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قسم المعلومات الطبية

Skin cancer detection

Using deep learning algorithms &
Patient's metadata

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Abstract

Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. The advancement of lasers and Photonics based medical technology has made it possible to diagnose the skin diseases much more quickly and accurately. But the cost of such diagnosis is still limited and very expensive. So, image processing techniques help to build automated screening system for dermatology at an initial stage. The extraction of features plays a key role in helping to classify skin diseases. Computer vision has a role in the detection of skin diseases in a variety of techniques.

Finding out the type of cancer can take months for doctors as it is a very tedious practice and also requires the use of expensive devices and contraptions. This would waste a good lot of time for the patient which could have been utilized by the doctors to treat the patient in time. It is also monetarily very demanding on the patient's part, which could pose a problem if the patient is not financially settled.

Chapter 1

Introduction

1.1 Introduction

Diagnosis in dermatology is largely based on visual inspection of a lesion on the suspicious skin area. Therefore, diagnostic ability and accuracy depends greatly on the experience and training of dermatologists or general practitioners, in areas where dermatological services are not readily available. When dermatologists get no access to additional technical support, they have an approximately 65% - 70% accuracy rate in skin cancer diagnosis. If the lesion is suspicious, the visual inspection is supplemented with different diagnostic tools (e.g. dermoscopy, confocal microscopy or optical coherence tomography) providing the ability to explore the skin *in vivo*, in depth and at a higher resolution. However, access to these instruments remains limited due to time, logistical and cost concerns.

Even when this technical support is feasible, dermatologists rarely achieve average rates greater than 85%. The situation is even worse if we consider that there is a shortage of dermatologists whilst diagnostic accuracy of non-expert clinicians is sensibly below than what is observed with dermatologists, reaching estimate rates between 20 and 40%. Thus, new diagnostic tools assisting dermatologists or general practitioners to accurately diagnose skin lesions should be developed, evaluated and optimized.

Analyzing cancers isn't an easy task. It requires intensive examining. More than 50% of lesions are confirmed through histopathology (histo), the ground truth for the rest of the cases is either follow-up examination (follow-up), expert consensus (consensus), or confirmation by in-vivo confocal microscopy (confocal). The lack of experts (radiologists) has always been a bottleneck. Now there are three things that we have to consider here:

Given the fact that there are a limited number of experts, how can we make them more efficient? Can we aid them using state of the art machine learning techniques? If yes, how?

Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available dataset of dermatoscopic images. Labelled data in healthcare is another bottleneck. With the available limited data, how much can we do?

As Machine Learning Engineers, if we can't help the doctors and ultimately the society, then what are we good at? Healthcare is a complicated field and using Machine Learning in this field has its own advantages and disadvantages. There is a limit to which we can do things with ML in healthcare but whatever we can do, it matters!

The first step to identify whether the skin lesion is malignant or benign for a dermatologist is to do a skin biopsy. In the skin biopsy, the dermatologist takes some part of the skin lesion and examines it under the microscope.

The current process takes almost a week or more, starting from getting a dermatologist appointment to getting a biopsy report. This project aims to shorten the current gap.

The approach uses Convolutional Neural Network (CNN) to classify 7 types of skin lesions:

- Actinic keratosis and intraepithelial carcinoma: common non-invasive variants of squamous cell carcinomas. They are sometimes seen as precursors that may progress to invasive squamous cell carcinoma.
- Basal cell carcinoma: a common version of epithelial skin cancer that rarely metastasizes but grows if it isn't treated.
- Benign keratosis: contains three subgroups (seborrheic keratoses, solar lentigo, and lichen-planus like keratoses (LPLK)). These groups may look different but are biologically similar.
- Dermatofibroma: a benign skin lesion that is regarded as a benign proliferation or an inflammatory reaction to minimal trauma.
- Melanoma: a malignant neoplasm that can appear in different variants. Melanomas are usually, but not always, chaotic, and some criteria depend on the site location.

- Melanocytic Nevi: these variants can differ significantly from a dermatoscopic point of view but are usually symmetric in terms of distribution of color and structure.
- Vascular Lesions: generally categorized by a red or purple color and solid, well-circumscribed structures known as red clods or lacunes.

The overarching goal is to support the efforts to reduce the death caused by skin cancer. The primary motivation that drives the project is to use the advanced image classification technology for the well-being of the people. Computer vision has made good progress in machine learning and deep learning that are scalable across domains. With the help of this project, we want to reduce the gap between diagnosing and treatment. Successful completion of the project with higher precision on the dataset could better support the dermatological clinic work. The improved accuracy and efficiency of the model can aid to detect skin cancer in the early stages and can help to reduce unnecessary biopsies.

We aim to make it accessible for everyone and leverage the existing model and improve the current system. To make it accessible to the public, we build an easy-to-use mobile app. The user or dermatologist can upload the patient information with the skin lesion image. With the image and patient information as input, the model will analyze the data and return

the results within a split second. Keeping the broader demographic of people in the vision, we have also tried to provide the basic info of the skin cancer and the seven skin lesions , which provides a generalized overview about skin lesions and steps to use the online tool to get the results.

1.2 Related Discussion

Despite the advancements in technology, however the inefficiency within the clinical dataset has restricted the utility of deep learning in biological data. Melanoma is a most usual skin cancer that showed huge mortality rate. It is estimated that nearly 9,730 deaths have occurred due to melanoma in 2017.

Basal cell carcinoma commonly referred to as BCC is the most usual skin cancer, however is commonly not fatal. So it is very important for both health care services to diagnose the type of cancer and to develop an efficient method to discriminate different types of skin cancer will be useful for initial screening. To improve a classification tool using biological images of 7 different known skin lesions - Dermatofibroma, Melanocytic nevi, Basal cell carcinoma, Benign keratosis, Actinic keratosis, Vascular lesions, Melanoma.

Huge efforts should be made to improve an image classification methods for more precise prediction of lesions. In one of the old

studies, machine-guided diagnostic methods depending on feature extraction method imaged a considerable diagnostic capability with some types of skin cancer, which includes melanoma. However, an AI algorithm would not create precise diagnoses over a large varieties class of skin cancers. Not very long back, deep CNN architectures became popular in object classification going feature learning especially with image data. Extensive research from ILSVR (ImageNet Large Scale Visual Recognition Challenge) has depicted that object classification abilities of CNNs can exceed over that of human diagnosis abilities.

Many dermatologic studies showed the uses of machine or deep learning. For example, Liao et al. Used a CNN based model to Classify top level 23 Categories Such as, viral infections, bullous diseases etc. With 23000 images. It showed an accuracy of 73.1% and 91.0% respectively for rates at which a model gives Output of the correct label with top-1 and top-5 predictions for a given image. They have used a binary classification CNN based model which gave an AUC of 0.96 for carcinoma diagnosis using the above mentioned Edinburgh dataset with 707 cases and gave AUC of 0.96 for melanoma diagnosis which has 225 cases.

Chapter 2

Previous work

2.1 Related work

As we know there are many apps that try to detect skin lesions much easier. At the start of our project we have inquired about some auxiliary assets dependent on this. From these have access to machine resources sources, we have had the option to know the current capacities and decided our work plot.

There is an application called Medical Dermatology it's a one of the app in this field. It provide availability to make classification for skin lesion and metadata like gender, age, etc. The drawback of the app that it has bad interface that doesn't attract users to use and less metadata.

