A

**Project Report**

On

# "SkinSight AI: Skin Cancer Prediction system using Deep Learning and Explainable Artificial Intelligence."

Submitted for partial fulfillment of requirement for the award of degree

of

**Master of Business Administration**

of

**GRAPHIC ERA (Deemed to be University)**
**DEHRADUN (UTTRAKHAND)**

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# DECLARATION

I hereby declare that the **Field Project** entitled "**SkinSight AI: Skin Cancer Prediction using Deep Learning and Explainable Artificial Intelligence**" submitted for the Degree of Master of Business Administration, is my original work and the **Field Project** has not formed the basis for the award of any degree, diploma, associateship, fellowship or similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

**(Signature of Student)**

**Lakshya Singh Bisht**

# CERTIFICATE BY INTERNAL GUIDE

I have the pleasure in certifying that Mr. Lakshya Singh Bisht is a student of Graphic Era(Deemed to be University) of the Master's Degree in Business Administration Artificial Intelligence and Data Science (MBA AI DS). His University Roll No is 14AI063.

He has completed his Field Project titled as "**SkinSight AI: Skin Cancer Prediction using Deep Learning and Explainable Artificial Intelligence**" under my guidance.

I certify that this is his original effort & has not been copied from any other source. This project has also not been submitted in any other university for the purpose of award of any Degree.

This project fulfils the requirement of the curriculum prescribed by Graphic Era (Deemed to be University), Dehradun, for the said course.

I recommend this Field Project for evaluation & consideration for the award of Degree to the student.

**Signature:** **Name of the Guide: Mr. Chandra Prakash**

**Signature:** **Name of the HOD: Dr. Navneet Rawat**

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# Abstract

Various types of viruses and diseases are affecting people globally. Due to changes in lifestyle and environment various new diseases are developing very rapidly. Skin disease is the major one which is the cause of environmental changes. Apart from the major metropolitan cities, dermatologist and skin disease treatment is scarce. Remote areas have no accessibility for better treatment. Advanced technologies like artificial intelligence and machine learning are helping people to diagnose disease very fast and accurately. This is not only saving time but also the cost. Prevention is always better than cure technologies are proving it cent percent. Convolutional neural network the algorithm of learning having multilayer architecture which is recognize hidden pattern from images captured using various devices. In this study we propose a deep learning model using CNN and XAI to classify skin disease data images having seven different types of skin diseases. The proposed model consists of 13 layers including convolutional layer, pooling layer and fully connected layer to classify skin disease image dataset. The data consists of 10,000 skin images collected globally. We are also implementing explainable artificial intelligence along with CNN to interpret the outcomes of the model so that we can have a good explanation about our prediction. The CNN and XAI technology combinedly give the best accuracy to detect skin disease. This model can help dermatologists to make data-driven decisions more precisely and accurately. The model is evaluated with various performance parameters such as accuracy precision recall F1 score and support. The model shows the accuracy between 80 to 86%. The multilayer CNN architecture is very much potentially strong to perform skin disease classification and explainable artificial intelligence helping in interpretation you can major add on to it.



Keywords: Deep Learning, Machine Learning, CNN, XAI, SHAP,

# *Chapter – I*

# *Introduction*

# 1. Introduction

## 1.1 General Description

According to the World Health Organization the graph of deaths is around 12 million per year due to any underlying disease in humans. The improper diagnosis, late detection[1] and improper treatment is one of the causes of so many deaths. Prediction of diseases is regarded as one of the important topics in the area of data science and analytics. The load in the healthcare sector has been rapidly increasing all over the world for just the past few years. Researchers are working in every area to help the healthcare sector in early diagnosis of disease many major diseases like heart disease and cancer are highlighted as a silent killer for human. The change in climatic conditions due to unnecessary construction, uses of chemicals, pollution, unhealthy food, unhygienic conditions are major causes of widespread diseases. The early diagnosis of any disease is vital in making strategies for the proper treatment of the patient.

Due to global warming and ozone layer depletion the chances of getting skin cancer are increasing day by day[2]. The ratio is increasing day by day as every person has sun exposure and even the lifestyle changes are leading to different skin disease.

Skin is one of our five senses. It is the largest Organ which helps us in protecting against the temperature, microbes and the outside environment. The skin is classified in three layers. the first layer is epidermis[3], it is the outmost layer which consist of skin tone and the waterproof barrier. The second layer is called dermis which contains tissues and hair follicles the last and third layer is called hypodermis which are having deep tissues and fat. that skin is not just about the skin tone it absorbs various things from atmosphere[4] and supply it to the body through the tissues. skins are of different types like dry skin, oily skin and sensitive skin and many more. Skin is having direct connection with the mind as when it senses anything from outside like hot and cold, it responds accordingly.

With the change in climate, food, diet and other factors the skin is also having effect on it. due to global warming the ozone layer is depleting and allowing the UV rays to enter the earth which is leading to the disease call skin cancer[5]. skin diseases are of many types it can be rashes eczema, acne, Melanoma, ringworm, dandruff and skin cancer.

### 1.2 What Causes skin Disease?

The underlying disease inside the body and certain lifestyle factors[6] can lead to skin diseases. Sometimes we have some hidden diseases inside body like poor gut health, kidney problems, infections and other diseases these show up in the form of acne and pimples in the parts of face. some reasons can be:

- Low immune system.
- Thyroid and kidney problems.
- Allergy to dust and certain food elements.
- fungal infections and parasites.
- Viruses.
- Genetical Problems.
- Contaminated Water.

### 1.3 Symptoms of skin disease

Skin disease symptoms vary according to the disease. Sometime unnatural itching in the body is due to kidney problems. The excessive heat in the body can come out in the form of mouth ulcers and pimples. some common symptoms can include:

- skin pigmentation or patches.
- dry skin
- lesions or ulcers.
- rashes and itchiness
- bumps filled with pus[7].
- Yellowness due to jaundice.

### 1.4 Treatment

Healthcare has so many kinds of treatment for skin disease. Some diseases can be cured with normal medication whereas some need proper long treatment. According to the condition a dermatologist or a super specialist doctor is recommended. Dermatologist is doctor practicing specialized skills for skin treatment. Dermatologist recommends healthy diet, hygiene[8], exercise, Antibiotics, medication, creams and ointments.

Some skin problems need advanced treatment like:

- Dermoscopy is use of a device known as dermatoscope [9] which helps in detecting the skin lesions.
- Black light examination uses ultraviolet light examine that the skin's pigment more accurately.
- Laser skin resurfacing uses laser[10] smoothen that damaged skin. it removes the outer damaged layer of skin using laser peel technology.
- Acne blue light therapy uses blue light band to breakdown the tissues which are causing Acne.
- Microdermabrasion treatment clears the acne scars and spots by using exfoliating crystals to make skin look smoother and clear.

## 1.5 Advancement in technology

Technological advancement in healthcare sector gave Manny better and accurate solutions for the treatment of diseases. modern day technologies like artificial intelligence[11], machine learning, deep learning, data science, computer vision and many more are helping and disease treatment.

The popular quote “prevention is better than cure” is very much helpful when it comes to the life of a person. prevention from diseases is way better than going for treatment. Technological advancements are very much more helpful to prevent us from diseases than facing consequences afterwards.

### *1.5.1 Artificial intelligence*

AI is the umbrella of technology which works on making the machines smarter, which needs less human intervention. There are chances of error and risk when it comes to working with the large amount of data[12] especially the big data. AI can handle huge chunks of data[13] and can help to recognize patterns from the data.

### *1.5.2 Machine learning*

ML technology feeds data to its model and then makes it learn itself. it is having various algorithms and models which works according to the data and predicts[14] the outcome. Machine learning identify the trends and pattern from the historical data and makes prediction about medical outcomes[15]. It Also identify the correlation between the features to identify changes causing the problem. Machine learning uses supervised, unsupervised[14] and reinforcement learning techniques to implement various algorithms according to the dataset. The the labeled data is used in supervised algorithm and unsupervised uses the unlabeled data where reinforcement learns from the outcomes and responses.

Algorithms like logistic regression, random forest, K means clustering, support vector machine, K- nearest neighbor[16] etc. are used to build the models which can help in implementing the projects. These algorithms are best suitable to predict disease outbreaks, drug performance discovery, medical imaging analysis and high-risk patients[17].

#### *1.5.3 Deep learning*

This technology also comes under machine learning but it's working is like [18]human neurons. It has advanced algorithms which can work more precisely on large data with more accuracy. it is having activation function and weighted average[19] which makes process faster and accurate. It consists of various layers[18] which increase the accuracy of implemented model.

### 1.6 AI and Healthcare

Artificial intelligence is not behind in any sector. AI is working to make the life of people easier with the automation of tasks. AI is implemented in healthcare[11] in the form of robots, smart management tools and assistants[20]. Artificial intelligence is helping healthcare by predicting diseases, scanning the radiological images[21] and health records from the test reports. Recent invention is of AI dentist[22] which are operating the tooth problems by machine access with no human need. It gives quality care and cost-effective treatment to millions of people worldwide. Tech giants like Apple, Microsoft, Amazon and IBM are investing[23] in artificial intelligence technologies in the healthcare sector. AI can diagnose the disease more accurately if the machine learns effectively. it can help doctors to make data-driven decision[24] Which can save the life of patients.

#### *1.6.1 Image analysis*

Deep learning algorithm like convolutional neural network is used to analyze images[25]. In healthcare these algorithms work on MRI results, X-rays and sonographic reports. This analysis diagnoses the disease by processing images[26]. CNN algorithms are also surpassing the human accuracy of diagnosis by analyzing the detailed features from images. much research shows that the trained algorithm for analyzing dermatological images identifies disease more accurately and specifically than doctor examination. Research shows up the 94% accuracy[27] at identifying skin cells from the image data.

All the technologies mentioned above are individually and combinedly helpful in healthcare for the diagnosis and prediction of disease. Many diseases like cancer, lung infection diabetes, Parkinson disease, heart disease etc. Can be predicted by analyzing the large amount of hospital data of patients. Different types of cancers like breast cancer skin cancer can be classified using the algorithms of machine learning as well as deep learning.

Nowadays many applications are presented where we can check our health by ourselves. diabetes machine is also an example of the same. There are various software and applications where we can feed our diagnosis data and it will automatically tell whether we are having any disease or not. Many big companies and tycoons are investing[23] in this sector as this is Evergreen growing sector and it will be giving very much profit to them.

Methodology like natural language processing is also helpful in the prediction of disease[28] by extracting useful information from the health records. These technologies create the prediction model which tells the chances of disease accurately. Feeding more and more data to these algorithms will train them for the fastest and most accurate decisions.

Deep learning is in demand for the precise identification of disease and to classify it using X-ray images, MRI, CT scans, ECG signal data and EEG data[29].

Electronic health records can be analyzed to identify trends and patterns thing the outcomes. This will help doctors to make data-driven decisions[30] about treatment and the risk developing conditions.

Artificial intelligence will also help researchers speed up the process of drug development. It will be a cost-effective and time-saving process. The first development of vaccines like COVID vaccines are because we can analyze the data related to COVID-19 using the advanced technologies very fast.AI is also helping the healthcare sector by involving virtual assistants and chatbots[11, 31] into the service. They are making medical process fast which is most required in the country like India.

AI powered robots are assisting in surgery[11] and medical procedures and interventions for better outcomes and less errors.

### 1.7 Contribution

This skin disease classification model uses deep learning algorithms to predict the presence of any disease and that skin by analyzing[32] the image data of patients. The convolutional neural network will be diagnosing the disease present in the skin Mainly cancer.

The project is contributing to providing great help in the healthcare sector. The project aims to help the doctors as well as the patients. Sometimes there are chances of error and human intervention of disease because various factors vary from person to person according to the disease. This model contributes in many ways. In a country like India, the healthcare needs to be improved very much. We are a developing nation, and our healthcare sector is also improving no doubt but due to the large population or inaccessibility to some remote areas, we need effective systems. The technologies like AI can help us to make our healthcare system efficient and effective.

