 0, 'Melanoma': 1, 'Psoriasis': 2, 'Rosacea': 3, 'Vitiligo': 4)

In [16]: model.compile(loss = 'categorical_crossentropy', optimizer = 'adam', metrics = ['accuracy'])

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In [18]: model.fit_generator(x_train, steps_per_epoch = 100, epochs = 100, validation_data = x_test, validation_steps = 43)

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00:00 [=====] - 20s 413ms/step - loss: 0.6514 - acc: 0.7456 - val_loss: 0.3195 - val_acc: 0.4319
Epoch 07/100
00:00 [=====] - 20s 414ms/step - loss: 0.6392 - acc: 0.7527 - val_loss: 0.3036 - val_acc: 0.4078
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00:00 [=====] - 20s 409ms/step - loss: 0.6524 - acc: 0.7599 - val_loss: 0.6682 - val_acc: 0.3954
Epoch 09/100
00:00 [=====] - 20s 399ms/step - loss: 0.6331 - acc: 0.7586 - val_loss: 0.2384 - val_acc: 0.4216

Out[18]: <keras.callbacks.History at 0x1a0c040e08>

In [19]: model.save("Skin_Disease.h5")

In [ ]:
```