Another application called SkinVision it's a mobile application published and used in widely range only.it has a good and creative user interface that help the patient to get good and satisfy result.

Another application called Aysa it's a mobile application with a lot of features.it has the best and most creative user interface and it is totally free and save patient history with a lot of medical knowledge questions to reach the best accurate result.

Another application called Visus it's a mobile application that provide image classification for 7 types of skin lesion with bad and not accurate accuracy.

Another application called AI Dermatologist it's a mobile application with amazing user interface to classify image lesion but limited features and not free.

Another application called SmartSkin it's a mobile application with bad user interface and limited features and its accuracy not accurate.

There are also a lot of applications that target skin lesions classification but not reach the level to rely on it like All Skin Dermatologist, Skin Diseases, AISkin, Scanoma and more.

2.2 Comparing Our System with Existing Systems

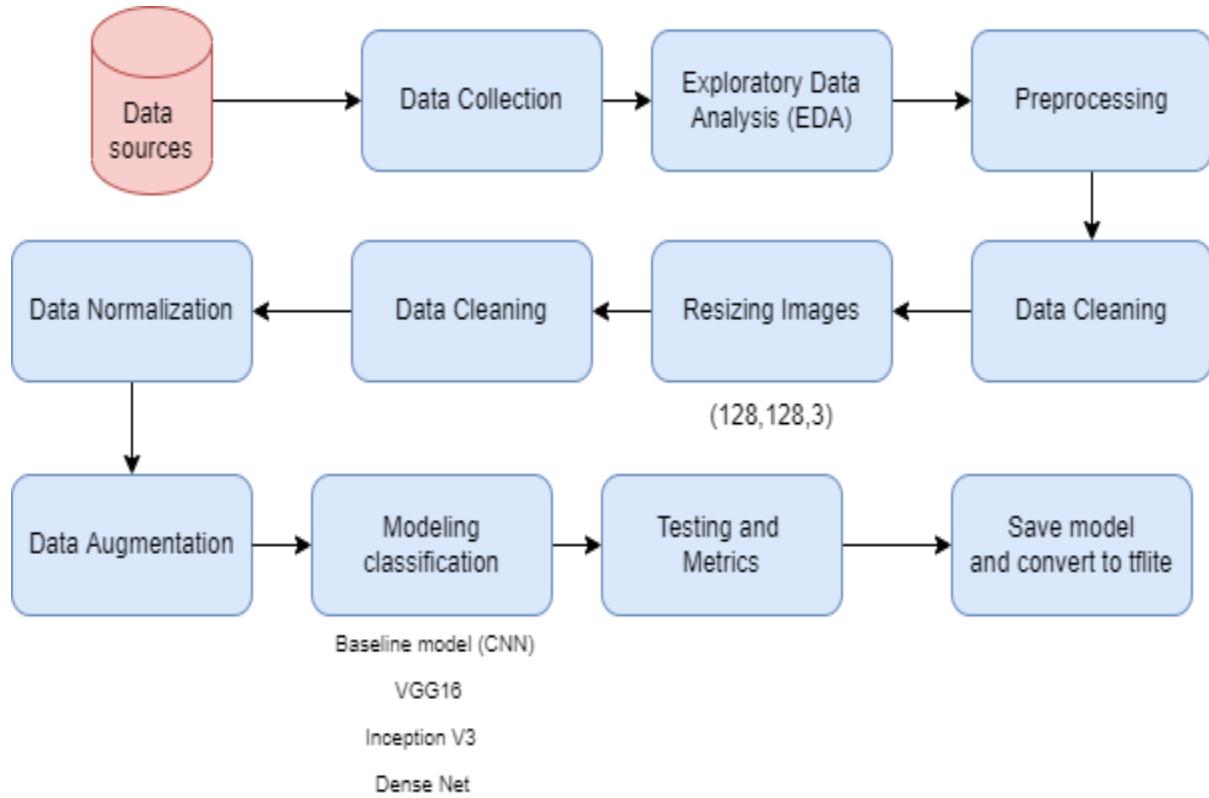
In our mobile application user all data will be stored with local database so he doesn't need to share his private data with informal organizations. We developed malignant melanoma detection based on dermoscopic images and patient's metadata using an artificial intelligence (AI) model that will work on low-resource devices with a good and creative user interface that help the patient to get good and satisfy result supporting android and iOS.

For find suitable doctor we provide feature that help you to find the nearest doctor or hospital in your local area according to GPS. Also we try to provide a lot of information about skin cancer and its symptoms especially for 7 lesions with difference between benign lesions and malignant lesions.

Chapter 3

Methodology

Brief about the algorithm and its steps



3.1 Exploratory Data Analysis (EDA)

Here we discuss about the different features of the dataset, their distributions and the count of that types present in the dataset. This is helpful to analysis the nature of our data and helps us in the data processing step. First we will see the number of instances of data present for every possible values of every feature of data feature wise study of the data. Before jumping into analysis part let us look at from where the data is collected.

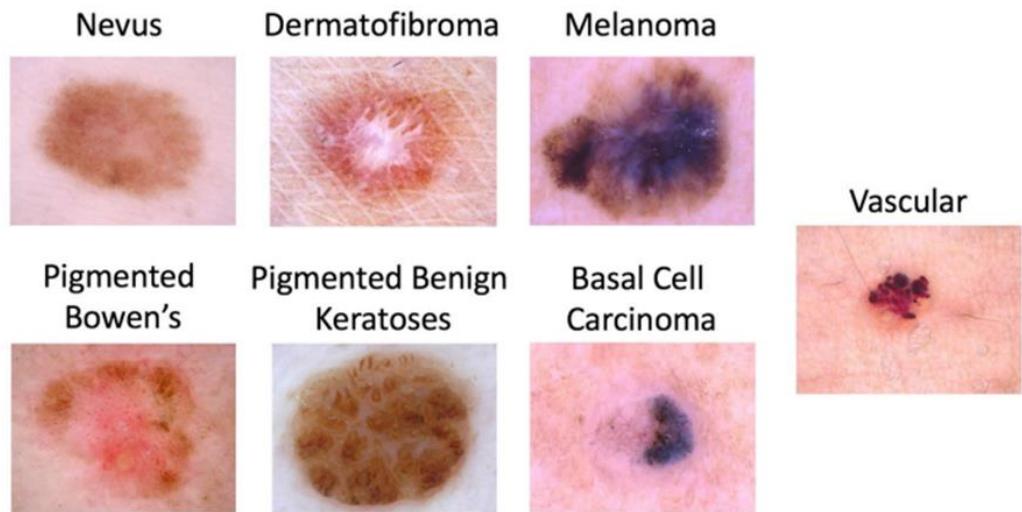
3.1.1 Data Collection

This is the HAM10000 ("Human against machine with 10000 training images") dataset. It consists of 10015 dermatoscopy images which are released as a training set for academic machine learning purposes and are publicly available through the ISIC archive. This benchmark dataset can be used for machine learning and for comparisons with human experts.