**Efficiency:** the whole process will become efficient as the model we'll diagnose the disease faster which will reduce the workload of dermatologists so that the treatment for the disease will get easier and faster

**Early detection:** the main motive behind every prediction model for healthcare is to predict the disease earlier. It can save a person's life or can also save someone from a risky disease. A little detection can lead the process to better and more effective outcomes.

**Awareness:** the project will also create awareness among people about various kinds of skin diseases along with the prevention and treatment of the symptoms.

**Accuracy:** sometimes experienced doctors and experts can do mistakes in the diagnosis and detection of disease. We are seeing changes in the atmosphere, climate, and lifestyle of people, due to which various kinds of new viruses and diseases are coming. Doctors may have problems detecting the disease accurately. Healthcare professionals can make this technology to assist them in the diagnosis of diseases which can lead to effective treatment and outcomes using the classification models.

**Cost:** the disease prediction model is very helpful in saving the cost of treatment. Many people die because they can't afford good treatment for their disease. These prediction models can help people ally diagnose their disease so that they can save money and it will also accurately diagnose the disease so that proper and accurate treatment would be given to the patient without any mistake or wastage of money due to any mistake.

**Research:** This model will also help build proper research for the upcoming project related to healthcare. Some trends and patterns can be analyzed from the model to develop new treatment methodologies and strategies for the prevention of disease.

**Accessibility:** there are various places where we can't build a large healthcare system so we can use technologies like telemedicine and have applications to reach remote areas for the diagnosis of disease. People in remote areas can get assistance from a small setup that can send their data and images of disease to the healthcare professional for the analysis of disease. This will make it easy for both doctors and patients.

# *Chapter – II*

# *Review of Literature*

## 2. Literature Review

Malignant melanoma is very rapidly growing type of skin cancer in the world. CNN can be seen much effective in early detection of skin cancer. Literature work have reached so far in studying deep learning use to predict skin diseases. Accuracy of model reached from 72% to 92% when they used CNN with One-Versus-All (OVA) [33]method than the alone CNN.

ZHE wu et al. in his research[34] found out that skin problem is not just a physical problem. It can be the psychological problem as well for the people suffering from face skin problem.

Convolutional neural network automates the process to classify the disease present in the skin. The variation in skin tone[35], image specification and the location of skin disease are some of challenges in the process.

A review shows that noisy data from heterogenous dataset can alter the accuracy of model to predict the disease. Existing data set of skin images are mainly high-resolution images clicked using DSLR[36]. The same model can be hard enough to diagnose the disease when images are clicked from phone with different lighting and cameras.

Conventional multimodel fusion method[37] uses image as input to various CNN's. The feature extraction is done by various CNN's to obtain probability value of each category segment. At last category of maximum probability value is obtained using fusion model.

Evgin goceri in his study featured the important aspect in skin disease prediction. There was accuracy problem due to hairs and their shadow on skin[38]. They used six state of art algorithms to inpaint the hair pixels[38].

Parvathaneni Naga Srinivasu et. al. in their research project found Long short-term memory [29]and mobilenetV2 like state of art techniques to classify the skin disease more accurately. LSTM model outperformed with more than 85% accuracy.

Deep learning techniques like Artificial Neural Network(ANN) and Convolutional Neural Network(CNN) are most used in diagnosing the patterns from radiological images. The approach using convolutional neural network is seen to be performing best and recognizing that disease. Both the approaches of neural network the CNN and ANN needs a lot of training data for good model performance and hence much computational power is needed[39].

Alam et al. worked on the detection of skin disease called eczema[40] and applied machine learning algorithm support vector machine with image processing technique for accurate predictions. The noise present in the image data it's challenging to be handled by support vector machine model.

Andre Esteva et al. concluded that Convolutional Neural Networks (CNNs)[41] have potential for general and highly variable tasks across many fine-grained object categories[41]. This paper is helping in classification of skin disease using a single convolutional neural network, trained end-to-end from images directly, using only pixels and disease labels as inputs[42]. CNN achieved performance on par with all tested experts across both tasks, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists. Mobile devices can potentially provide low-cost universal access to vital diagnostic care[41].

American Academy of dermatology published that deep learning algorithm good help in predicting skin cancer[43] an accuracy of 91% whereas the International Journal of dermatology[44] in 2020 found that 97% of accuracy is showing up in predicting the psoriasis disease.

Another study published in the journal of PLOS one Not only found that deep learning is able to diagnose the type of skin disease[45] but is also able to identify the subtypes of skin disease like Melanoma which is sometimes difficult for dermatologists to find.

A dermoscopic image analysis using deep learning framework study is done which helps in detecting basal cell carcinoma and differentiating it from the similar looking non-cancerous lesions[46]. This framework achieved accuracy of 95%.

Another part of research also concluded that the studies related to deep learning in the field of dermatology is helping very much but there's still need for more research go work on the issues such as interpretability, more accuracy, generalizability and data bias[47].

# *Chapter – III*

## *Methodology and Data Collection*

# 3. Methodology and Data Collection

For the desirable performance of the model, we need to train the model at best. The data set is vital in the training part for diagnosis of skin cancer. The data set used in the project is the from Kaggle public dataset named as human against machine 10,000 abbreviated as HAM10,000. There is a total of 10,015 images present in the data set of skin lesions. The images were collected from all over the globe from various clinics and healthcare centers.

The data set contains seven types of skin problems which are Actinic Keratosis and Intraepithelial Carcinoma [AKIEC], Vascular Lesions [VASC], Basal Cell Carcinoma [BCC], Melanoma [MEL], Dermatofibroma [DF], Melanocytic Nevi [NV] and Benign keratosis like Lesions [BKL][48]. The image resolution is of 600 into 450 pixels with JPEG format with the name corresponding to their diagnosis.

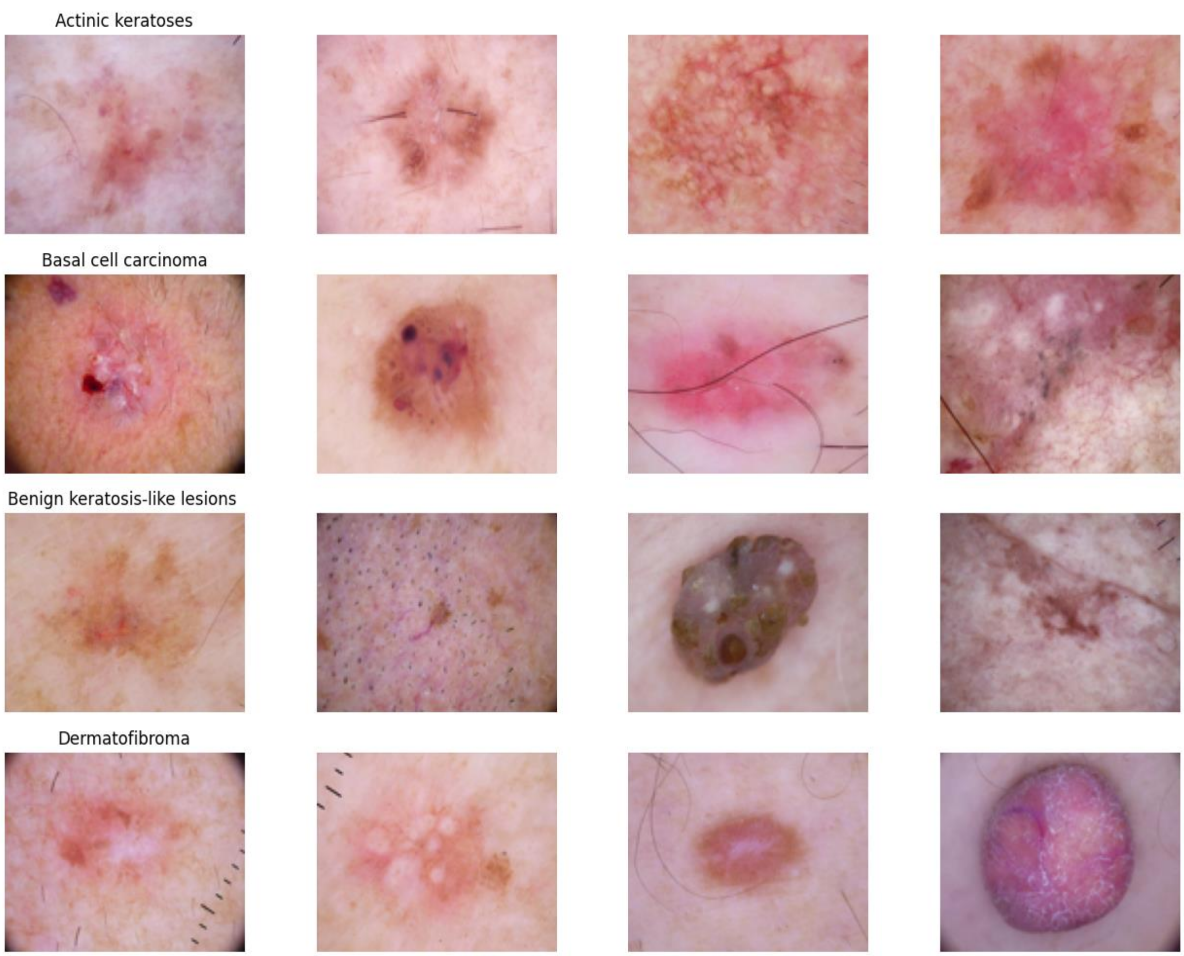



**Fig 3.1 Types of skin disease (i)**

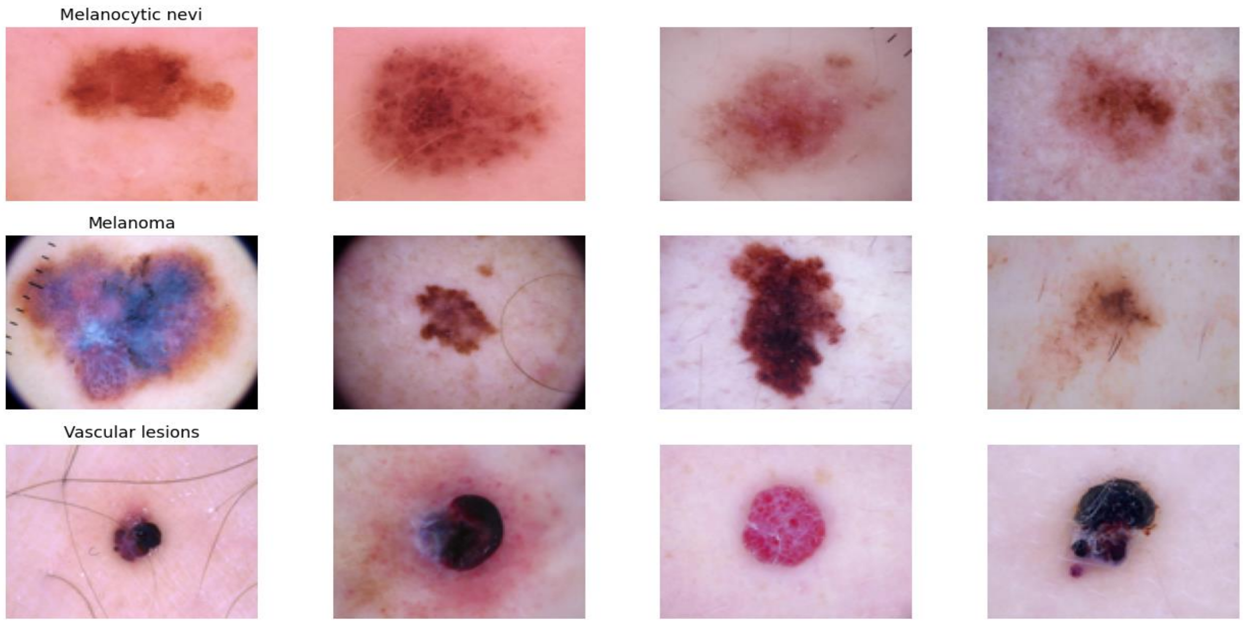



**Fig 3.2 Types of skin disease (ii)**

The data is categorized for training and testing phase. The training data is 75% of total and 25% data is for the testing the model.

## 3.1 Data Overview

The HAM10000 data folder consists of two files HAM10000_metadata.csv" and "HAM10000_images_part_2. The very first file is of metadata explaining the information about images of people such as their age sex and anatomical location. The images were captured using different imaging equipment, cameras, and mobile devices which are creating variations into the pixels of image. For the project we preprocessed the image data set and worked on resizing and pixel normalization along with grayscale conversion.

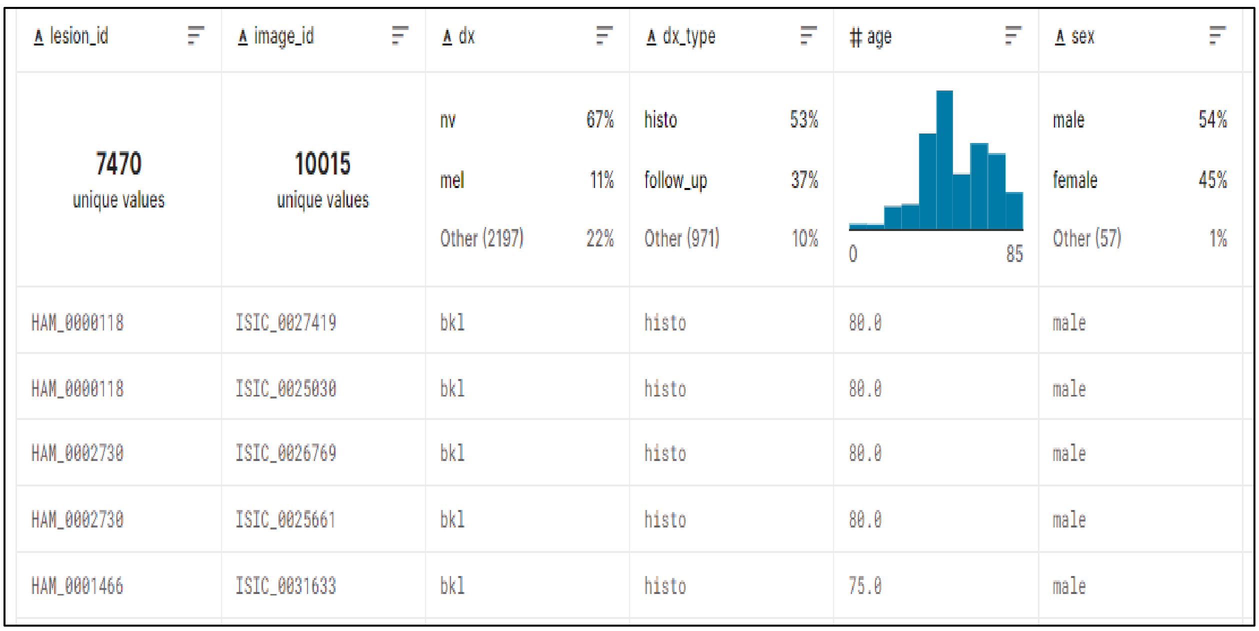
| lesion_id | image_id | dx | dx_type | age | sex | localization |
|---|---|---|---|---|---|---|
| HAM_0000118 | ISIC_0027419 | bkl | histo | 80 | male | scalp |
| HAM_0000118 | ISIC_0025030 | bkl | histo | 80 | male | scalp |
| HAM_0002730 | ISIC_0026769 | bkl | histo | 80 | male | scalp |
| HAM_0002730 | ISIC_0025661 | bkl | histo | 80 | male | scalp |
| HAM_0001466 | ISIC_0031633 | bkl | histo | 75 | male | ear |
| HAM_0001466 | ISIC_0027850 | bkl | histo | 75 | male | ear |
| HAM_0002761 | ISIC_0029176 | bkl | histo | 60 | male | face |

**Table 3.1: Metadata**

| pixel0000 | pixel0001 | pixel0002 | pixel0003 | pixel0004 | pixel0005 |
|---|---|---|---|---|---|
| 172 | 182 | 191 | 183 | 180 | 181 |
| 98 | 149 | 170 | 193 | 183 | 162 |
| 165 | 164 | 179 | 172 | 152 | 163 |
| 109 | 159 | 167 | 166 | 163 | 159 |
| 173 | 202 | 210 | 194 | 208 | 248 |
| 17 | 155 | 229 | 233 | 234 | 205 |
| 168 | 170 | 169 | 178 | 177 | 174 |

**Table 3.2: Pixel Information**

## 3.2 Data Statistics



| lesion_id | image_id | dx | dx_type | # age | sex |
|---|---|---|---|---|---|
| 7470 unique values | 10015 unique values | nv 67%<br>mel 11%<br>Other (2197) 22% | histo 53%<br>follow_up 37%<br>Other (971) 10% | 0 – 85 | male 54%<br>female 45%<br>Other (57) 1% |
| HAM_0000118 | ISIC_0027419 | bkl | histo | 80.0 | male |
| HAM_0000118 | ISIC_0025030 | bkl | histo | 80.0 | male |
| HAM_0002730 | ISIC_0026769 | bkl | histo | 80.0 | male |
| HAM_0002730 | ISIC_0025661 | bkl | histo | 80.0 | male |
| HAM_0001466 | ISIC_0031633 | bkl | histo | 75.0 | male |

**Fig 3.3: Data Overview**

The images Fig 3.3 and Fig 3.4 are showing that there are 7470 unique values in lesion_id column and 10015 unique columns in image_id. Proportion of male female and other sex is 54 percent 45% and 1% respectively. Total values count is 9958. The mean of the data is 51.86 and it's deviated to the value 16.96. You can clearly observe the other data statistics from both the images.

| | |
|---|---|
| count | 9958.000000 |
| mean | 51.863828 |
| std | 16.968614 |
| min | 0.000000 |
| 25% | 40.000000 |
| 50% | 50.000000 |
| 75% | 65.000000 |
| max | 85.000000 |

**Fig 3.4: Data Statistics**

## 3.3 Data Preprocessing

We must check for missing values in the metadata file which consists of disease type patient's age and gender. We have to load this metadata into pandas data frame and check for missing values using isnull() and sum() function to count the presence of any missing value in particular column. We can put nearest value and mean value in the space of missing values.

We observed 57 null values in the eighth field of data, and we replaced this with the mean value to reduce loss of data.

## 3.4 Data Analysis

Data plays the crucial role in training models but only the clean and correct data can give accurate performance to the model. Data analysis process is to identify trends and patterns in the data for implementation of any model. Data cleaning starts late checking off any missing or inconsistent data. The inconsistency in the data can alter the accuracy of model presence of any missing value can bring tremendous changes and the result. Our data HAM 10,000 is already labeled so it is not needed to perform any image processing technique.

### *3.4.1 Exploratory data analysis*

Exploratory data analysis abbreviated as EDA is an important process to create a summary of data to understand its statistics for identification of trends and patterns. Exploratory data analysis also involves the visualization of data into different formats. We are using the bar chart to visualize seven different classes of disease present in the data to help us understand the most common and rare disease.

Image visualization of the skin will give us the gist of relation among different images. This will help us to correlate the features what characteristic of images for example the Melanoma disease contrast color variation and irregular borders on the skin.

Exploratory data analysis will help us to select preprocessing techniques, appropriate models and algorithms.

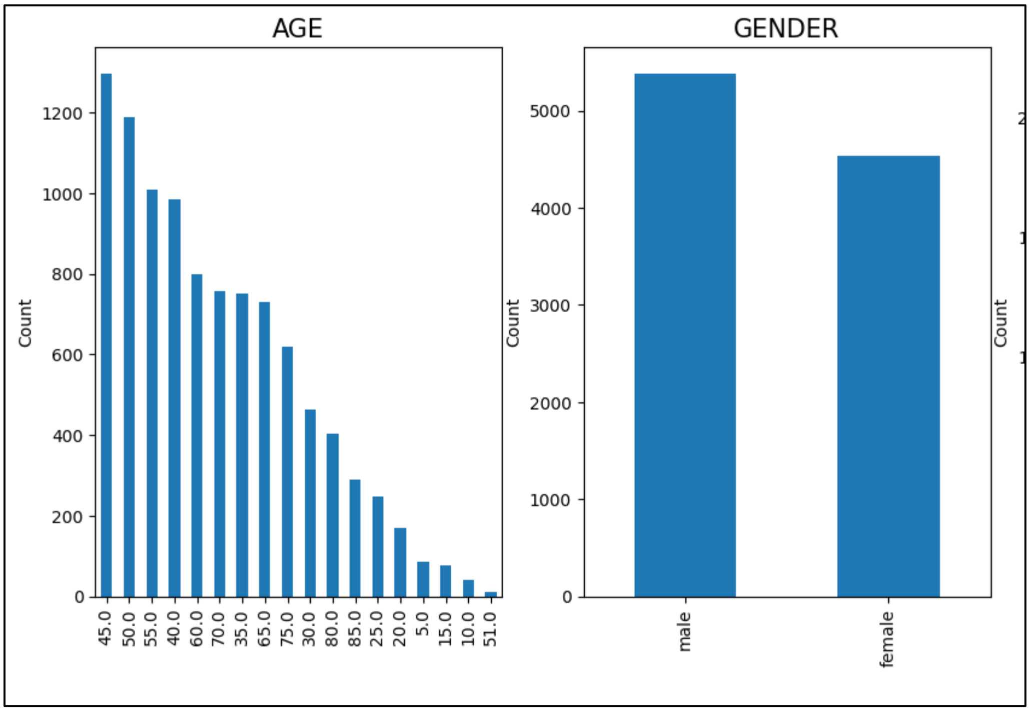



**Fig 3.5: data analysis of Age & Gender**

Analysis of data showing that there are more males than females in data having skin disease. The maximum number of people are of age 45 and minimum are below age 10 having skin disease. This means that chances of disease increase with age.

EDA process gave us many more insights about data. Some key points are:

- Melanocytic Nevi is the most found disease and the least count is of dermatofibroma.
- The histopathology method is used most in discovering skin disease followed by the other three methods - the follow up examination, consensus and confocal technique respectively.

- The most affected body part is the back area in men's and lower extremity of body in women.
- Benign keratosis like lesions infected the face of most people of age group 80 to 90 mostly.
- There is no age group unaffected by melanocytic Nevi.

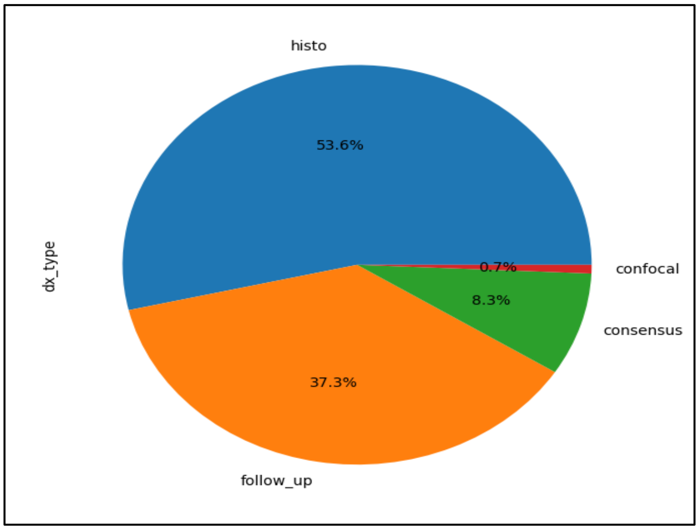



**Fig 3.6: Skin Discovery Method Pie chart**

53.6% of total diseases are discovered by histopathology, 37.3% by follow up examination, 8.3% by consensus method and 0.7% by confocal method.