<https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T>

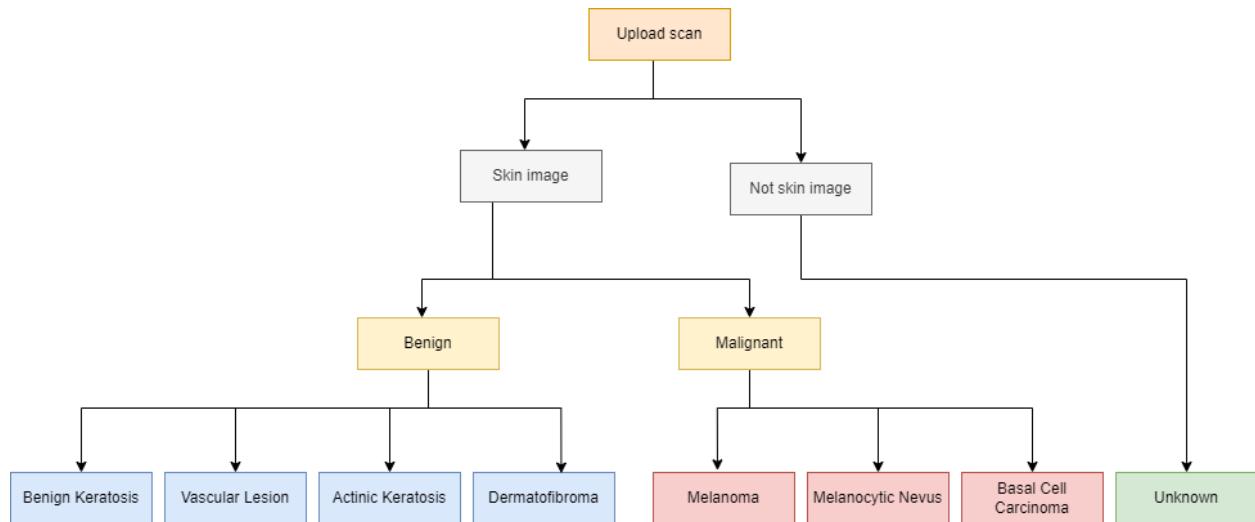
It has 7 different classes of skin lesion which are listed below:

- Melanocytic Nevi (NV)
- Melanoma (MEL)
- Benign Keratosis-like Lesion (BKL)
- Dermatofibroma (DF)
- Basal Cell Carcinoma (BCC)
- Actinic Keratoses (Akiec)
- Vascular Lesions (Vasc)



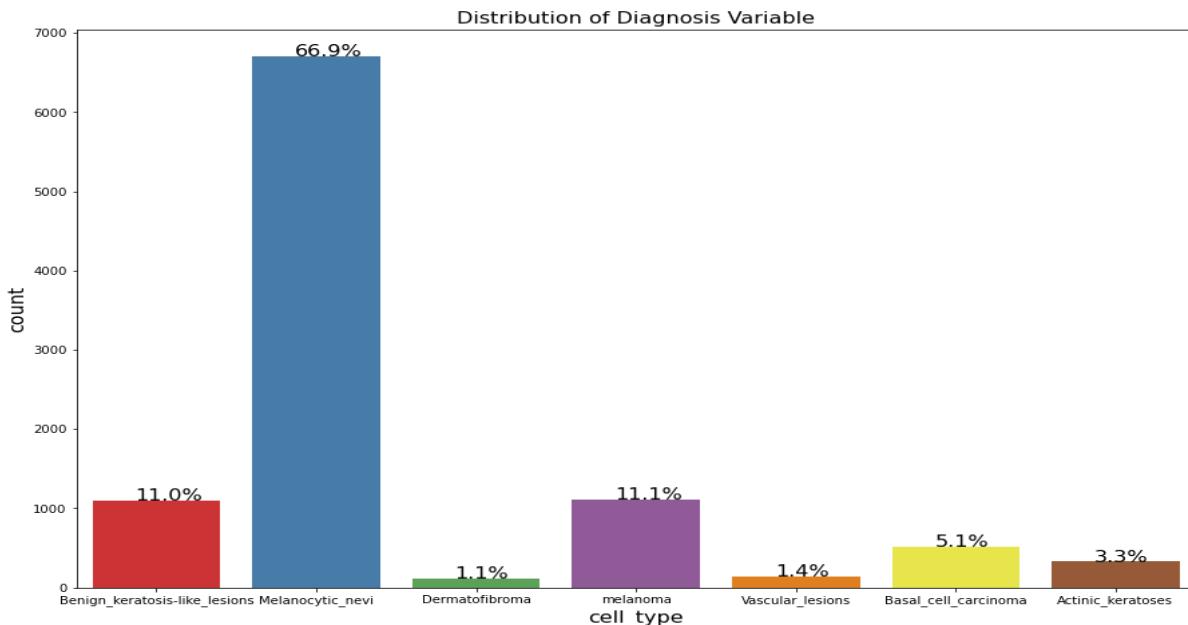
Melanocytic nevi, keratosis, vascular and dermatofibroma are benign lesions