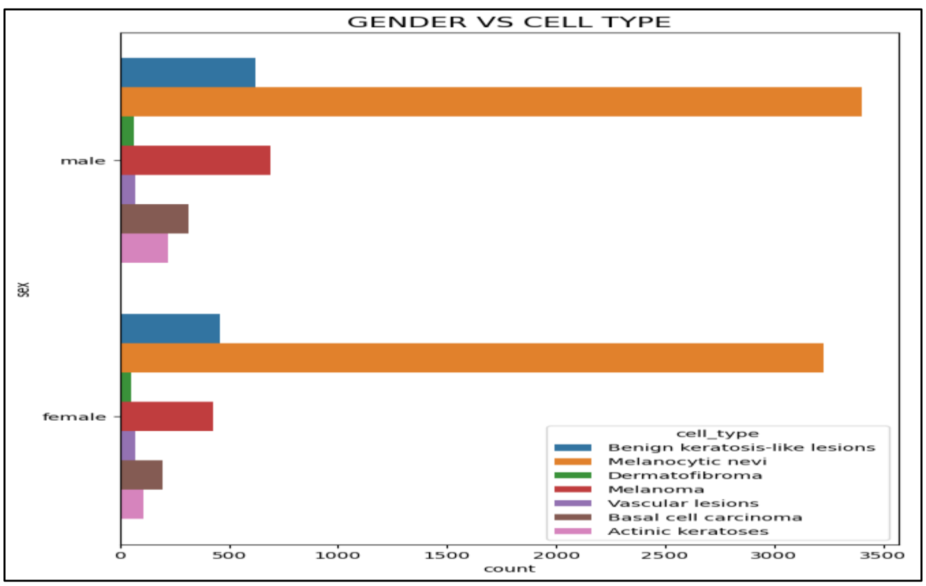



**Fig 3.7: Gender vs Cell Type**

Melanocytic Nevi is highest in both male and female.

### 3.5 Convolutional Neural Network (CNN)

Have you ever imagined how object detection works in self-driving cars[49] and how facial recognition works in smartphones. How smart system recognizes our facial expression correctly or disease are diagnosed from the images? Deep learning plays a significant role in analyzing images[21] accurately. Marketing, Retail, Healthcare and Automation are the sectors where the application of CNN and computer Vision is widely used. The convolutional neural network is all behind it.

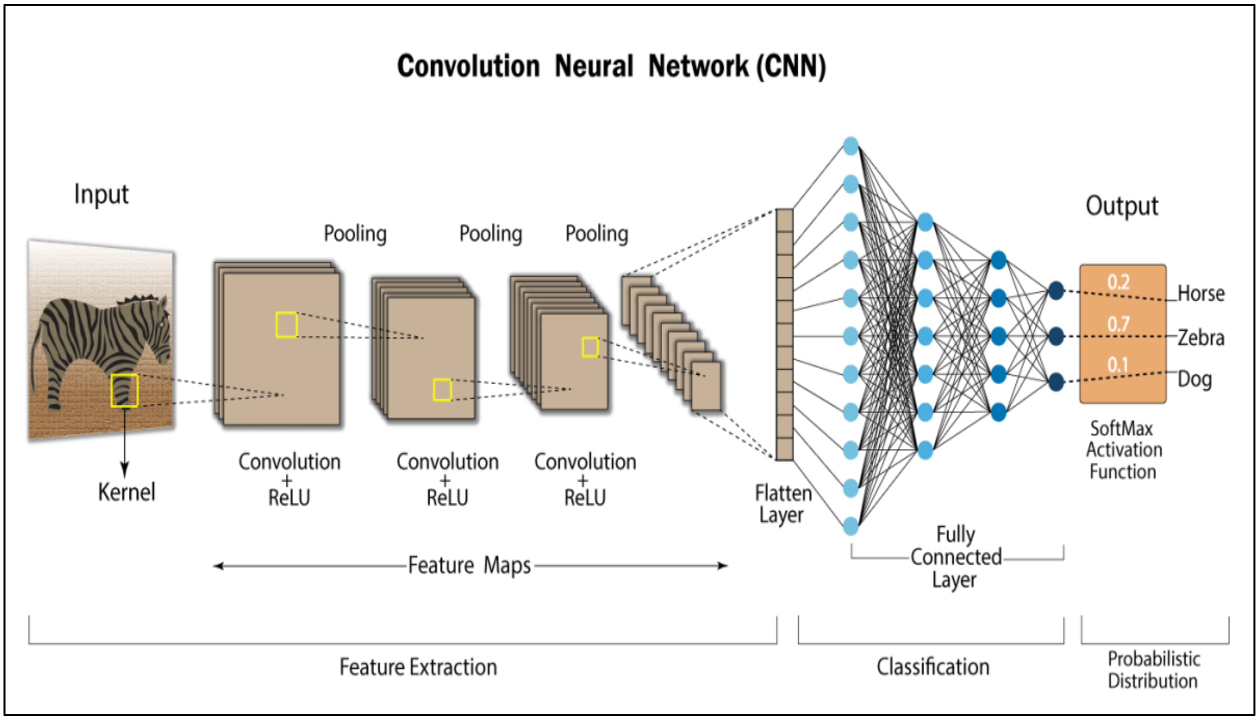



**Fig 3.8: Convolutional Neural Network**

The pixels of the image are passed in the form of an array to the neural network input layer[50]. Feature extraction[51] is done by hidden layers of neural network. The hidden layers like convolutional layer, ReLU[51] and pooling layer extract the features[50] correctly and tells us the correct information about the object.

Convolutional neural network helps to classify the object in the images. CNN can also work on audio and signal data as well. CNN comprises of a convolutional layer [CL], a pooling layer [PL] and a fully connected layer [FC].

CNN consists of multiple layers. A filter is applied to each image[52] which increases its complexity after each layer. The output after each iteration works as input for the next layer. In each layer the filter tries to uniquely identify the object partially. The last fully connected layer recognizes the object[53].

The CNNs are using the back propagation algorithm[54] for its training where the weight of the filters can be adjustable according to the need of the outcome. Data augmentation techniques like adding noise rotation and flipping the images[55] can help strengthen the performance of CNN for accurate results.

The meta-analysis[56] of studies for CNN's and skin lesion diagnosis showed that it achieved sensitivity of 91.2% and specificity of 76.4% suggesting that it can be a powerful tool for improving the efficiency of the skin disease diagnosing models.

The sigmoid function of convolutional layer to compute nonlinearity input to some unit, we will add all previous layer contribution[57] like:

$$\boldsymbol{x_{ij}^{l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \omega_{ab} y_{(i+a)(j+b)}^{l-1}}$$

m×m filter is ω and N* N is size of neuron layer.

### *3.5.1 CNN Architecture*

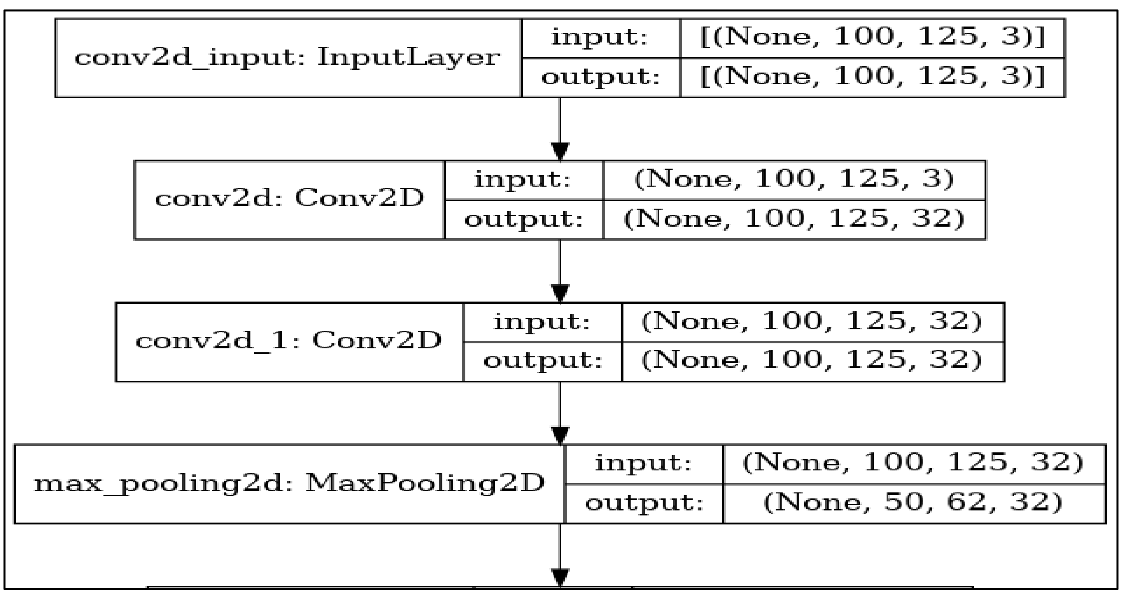



**Fig 3.9: CNN Model Flowchart (i)**

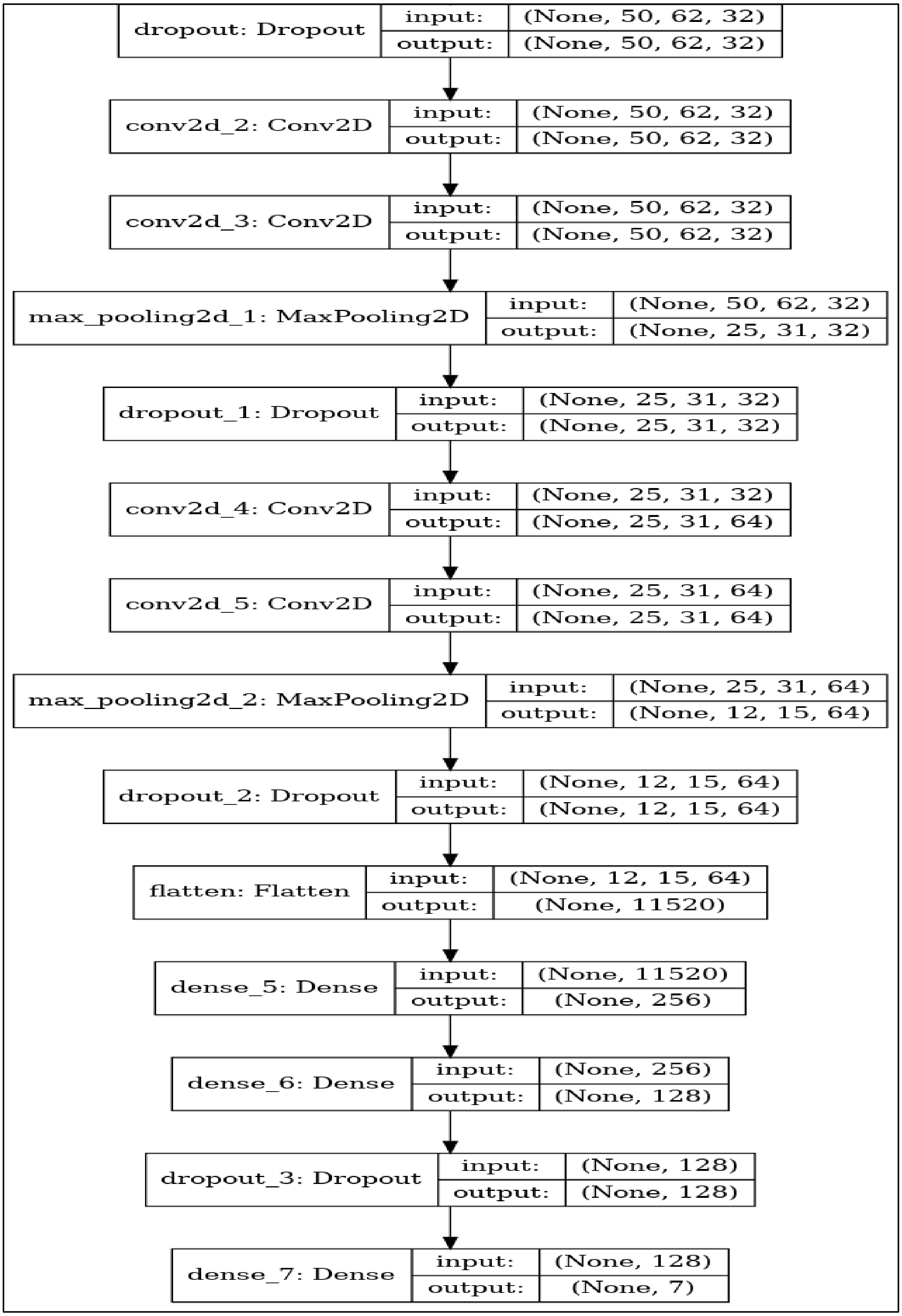



**Fig 3.10: CNN Model Flowchart (ii)**

For the feature extraction from images, we calculate the map values using the following formula, where image is denoted by p and the filter by q. The rows and columns of the result matrix are denoted by m and n respectively.

$$G(m,n) = (p,q)[m,n] = \sum_j \sum_k q[j,k]p[m-j,n-k]$$

*Input Layer*

The very first layer of architecture takes images with the image size of 100*125 pixel and with three (R, G, B) channels.