Melanoma, basal cell carcinoma and actinic keratosis are malignant lesions



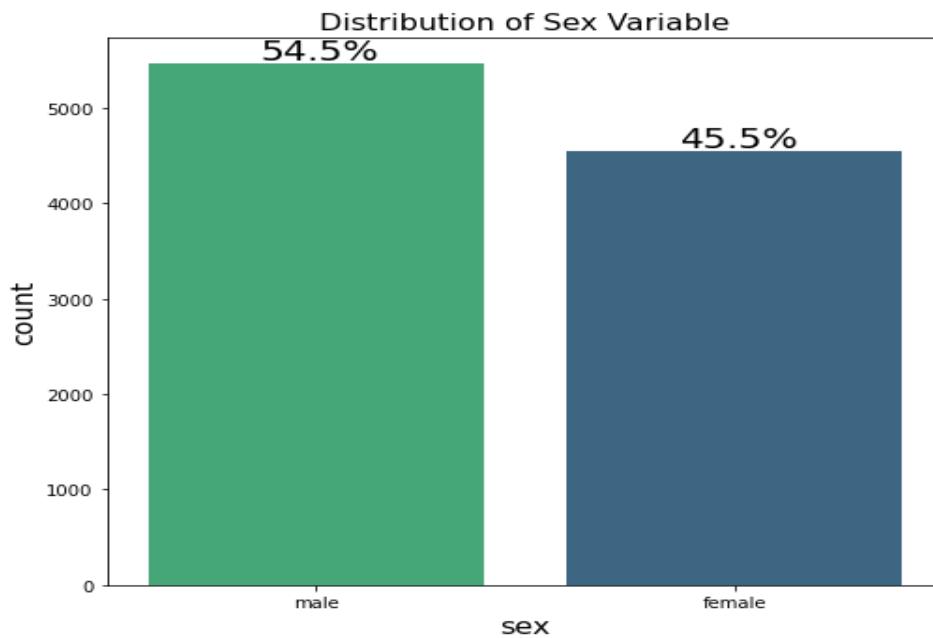
3.1.2 Feature wise study

1) Diagnosis

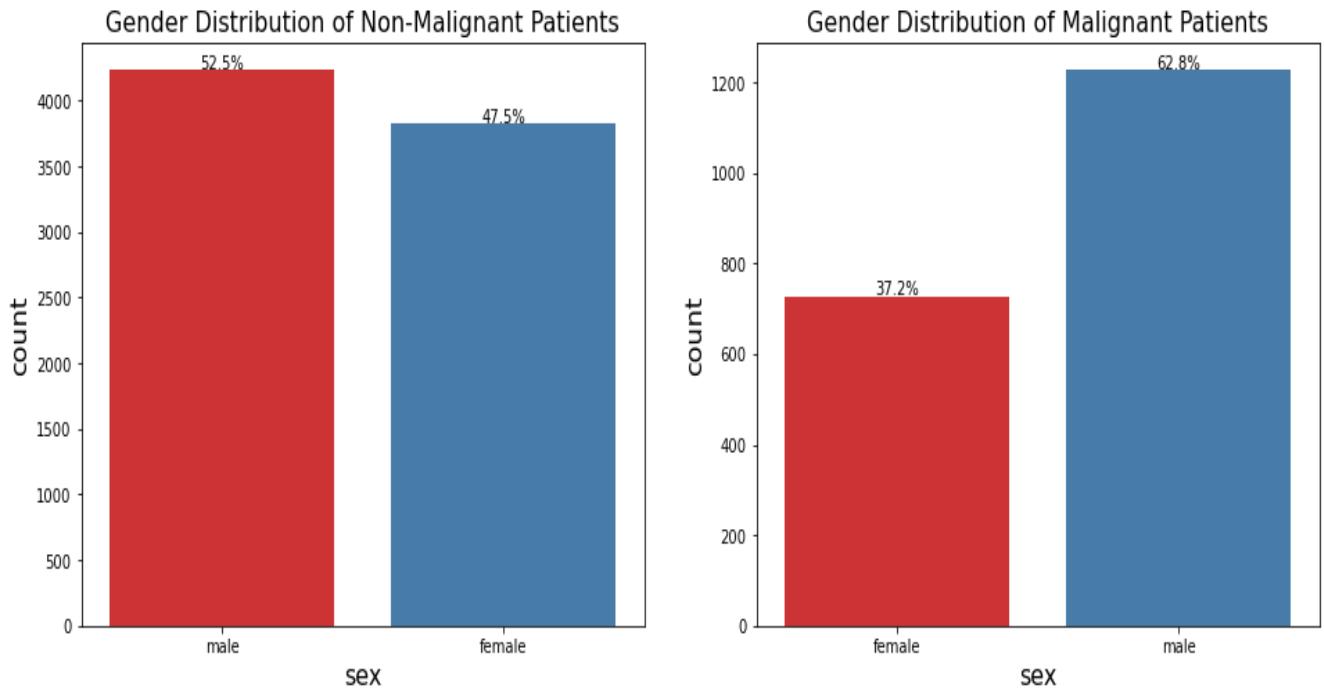


It seems from the above plot that in this dataset cell type melanocytic nevi has very large number of instances in comparison to other cell types

2) Gender



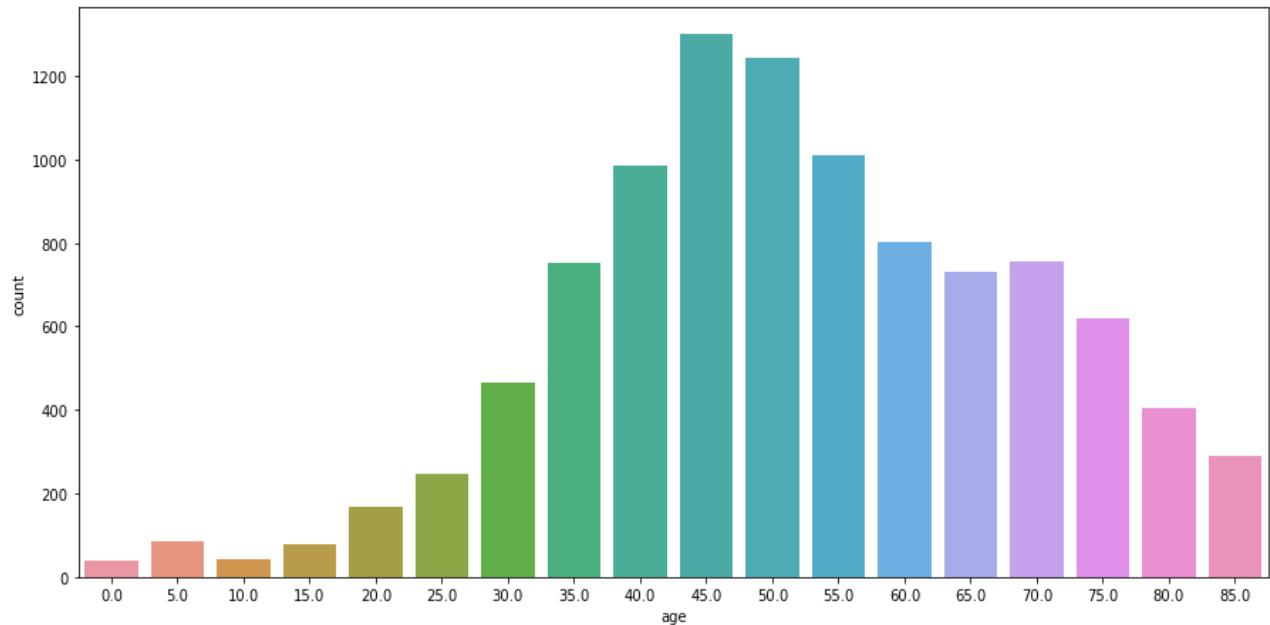
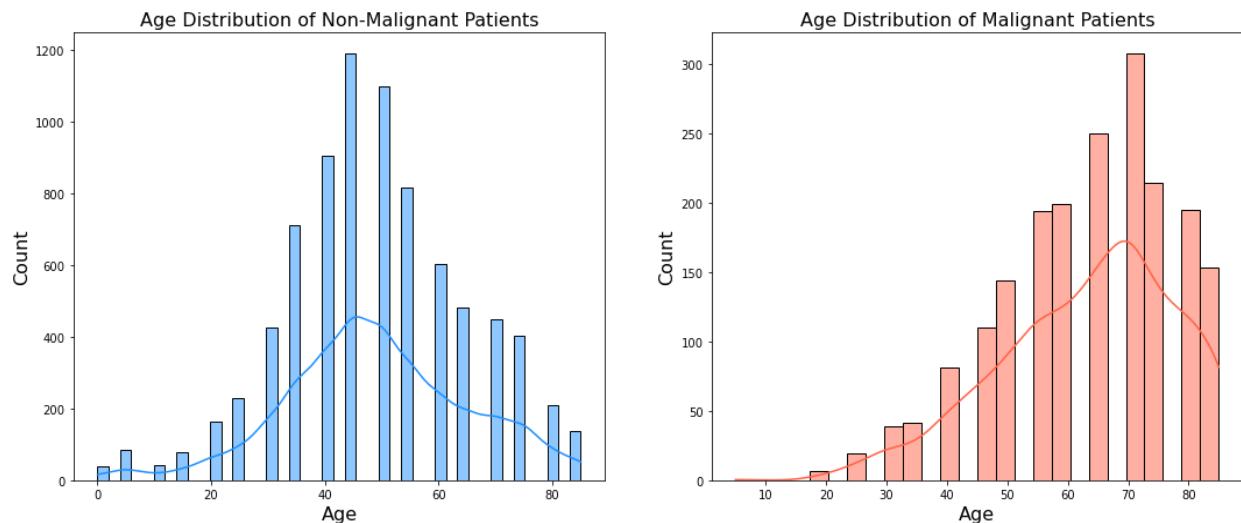
55/45 distribution, dataset matches industry established distribution



There is a 60/40 split in the Malignant population for males and females due to the fact that under 50, melanoma occurs more frequently in women, while above 50, occurs more often in men and increasingly so moving into 80.

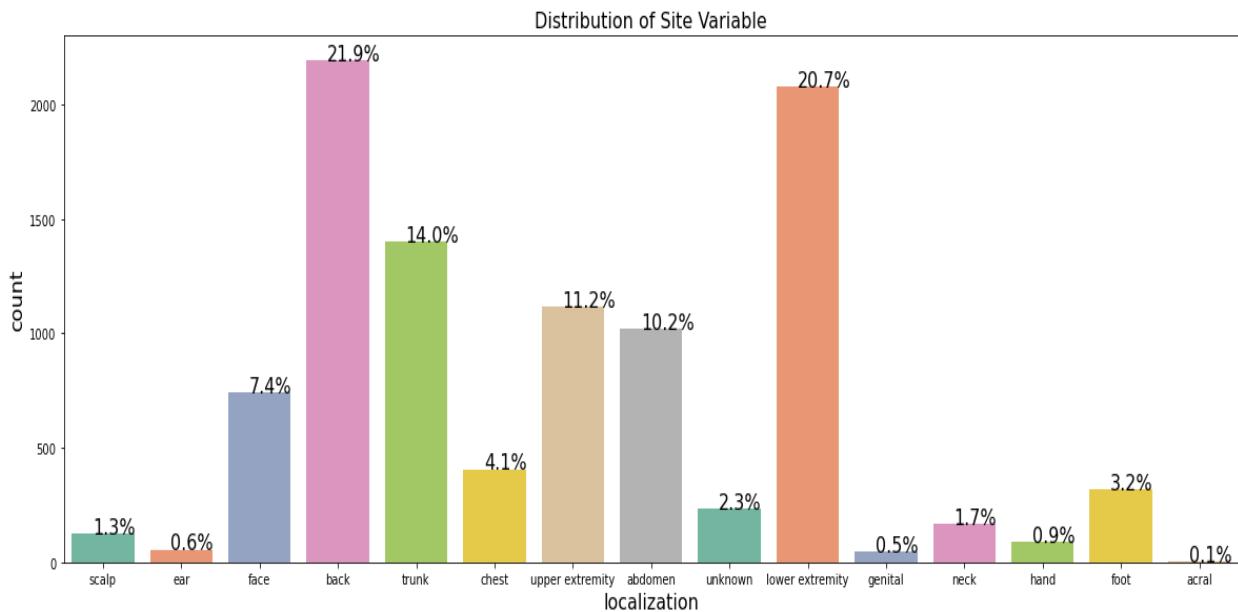
<https://www.cancer.net/cancer-types/melanoma/statistics>

3) Age



It seems that there are larger instances of patients having age from 30 to 60

4) Site



It seems back, lower extremity, trunk and upper extremity are heavily compromised regions of skin cancer

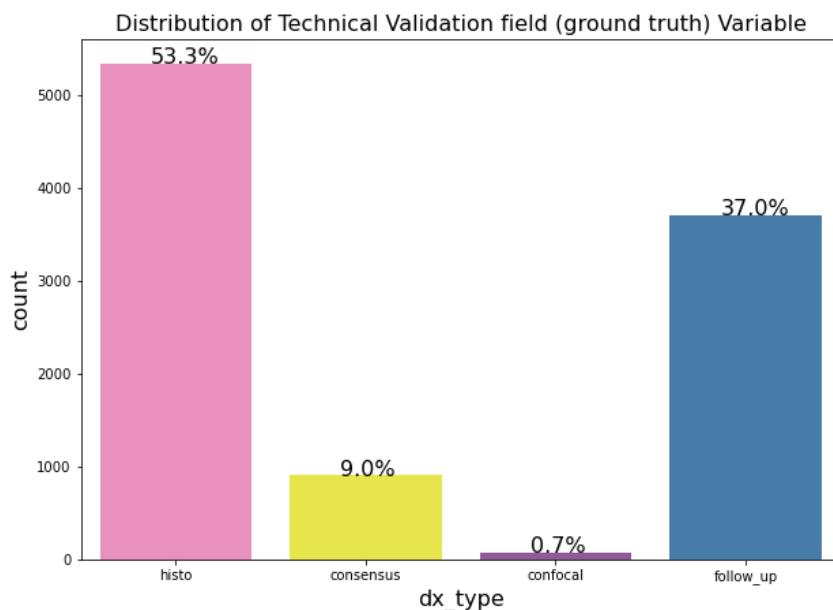
5) Technical Validation field (ground truth)

The distribution of its 4 categories which are listed below:

- 1) Histopathology (Histo): Histopathologic diagnoses of excised lesions have been performed by specialized dermatopathologists.
- 2) Confocal: Reflectance confocal microscopy is an in-vivo imaging technique with a resolution at near-cellular level , and some facial benign with a grey-world assumption of all

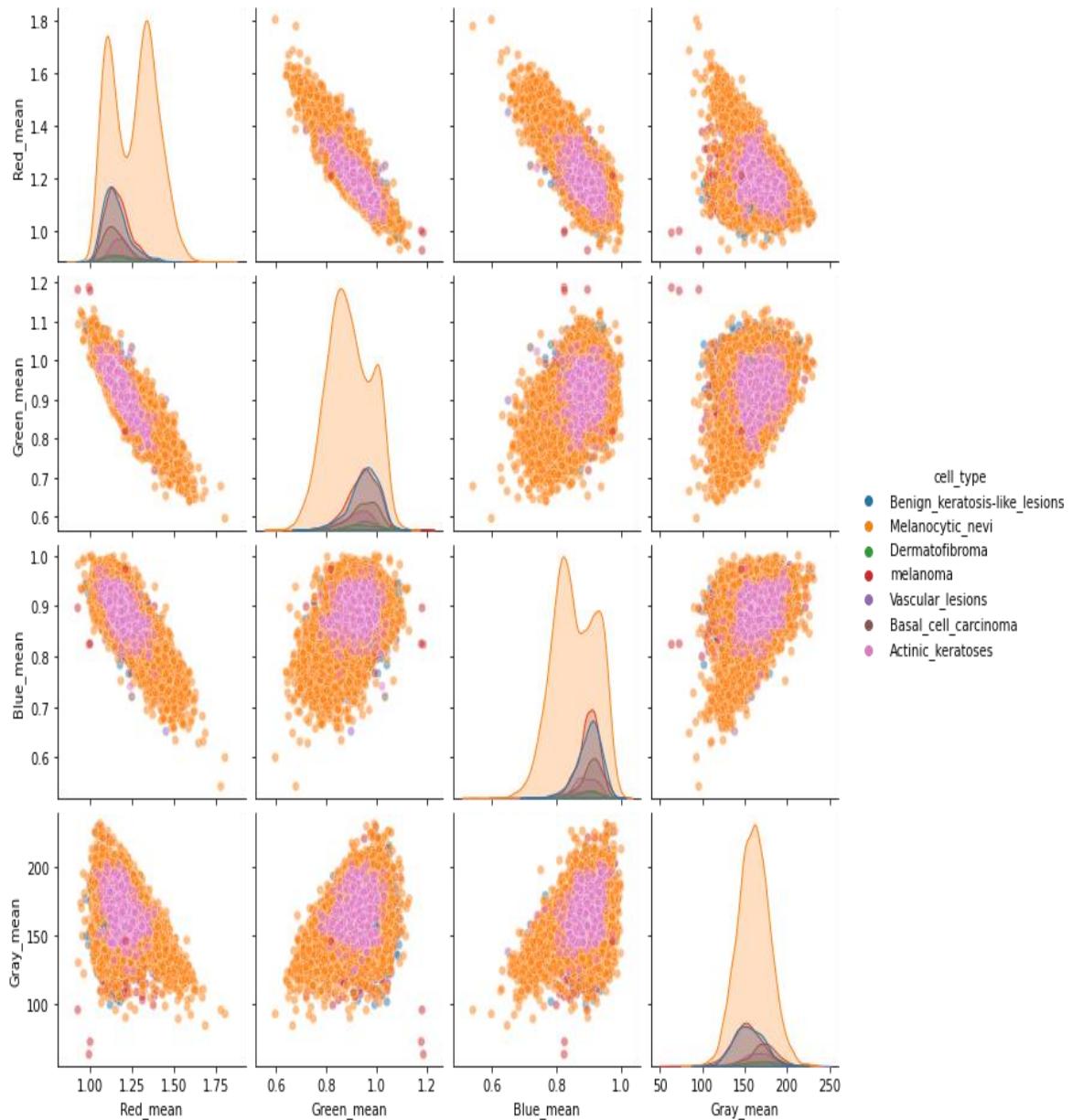
training-set images in Lab-color space before and after manual histogram changes.