*Convolutional Layer*

This layer consists of 32 filters of size 3*3. The rectified Linear Unit activation function is used in this layer[58]. To get the output with same dimension as of the input the padding parameter is set to the 'same' option.

$$n_{out} = \left[\frac{n_{in} + 2P - K}{s}\right] + 1$$

Here $n_{in}$ is number of input feature and $n_{out}$ is number of output feature, K representing the kernel size and P is padding size and s refers to convolutional stride size.

*Pooling Layer*

The pooling layer mainly works on reducing the dimensions of data by combining outputs into single neurons. The pooling layers make the computation fast and prevents model to be overfitted. Max pooling and Average pooling are the common types where max pooling uses maximum value of each cluster of neurons present locally and average pooling opts for average value. To prevent overfitting a dropout layer is added after every max pooling layer.

$$\textbf{Output} = \frac{N}{K} * \frac{N}{K}$$

N * N layer is input layer and K*k is the region

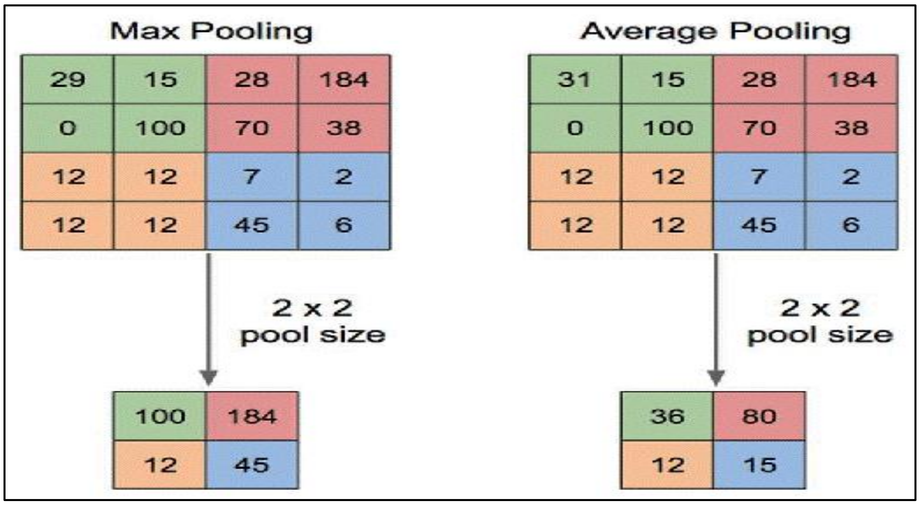



**Fig 3.11: Avg Pooling and Max Pooling**

*Third Convolutional Layer*

This convolutional layer will comprise of two layers with 64 filters of 3*3 dimensions. Here also the dropout layer will be added with the padding parameter at 'same' option.

*Flatten Layer*

To feed the fully connected neural network we must flatten the output from the last convolutional layer into one dimensional vector.

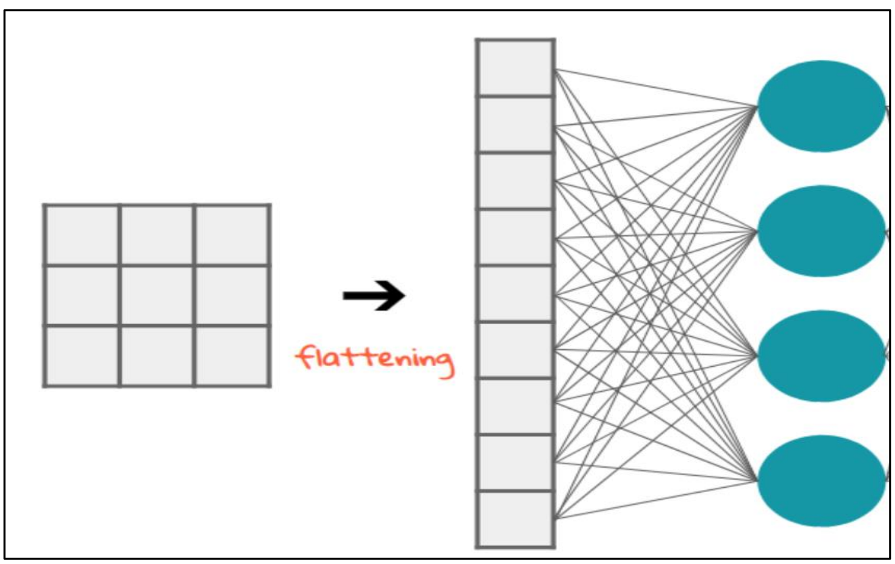



**Fig 3.12: Flattening**

*Fully Connected Layer*

The fully connected layer is the last layer which computes the final classification based on the feature extracted from the previous layer. In this layer linear transformation is applied to input vector with a weight matrix. The above two layers use ReLU activation function where the FC layer uses SoftMax activation function for the classification.

$$y_{jk}(x) = f\left(\sum_{i=1}^{n_H} w_{jk}\, x_i \, + \, w_{j0}\right)$$

f is a non-linear activation function. The dot product is taken between weight matrix W and input vector x. $w_0$ is bias term and optional one.

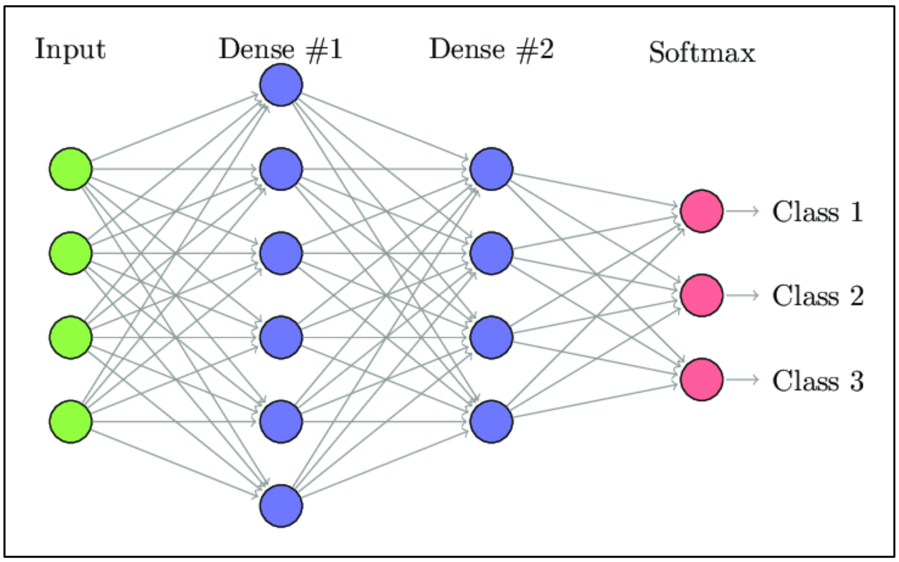



**Fig 3.13: fully connected layer**

*Output Layer*

There are 7 neurons in output layer for each class of data. The classification related problems the output layer have the softmax activation function. The output unit activation function is the softmax function.

$$y_r(x) = \frac{\exp\left(a_r(x)\right)}{\sum_{j=1}^{k} \exp\left(a_{j(x)}\right)} \quad where\ 0 \leq y_r \leq 1\ and\ \sum_{j=1}^{k} y_j = 1$$

This architecture contains a total of 13 layers which includes 8 convolutional layers, 3 dropout layers and 1 output layer. The whole architecture is effectively working in identifying the features from images while managing the model to be overfitted by using the dropout layer.

### 3.6 Explainable Artificial Intelligence (XAI)

Various research Showing that dermatologists are overwhelmed with the capability of deep neural network for the classification of skin cancer. The support of deep learning is really a benefit for dermatologists in nonclinical test setting. Some loopholes are present in the use of this system in clinical practice. Deep neural network is complex and tough structure which is making the decision making an untransparent process[59].

Explainable artificial intelligence is used to develop the models that can explain the facts behind the decision-making process. The limitation of AI system as a black box gave rise to XAI systems[59]. In the black box technique, the internal working is not transparent and interpretable by humans. Using such techniques can be highly concerning in many areas. Due to many reasons sometimes AI models might make a biased decision and in black box technique it is difficult to understand why the bias occurred[60], but XAI system can make it interpretable[59]. Explainable artificial intelligence consists of various algorithms that can generate explanation behind any decision. It can also visualize the features using some tools and techniques.

#### *3.6.1 XAI and Healthcare*

In the healthcare field transparency in decision is very vital. It is very important to know how much we can rely on the decision of machine diagnosing the diseases of person. Healthcare is directly connected to the life of a person, so we need to be highly sure about doing any practice and making any decision with the treatment of a patient.

In the remote areas where the scarcity of the healthcare system is at its peak and specialists like dermatologists are very much inaccessible there this kind of technology will be very beneficial[61]. This kind of system will be one of its own type helping people in diagnosis and saving their cost of the treatment. In every sector that decision is being data-driven but in the healthcare sector fairness needs to be paramount and we need to make informed and precise decisions so XAI will help to make reliable decisions[61]. Responsible AI term it's being used everywhere it is all the outcome of the explainable artificial intelligence. When general data protection regulation GDPR which promises the right to explanation when user data is processing in the automated system the XAI is very much needed there[62].

### 3.6.2 SHAP

SHAP or SHAPley Additive exPlanations is a machine learning tool that is used to explain the output of any model using visualization[63]. In any prediction model there are many features in the data which are affecting the prediction of the model so SHAP is used to explain the prediction. There are many libraries like tensorflow, keras, pytorch, scikit learn that we used for data modeling, but these libraries cannot explain the predictive models. SHAP will make it easier to understand the model for the users who cannot understand the technical concepts of machine learning models[64].

For e.g., if we are predicting any disease in humans, the data will have age, disease localization, gender features in it. Disease can be predicted by using any machine learning or deep learning model, but which feature is contributing more can be seen using SHAP.

Today we are using advanced technology like artificial intelligence in every field and for every use so we need That whatever prediction we are making should be correct so a completely explaining model can make us to rely on our prediction. So, the models like SHAP, LIME Are very much useful to keep explanation of the prediction models[64].

Some techniques like local interpretable model agnostic explanations LIME, generalized additive model, layer wise relevance propagation LRP are majorly used to implement XAI[65].

The prediction affected by a single feature Is the absolute SHAP value. The sum of all shape values can be calculated using the equation:

$$\boldsymbol{Sum(SHAP\ Values) = E[f(x)] - f(x)}$$

f(x) is the predicted value of model and E[f(x)] Is the expected value of target variable with the input X.

### 3.7 SkinSight AI : Prediction System for Skin Cancer using Deep Learning and XAI

A model driven architecture that uses deep learning algorithm for predicting skin cancer with improved accuracy. Deep learning algorithms are proven to perform classification on the image data set. We are using the convolutional neural network to predict skin cancer from the 10,000-image dataset collected from various clinics globally. The CNN architecture consists of 13 layers to learn complex features from the images and to classify according to the type of disease present in it. Model evaluation is done using the confusion matrix correlating between the actual and predicted labels of the model. We are also implementing explainable artificial intelligence to remove the black box limitation of the model. Here we are using SHAP algorithm to Explain the prediction of disease by computing the contribution of each feature to the prediction. The combination of both deep learning techniques and XAI will increase the robustness of this project by making it an effective and transparent process.