- 3) Follow-up: If nevi monitored by digital dermatoscopy did not show any changes during 3 follow-up visits or 1.5 years biologists accepted this as evidence of biologic benignity. Only nevi, but no other benign diagnoses were labeled with this type of ground-truth because dermatologists usually do not monitor dermatofibromas, seborrheic keratoses, or vascular lesions.
- 4) Consensus: For typical benign cases without histopathology or follow up biologists provide an expert-consensus rating of authors PT and HK. They applied the consensus label only if both authors independently gave the same unequivocal benign diagnosis. Lesions with this type of ground truth were usually photographed for educational reasons and did not need further follow-up or biopsy for confirmation.



3.1.3 Average Color Information

Here we get and normalize all of the color channel information, the shape of the image array is $(450, 600, 3)$, 3 are the 3 channels: Red, Blue and Green! Taking the mean across axis= $(0, 1)$ gives the mean for each 3 channels.



3.2 Data Processing

3.2.1 Data Cleaning

Data cleaning is an important step in machine learning. Data cleaning plays an important role in building a proper model. Proper data cleaning can make or break the project. There is a popular belief that "Better data beats fancier algorithms".

A different steps in data cleaning are,

1) Unwanted observations removal

This means deleting duplicate, irrelevant and redundant values from dataset. Duplicate data arise mostly during data collection. Irrelevant observations are those observations that does not fit the certain problem that we are trying to solve. Our data does not contain any unwanted or duplicate, we removed 57 unknown values in gender field

2) Handling missing data

This type of data poses tricky problems in machine learning. This data cannot be ignored or removed from dataset because this data may contain important features specific to the corresponding class other than that of missing feature. In this step we find all the null values in the data and replace them with mean and mode values of that field. In our data only 'age' field

has null data as shown in and they are replaced by the median values.

3.2.2 Resizing Images

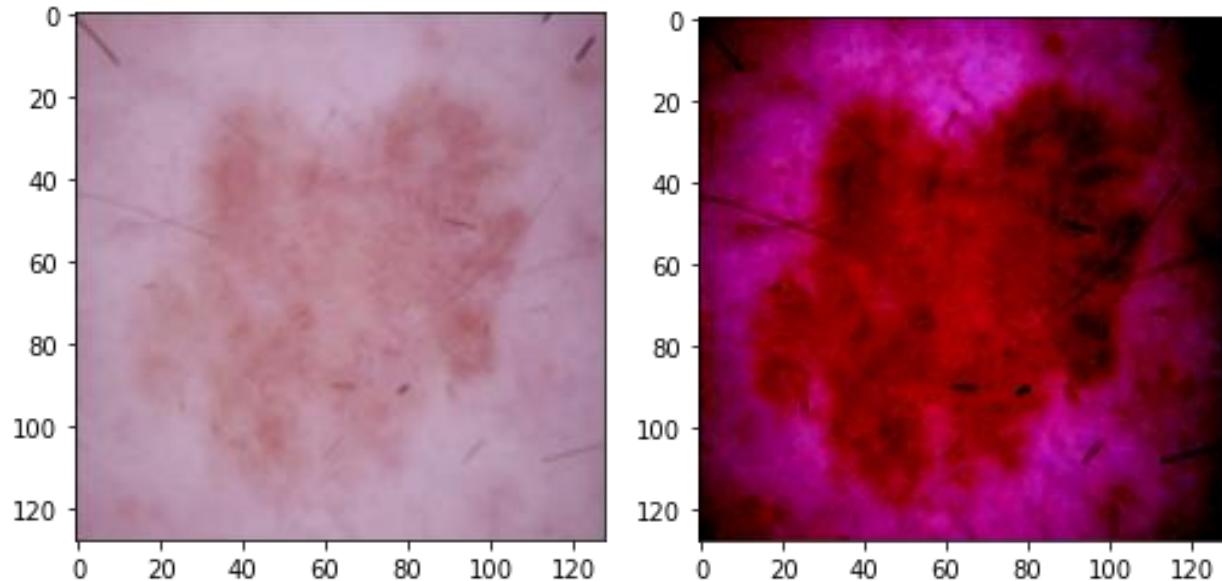
Original images in the dataset are all of same size but the size is very large. The images are of dimension (450 x 600 x 3) as seen this will have a huge computation time while training and TensorFlow cannot handle this.

Let us resize the images by keeping the same size ratio so that no information is lost. We have resized the images to dimension (128 x 128x 3).

3.2.3 Data Normalization

Original images are represented in color code format with 3 values of Red, Blue and Green for each pixel and each value ranging from 0 to 255. So the normalization is applied as follows, normalized image = $(\text{original Image} - \text{mean (all original images)}) / \text{standard deviation (all original images)}$

After normalization, each value of color code format changed to a range of -2 to 2 which is preferred by neural networks.



3.2.4 Data Augmentation

Deep neural networks perform better with large amount of data. Aim of this step is to create images that depict the features of its class in every possible angle. This makes sure that at whatever angle the image may be taken, our trained model can predict it with more precision.

Different techniques used for this are,

- 1) Randomly rotate the images in the range from 0 to 180 degrees
- 2) Randomly zoom images
- 3) Randomly flip images horizontally
- 4) Randomly flip images vertically
- 5) Randomly shift the images horizontally
- 6) Randomly shift the images vertically

Augmentation of images is done to deal with the problem of skewed classes, overfitting, and training image scarcity. As can be seen from the frequency table of classes, the NV class dominates with approximately 67% of images in training data. Hence, to balance the distribution various augmentation techniques are implemented to increase the size of each class



3.3 Modeling

Convolutional Neural Networks are currently the most popular and effective technique for image classification. In this project, we aim to develop a CNN model for classifying Skin Lesion images into 7 different classes of lesions. There are various CNN models developed by companies like Google and researchers based on ImageNet dataset. We have explored some of these models by training them on ISIC 2018 Skin Lesion Image dataset to verify whether they provide expected accuracy. Moreover, we have developed custom models based on study of various research papers. In this report, we have described all the attempts made to develop a robust CNN model for classification.