#### *3.7.1 Flowchart*

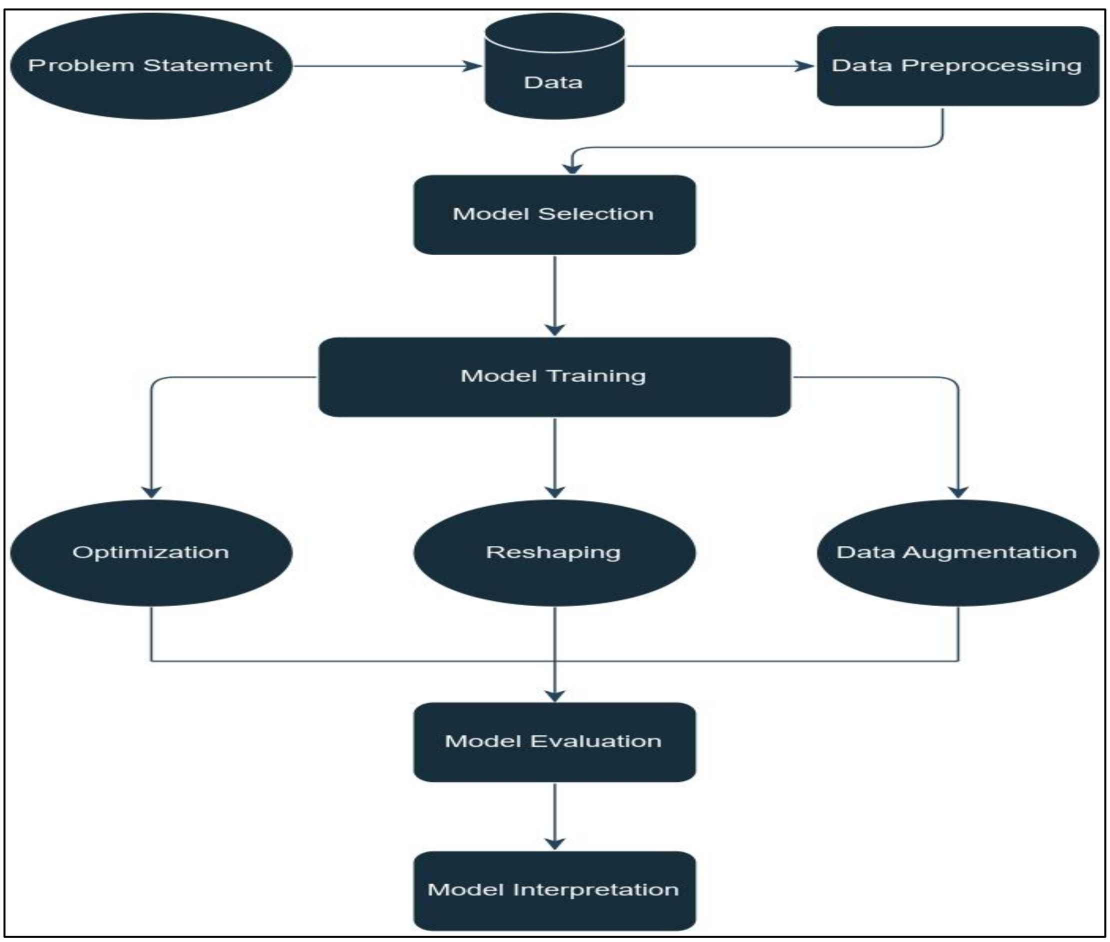



**Fig 3.14: Flow Diagram**

Our model of predicting skin cancer from the dermatological images is following various steps such as:

**Problem statement**: the first phase of any project is understanding the problem statement. In this we will deeply understand all the aspects of our problems treatment so that we can collect proper data to implement the project.

**Data collection**: In the project process this will be the first step. This is the process of gathering data from different sources. It should be the relevant data to solve the problem. We are using data which consists of 10,000 dermatological images containing 7 classes of skin cancer disease. The data consists of two files folder including the main data and the metadata which is providing information about the data.

**Data preprocessing** step is to prepare the data for further use and for implementing the algorithms on the data. data preparation means preparing the data according to the model we are implementing on it. It includes removing any kind of irrelevant data, null values and transforming the data into the usable format for the algorithms. In our project we removed 57 null values and replace it with the mean values data is in the proper format for the further use.

**Model selection** involves selection of an appropriate model for the problem at hand. Keeping accuracy in mind we must select the appropriate model. Our data is image data of dermatology, and we must classify the disease from the images, so we are using the convolutional neural network to perform feature extraction from the images.

**Model training** begins from the splitting of data into training and testing set. The model is trained on the collected data to ensure that it can predict the output accurately and effectively.

**Model evaluation** is the phase in which the performance of the of the model is calculated. It includes checking the accuracy of the model and comparing it. Model should not be overfit or underfit. It should be able to accurately predict the output given the input data. We are using the confusion matrix to correlate between the actual and predicted labels of the model.

**Model interpretation** is the added phase in which we are using explainable artificial intelligence to interpret results from the model we implemented. We are using SHAP algorithm of explainable artificial intelligence to know the most important features of the data. It will also tell which feature is playing a major role in the prediction of any class. For example, in our interpretation we observed that localization plays a major role for the class three of the disease.

In healthcare we need this kind of system which can ensure the reason behind the decision made by any algorithm

### *3.7.2 Libraries*

**matplotlib.pyplot**: A plotting library used to create visualizations such as line charts, scatter plots, and bar charts. In this code, it is used to plot various graphs and visualizations.

**PIL**: A library used for opening, manipulating, and saving image files. In this code, it is used to read and display images.

**seaborn:** A library used for data visualization and statistical graphics. It is built on top of matplotlib and provides a high-level interface for creating informative and attractive statistical graphics. In this code, it is used to create some visualizations.

**glob**: A library used to retrieve files/pathnames matching a specified pattern. In this code, it is used to retrieve the paths of the image files.

**sklearn.model_selection:** A library used for model selection and evaluation. It provides support for various operations such as train-test split and cross-validation. In this code, it is used to split the data into training and testing sets.

**keras**: A high-level deep learning API used for creating and training neural networks. In this code, it is used to define and train the deep learning model.

**tensorflow**: A library used for creating and training deep learning models. It provides support for various operations such as tensor manipulation and GPU acceleration. In this code, it is used to define and train the deep learning model.

**sklearn.preprocessing**: A library used for preprocessing and scaling data. It provides support for various operations such as normalization and standardization. In this code, it is used to standardize the data.

**shap**: This library is used to generate Shapley values, which are used to interpret the model's predictions. In this code, Shapley values are generated using a TreeExplainer, which uses a tree-based algorithm to estimate feature contributions to the model's predictions[66]. The shap_values variable contains the Shapley values for the test set. The library is also used to plot various

Shapley value visualizations, such as summary plots, dependence plots, and force plots. shap.initjs() is used to initialize the visualization library for Jupyter notebooks.

**alibi**: alibi is a Python library for model interpretation and explanation. It provides various tools for understanding and explaining machine learning models, including model inspection, feature importance calculation, and counterfactual generation[67]. It supports a wide range of machine learning models and integrates with popular deep learning frameworks such as TensorFlow and PyTorch.

**scipy**: scipy is a Python library for scientific computing. It provides a wide range of modules for mathematical and scientific computations such as optimization, interpolation, integration, linear algebra, signal processing, and statistics[68]. It is built on top of NumPy and provides additional functionality to it.

**XGBClassifier**: XGBClassifier is a gradient boosting machine learning model. It is an extension of the traditional gradient boosting algorithm and is designed to improve its performance and efficiency[69]. It builds a series of weak decision trees and combines them to create a strong model. It is known for its high accuracy and is commonly used in various domains such as finance, marketing, and image processing.

**RandomForestClassifier**: RandomForestClassifier is a machine learning model used for classification problems. It is an ensemble learning method that combines multiple decision trees to create a strong model. It randomly selects a subset of features and instances at each node of the decision tree to reduce overfitting. It is known for its high accuracy and is widely used in various fields such as bioinformatics, finance, and image processing.

**LabelEncoder:** LabelEncoder is a utility class in scikit-learn used for encoding categorical features into numerical features. It is used to convert categorical data into numerical data that can be used by machine learning models[68]. It assigns a unique integer to each category in the input data. It is commonly used in various preprocessing tasks such as data cleaning, feature engineering, and data normalization.

### *3.7.3 Development of prediction system*

After data preprocessing we splitted our data into 75% training set and 25% testing set. The unique values in cell type column are extracted music the function of TensorFlow library. One hot encoding hello is performed to convert categorical variable into binary vectors representing a category. The 10% of training data will be used for validation. After this reshape method is used to convert 2D image data in x_train, x_test, x_validate into 3D array of shape (height width channel). Most deep learning method requires data to be in this format that is why we performed this conversion.

A 13-layer architecture of Convolutional Neural Network(CNN) is used to extract the features from the dermatological image data. An Adam optimizer is used to optimize the deep learning algorithm so that we can update the weight of neural network for the training process[70].

That data augmentation is used to prevent overfitting. We performed rotation, zooming and flipping to increase the size and diversity of the data set[55].

We trained the CNN model using keras fit generator method may be defined the number of epochs and batch size for the process. The epochs mean the number of times the model will be trained on the data set and the batch size means the sample used in each iteration of training[71].

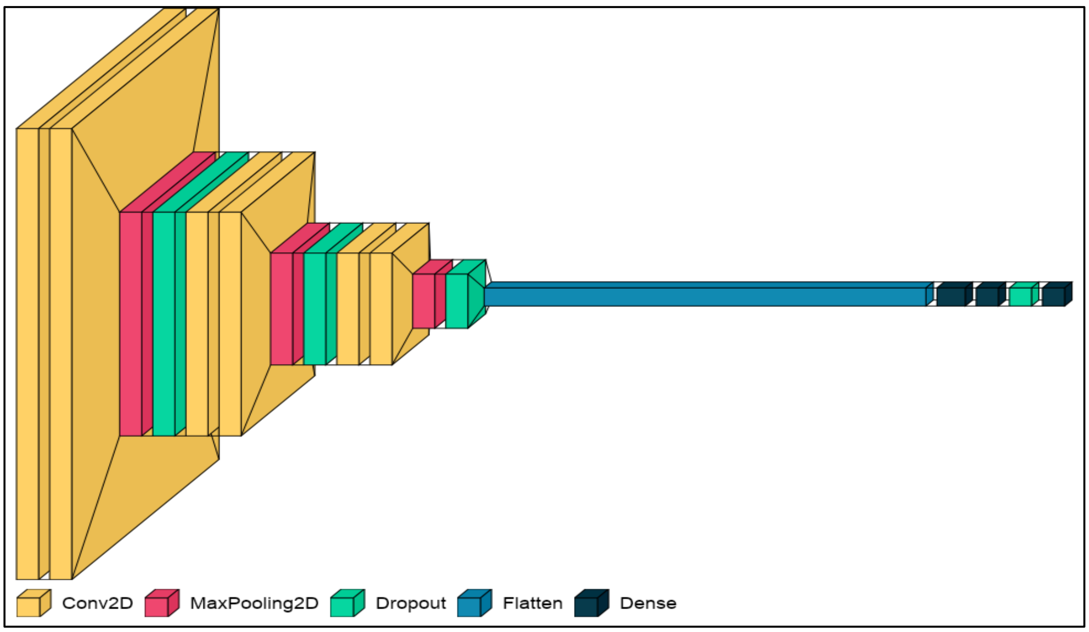



**Fig 3.15: Model Architecture using VisualKeras**

# *Chapter – IV*

## *Model Analysis and Interpretations*

# 4. Model Analysis and Interpretations

## 4.1 Model Evaluation

The model performance is evaluated on the test and validation set. model.evaluate function calculated the loss and accuracy of model. The calculated values are stored with the respective variables and then printed to console using formatted strings. In the last model is saved with file name model.h5 using model.save method so that we can use this prediction model in future on the new data files.