We did extensive research to understand the intuition behind making a robust CNN model especially for Skin Lesion classification. Most of the research work we reviewed were performing binary classification to detect whether a Lesion is Melanoma or not. These models achieved good accuracy due to binary nature of classification. Some of the research work was for all the 7 classes of ISIC dataset however, the dataset used to train was a small subset of 10k images that are available in ISIC archives. Although the models developed in these papers achieved good accuracy, they were not generalized model since the amount of data used to train was less.

As we developed an idea about the purpose of different convolution layers, number of filters, pooling and dropout, we

were able to tweak proposed and pre-implemented models to train them for our ISIC 2018 dataset.

The following is a detailed description of different attempts made to develop an efficient model along with limitations of each model.

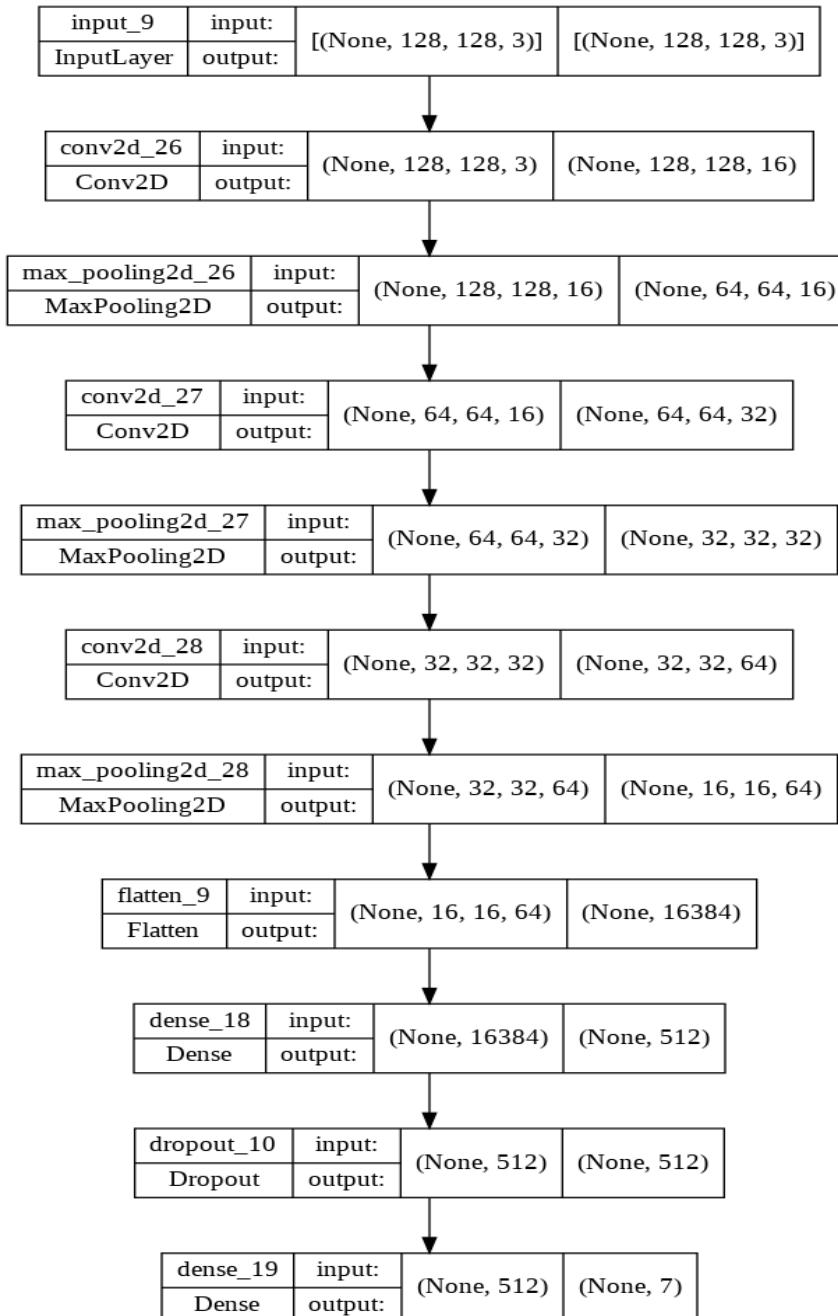
3.3.1 Baseline model (CNN)

CNN model proposed by researchers at Telkom University was first utilized to develop a CNN model for ISIC 2018 images. The researchers developed model for 4 different classes of images while for our dataset, we tweaked the model to work for 7 classes of output layer. We used this model as a base reference because it was used for skin lesion classification & achieved good accuracy. Also, it is a simpler model for implementation and understanding.

The architecture of this model is heuristically based we follow the convention in famous DCNNs: using the smallest (3x3) convolutional layers; and double the number of filters in the output whenever the spatial activation size is halved to maintain roughly constant hidden dimensions.

To train this model, data augmentation is employed. The intuition of this method is to transform the training dataset a bit in each epoch to produce variation and to guarantee that the model will never see the same image twice.

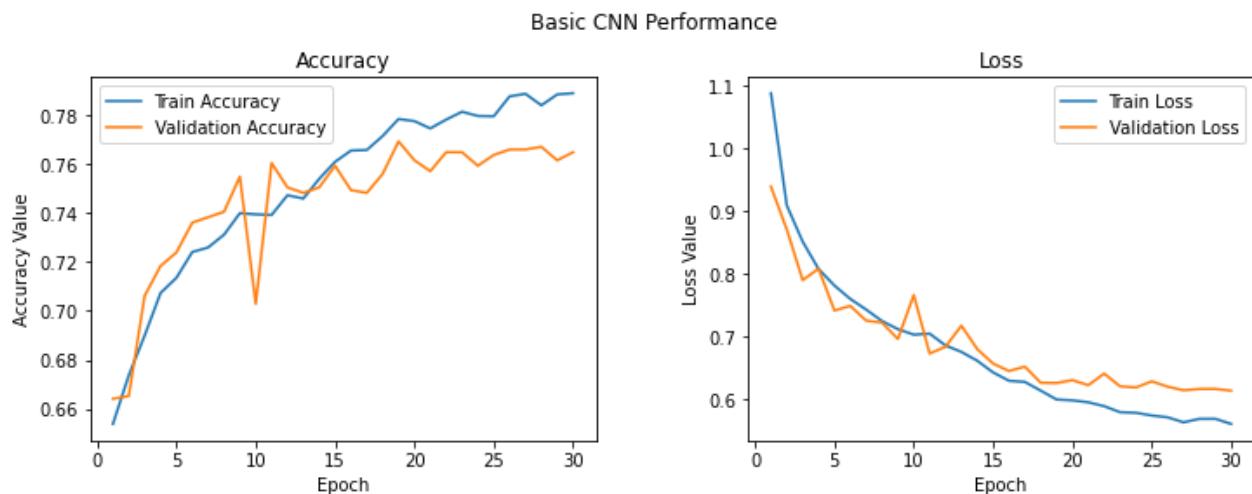
Learning rate is initialized at 0.01 and Adam optimizer is used. Learning rate decay is also used so that the learning rate will halve whenever the validation accuracy plateaus for 3 epochs. Baseline model is trained for a total of 30 epochs