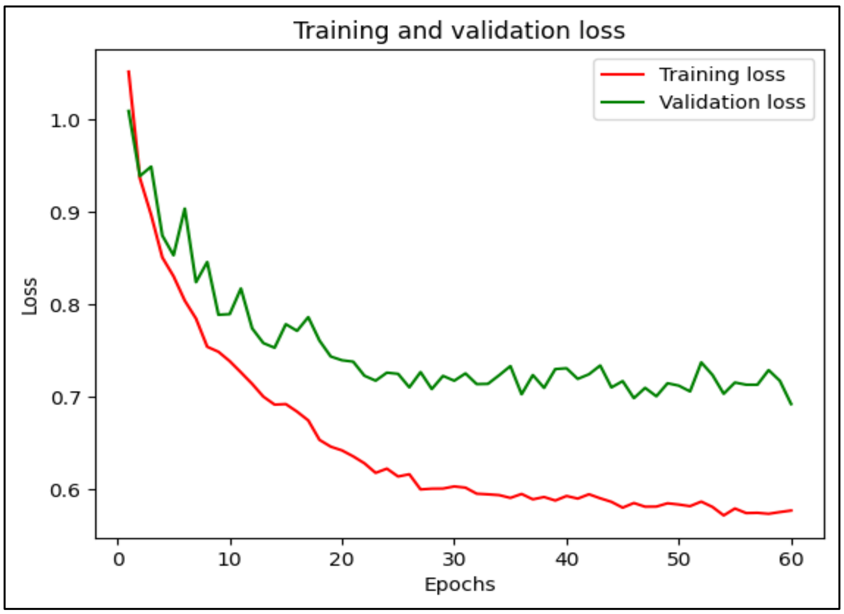



**Fig 4.1: Training and Validation loss**

Validation accuracy is 76.11% validation loss is 69.23% and the test accuracy is 76.70% and the loss accuracy in test is 62.95%.

| **Class** | **precision** | **recall** | **f1-score** | **support** |
|---|---|---|---|---|
| 0 | 0.39 | 0.37 | 0.38 | 71 |
| 1 | 0.46 | 0.63 | 0.53 | 128 |
| 2 | 0.55 | 0.57 | 0.56 | 270 |
| 3 | 0 | 0 | 0 | 29 |
| 4 | 0.87 | 0.93 | 0.9 | 1672 |
| 5 | 0.64 | 0.29 | 0.39 | 273 |
| 6 | 0.74 | 0.68 | 0.71 | 38 |
| **accuracy** | | | 0.78 | 2481 |
| **macro avg** | 0.52 | 0.5 | 0.5 | 2481 |
| **weighted avg** | 0.76 | 0.78 | 0.76 | 2481 |

**Table 4.1: Classification Report**

Prediction model of classification problems cannot be evaluated for their performance only based on the accuracy achieved. We must measure the Accuracy, Precision, Recall, F1-score and Support for all the seven classes of the skin disease so that we can conclude that our model is efficient or not.

Confusion matrix consist TP = True Positive FN=False Positive FP = False Positive TN = True Positive

When the model can predict the disease same as what it was labeled then it is true positive and otherwise it is false negative. If the model the disease other than what is indicated by the classification model, then it is false positive. For example, if an image is indicated as Melanoma by our classification model but it belongs to disease from another class. True negative is When for example a non-Melanoma disease image is suggested as non-Melanoma by the model.

**Accuracy** refers to the fraction the true prediction with all the classification prediction.

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + TN + FP + FN}}$$

**Precision** means the total percentage which are predicted positive out of the total positive. Precision helps us to calculate the proportion of positive predictions.

$$\boldsymbol{Precision = \frac{TP}{TP + FP}}$$

**Recall** means what proportion of actual positives was identified correctly. It is also referred to as sensitivity.

$$\boldsymbol{Recall = \frac{TP}{TP + FN}}$$

**F1 score** is the weighted average of precision and recall. Afghanistan code having the value one is the best and 0 is the worst.

$$\boldsymbol{F1 = 2 * \frac{\mathbf{Precision * Recall}}{\mathbf{Precision + Recall}}}$$

**Support** is the number of occurrences of class in the data set**.**

$$\mathbf{Support} = \boldsymbol{\frac{TN}{FP + TN}}$$

We were having the data set consisting of seven types of skin cancer disease. D7 types are classified into seven classes from zero to 6. For all the seven classes we computed all the parameters like accuracy precision recall F1 score and support. The table above provides the confusion matrix for all the seven classes.

## 4.2 Model Interpretation

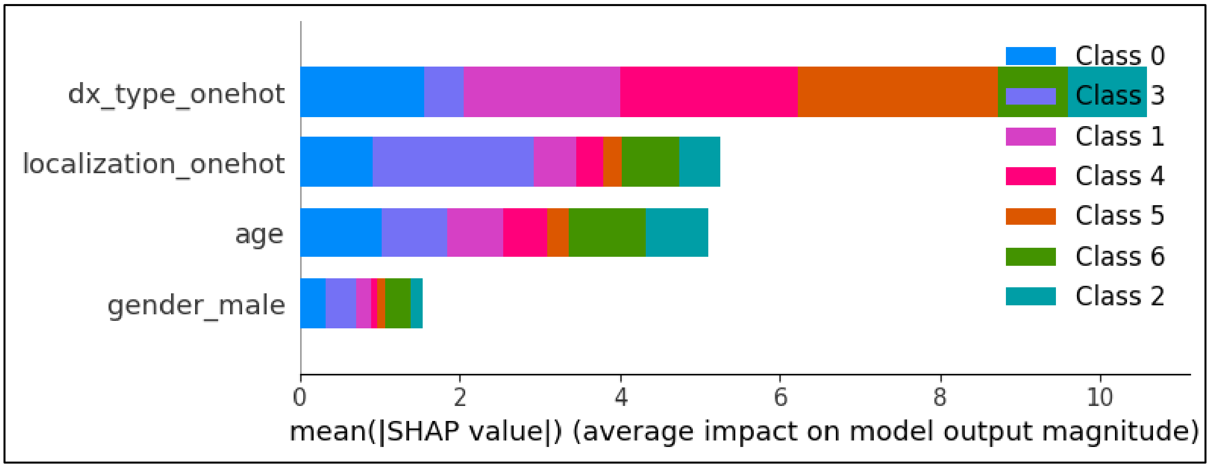



**Fig 4.2 Feature Importance Plot**

The above feature importance plot is not only showing us that which feature is most important but also telling us that which feature is playing a major role in the prediction of a particular class. We can observe that each feature plays vital role in the prediction of class zero disease real localization plays major role in predicting whether the disease belongs to class 3. DX type is showing its important role in the prediction of the disease for the class one class four and class 5.

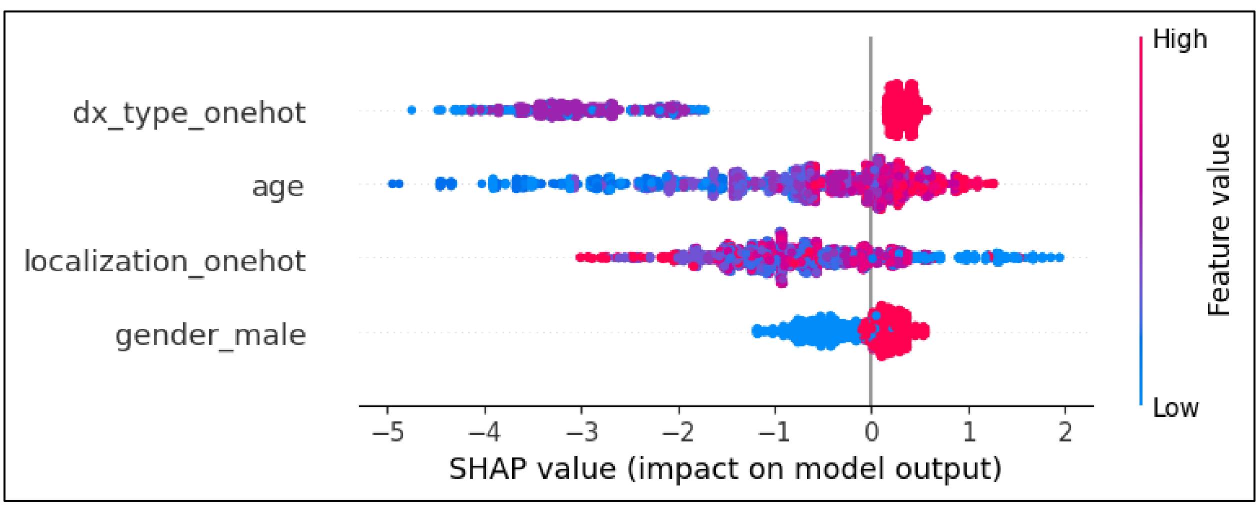



**Fig 4.3: Summary Plot**

This summary plot tells the effect of different values of each feature on the SHAP value. We can see that the higher values of dx_type_onehot are associated with a higher SHAP value.

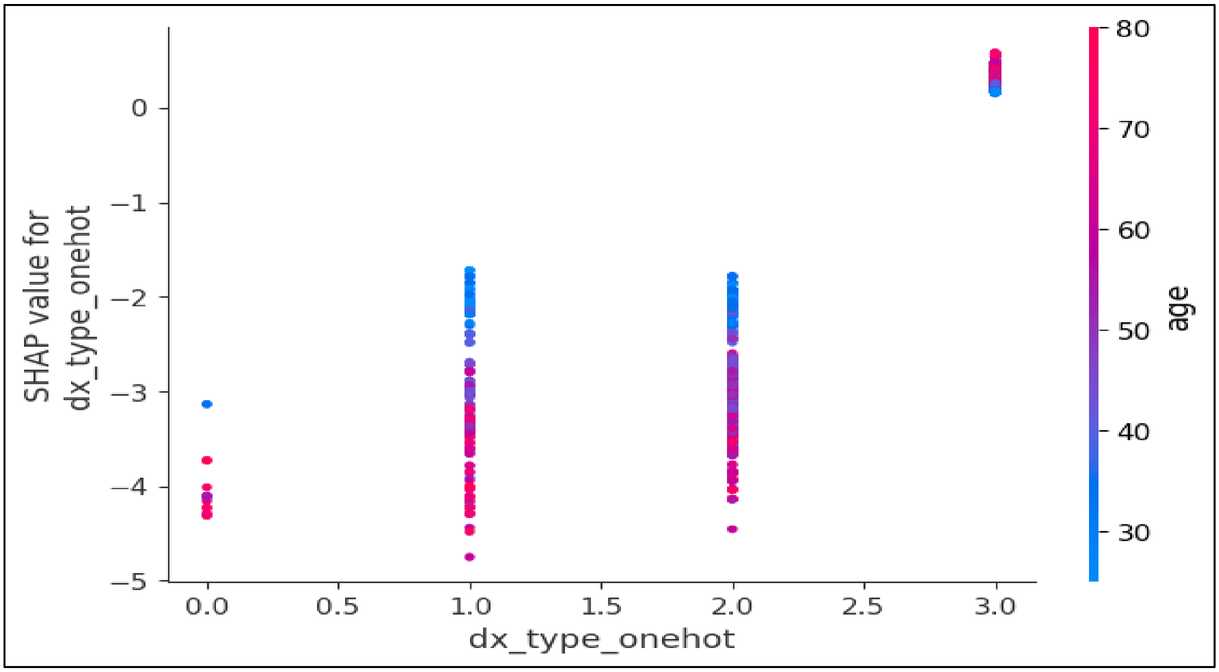



**Fig 4.4: SHAP graph for dx_type_onehot**

In this graph the effect of dx_type_onehot at a particular age is seen on the SHAP value.

We also observed through other visualization that localization and type of diagnosis impact the prediction positively as because of positive SHAP value whereas the age and gender of patient impacts the model negatively.

### 4.3 Model Validation using comparison with existing work

| Study | Data source | Classification Technique | Attributes | Model Performance |
|---|---|---|---|---|
| Parvathaneni Naga Srinivasu et. al.[29] | Kaggle | MobileNet V2; Deep Neural Network | Images | 80% |
| Parameshwar R. Hegde et. al.[72] | YUEC/366/2016 | Machine Learning | Images | 72% |
| Kemal Polat1, Kaan Onur Koc [33] | Kaggle | CNN, ANN, Image processing, OVA | Images | 77% |
| Tanzina et al.[73] | Dermnet | CNN | Images | 73% |
| Rola et al. [74] | Many online sources | CNN, VCG-16 | Facial Images | 88% |
| Our work | kaggle | DL, ML and XAI | Metadata, Images | 85% |

**Table 4.2: Comparison Table**

# *Chapter – V*

# *Result and Conclusion*

# 5. Result and Conclusion

## 5.1 Result and Discussion

Total test data is 2481 out of which we predicted 1903 accurately and 578 are wrongly predicted which gave the accuracy of 86.703%.

The below figure is created from a two-dimensional array to show the expected disease and how accurately we predicted it. We tried to predict actinic keratosis and were very successful in predicting it accurately.

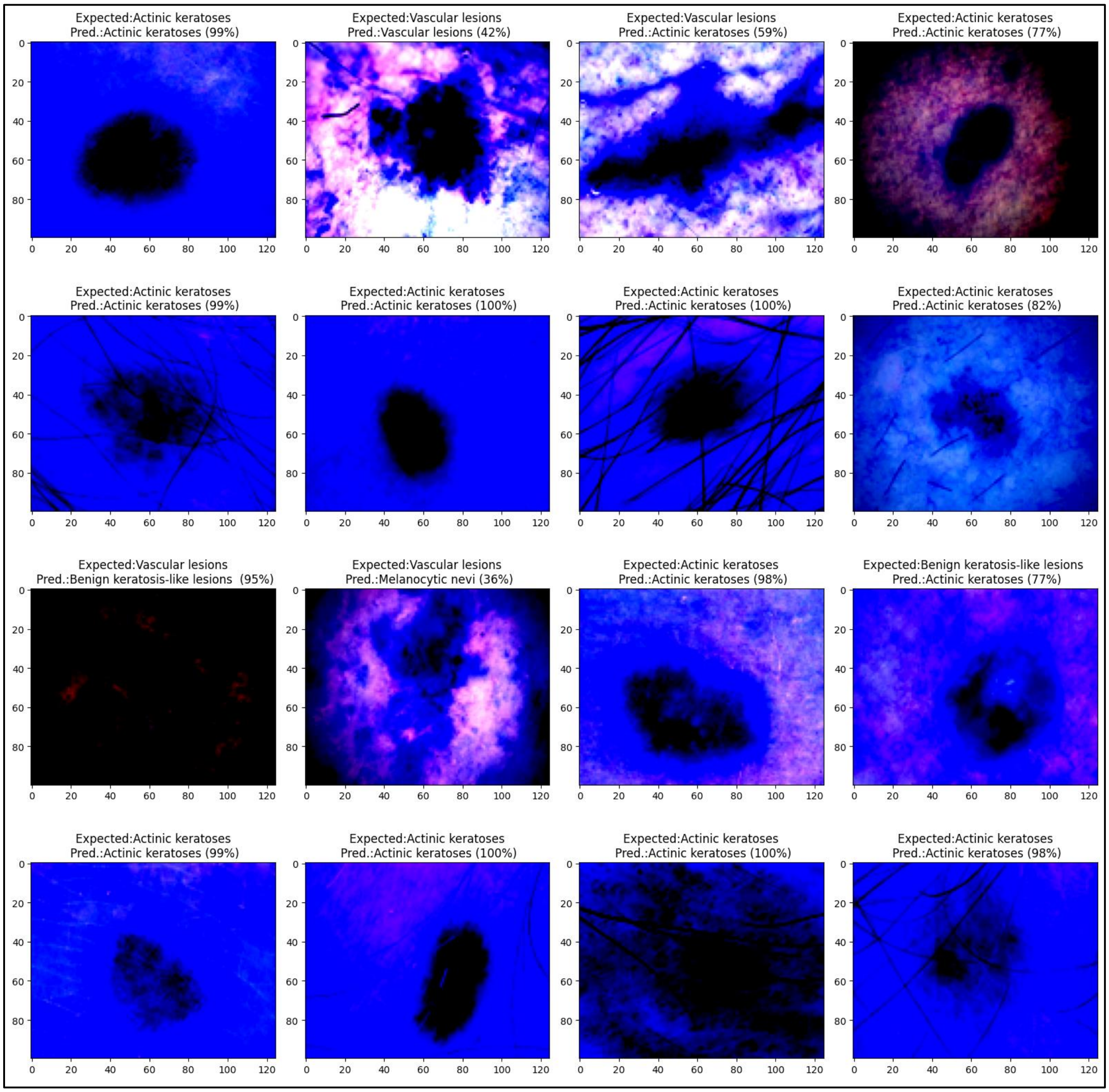



**Fig 5.1: Actinic keratoses prediction**

The confusion matrix is used for the model performance evaluation of the classification of prediction. It consists of predicted labels and true labels in that square matrix form the number of correct predictions for each class.

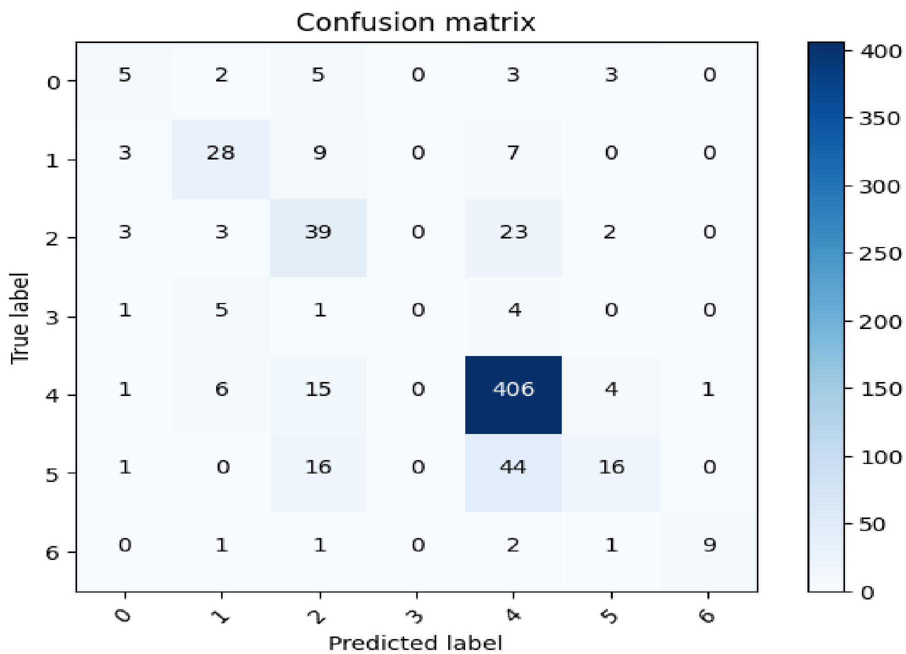



**Figure 5.2: validation set confusion matrix**

We can see clearly from our figures that 406 levels from the class four disease are predicted accurately.

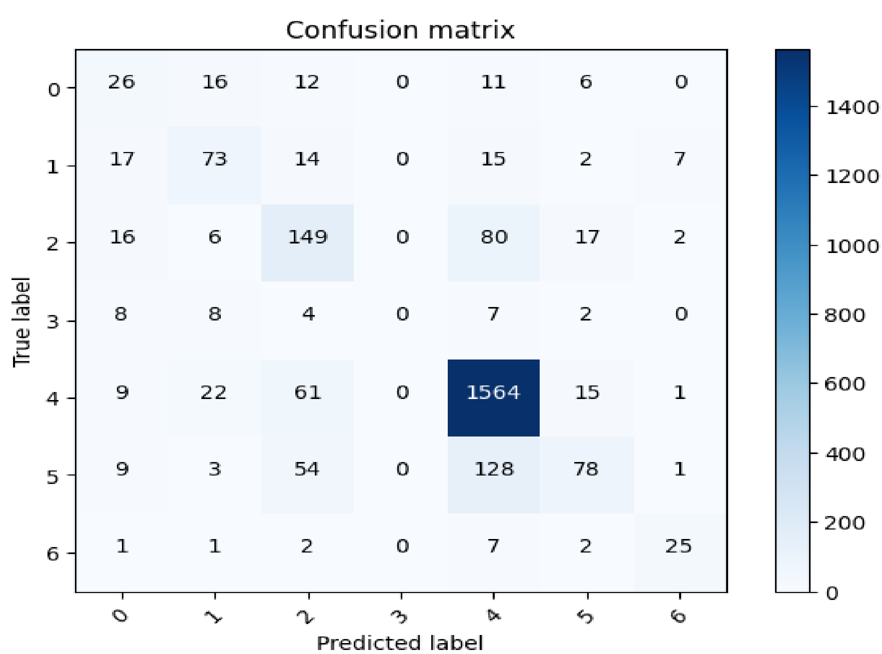



**Fig 5.3: test set confusion matrix**

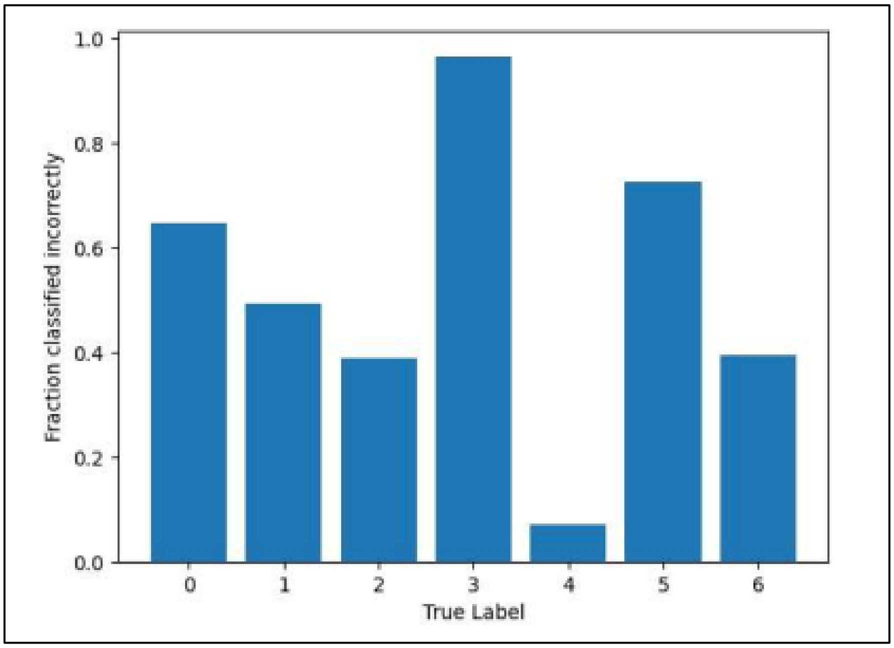



**Fig 5.4: graph for wrongly predicted and true label.**

The confusion matrix of test set shows that 1560 levels of the class 4 disease are predicted accurately. Overall, the validation accuracy comes up to 84.17% whereas the test accuracy is 86.82%. We can conclude that CNN gives good training and testing accuracy with the lowest error rate. The analysis shows through all the measures that the model using CNN provides accurate prediction for image classification. This will reduce the chances of misdiagnosis. The deep neural architecture of CNN with multilayer perception gives precise classification outcome.

## 5.2 Conclusion and future work

Skin disease classification needs accurate and precise diagnosis. The existing methods and technologies are time consuming as well as costly processes. Dermatologists physically examine the disease and diagnose it based on their experience and some symptoms. Technological advancement like AI and deep learning made this task very much easier by automating the process to diagnose the disease more precisely and accurately. It is time saving as well as cheaper than any method. In this study we use 10,000 dermatological skin disease images and analyze them using convolutional neural network. The data was classified into seven different categories of skin diseases. We had a metadata file and image data set. We merged both the files and converted the categorical values into numerical values. The analysis started with the exploration of data where we found skewness toward the younger age between 40 to 60. Most of the skin diseases were Melanocytic Nevi followed by benign ketosis like lesions. With the data augmentation technique on the training and testing data the risk of overfitting is reduced.

We built the CNN model of overall 13 layers with convolutional layer, pooling layer, dropout and fully connected layer. Hidden layers consist of ReLU activation function and the SoftMax activation function in output layer. The model is trained on 20 epochs with batch size of 16 on training dataset. We evaluated our model with confusion matrix and parameters like precision recall upon score and support. Overall, we achieved good results with the accuracy lies between 80 to 85%.

We can conclude that we have built a skin disease classification model with CNN multilayer architecture that is able to classify skin disease from seven different classes. We interpreted our model with the help of explainable artificial intelligence to provide precise explanation about the prediction.

This model can be used by dermatologists for skin disease detection to help patients and manage the process effectively. Future work will be to improve the model's performance and to extend the model to diagnose other skin diseases.

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