The model give training accuracy of 78% with loss 0.56 and test accuracy around 76% with loss 0.61

	loss	accuracy	val_loss	val_accuracy	lr
29	0.5613	0.7891	0.6142	0.7650	3.1250e-05
26	0.5639	0.7889	0.6149	0.7661	6.2500e-05
28	0.5694	0.7886	0.6170	0.7616	3.1250e-05
25	0.5718	0.7878	0.6206	0.7661	6.2500e-05
27	0.5694	0.7841	0.6169	0.7672	6.2500e-05
22	0.5800	0.7815	0.6212	0.7650	1.2500e-05
23	0.5790	0.7798	0.6193	0.7594	1.2500e-05
24	0.5747	0.7797	0.6291	0.7639	1.2500e-05
18	0.6002	0.7786	0.6265	0.7694	2.5000e-05
21	0.5896	0.7783	0.6414	0.7650	2.5000e-05

Show the changes in accuracy and loss training data and validation data during training process as the epochs progress



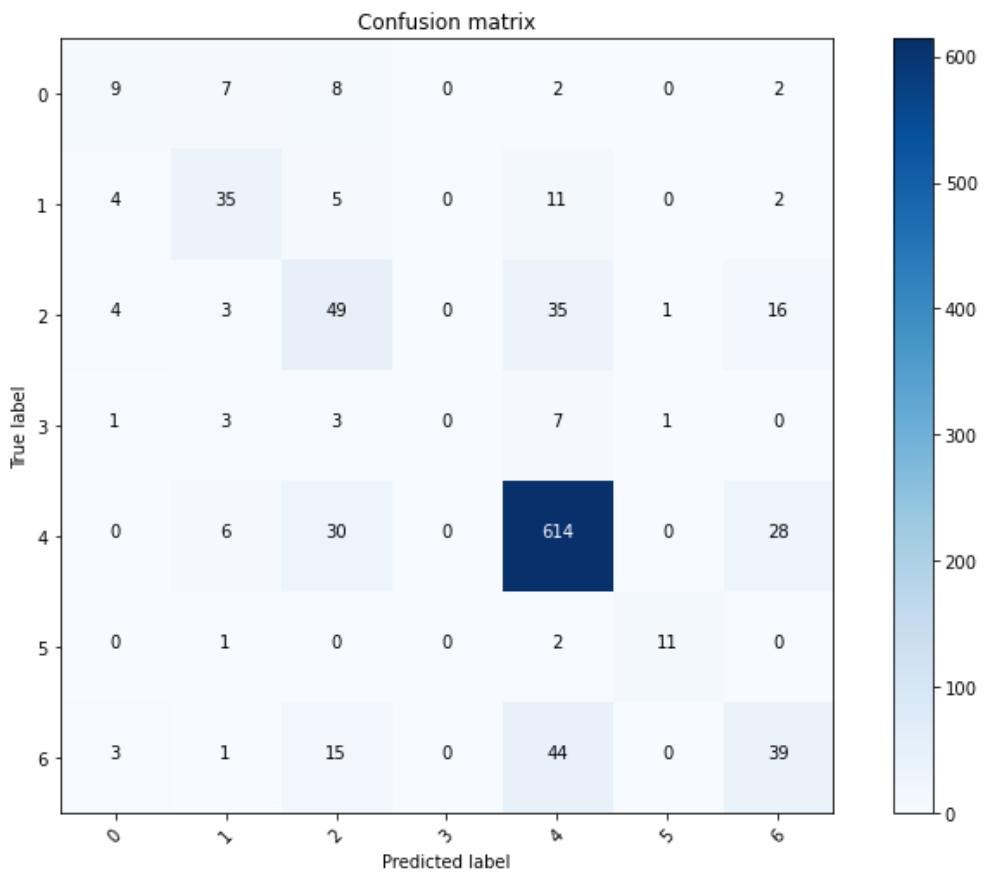
Even though there are some spikes in both the validation accuracy and loss, we can still say that this particular model with image augmentation is doing well

Training and validation accuracies are much similar now, which proves that the model is not overfitting

Showing the main classification metrics using classification report

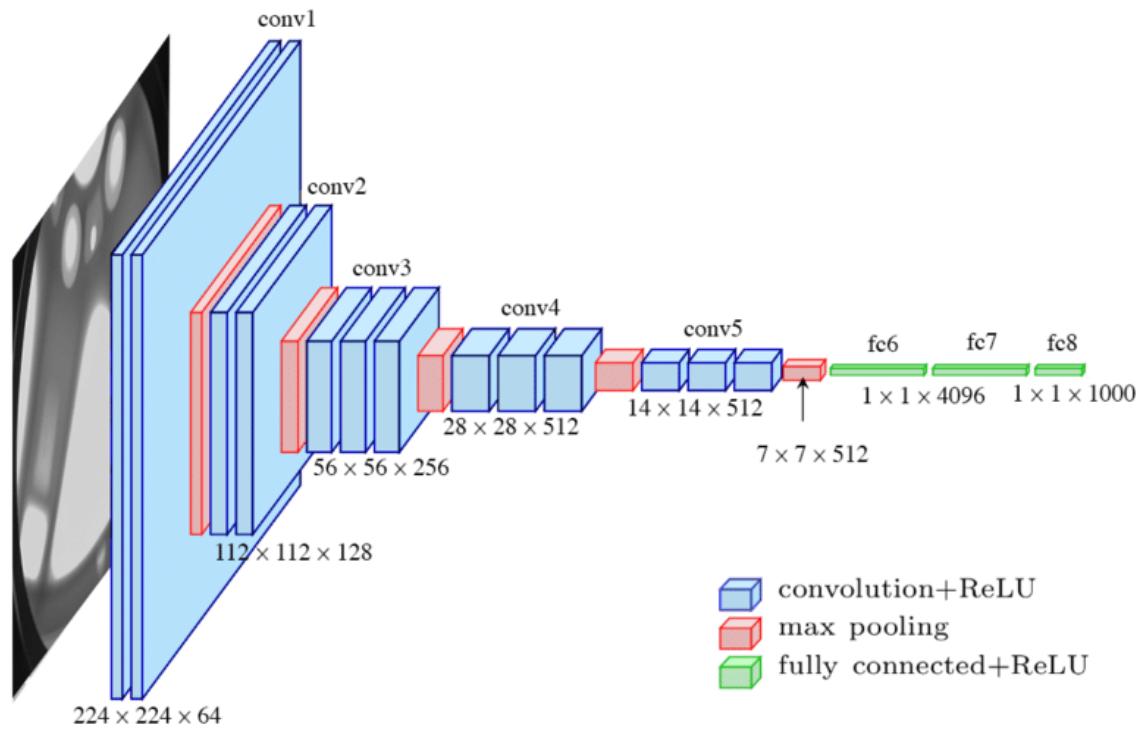
..	precision	recall	f1-score	support
0	0.50	0.11	0.18	28
1	0.69	0.42	0.52	57
2	0.55	0.38	0.45	108
3	0.00	0.00	0.00	15
4	0.88	0.88	0.88	678
5	0.91	0.71	0.80	14
6	0.54	0.34	0.42	102
micro avg	0.82	0.71	0.76	1002
macro avg	0.58	0.41	0.46	1002
weighted avg	0.78	0.71	0.73	1002
samples avg	0.71	0.71	0.71	1002

Computing confusion matrix to evaluate the accuracy of a classification.



3.3.2 VGG16

Even though there are many DCNNs model achieving better result on ImageNet than VGG16, we choose to fine-tune VGG16 given its simplicity. The best performing VGG16 net is similar except that the third, fourth and fifth convolutional block has 4 convolutional layers.



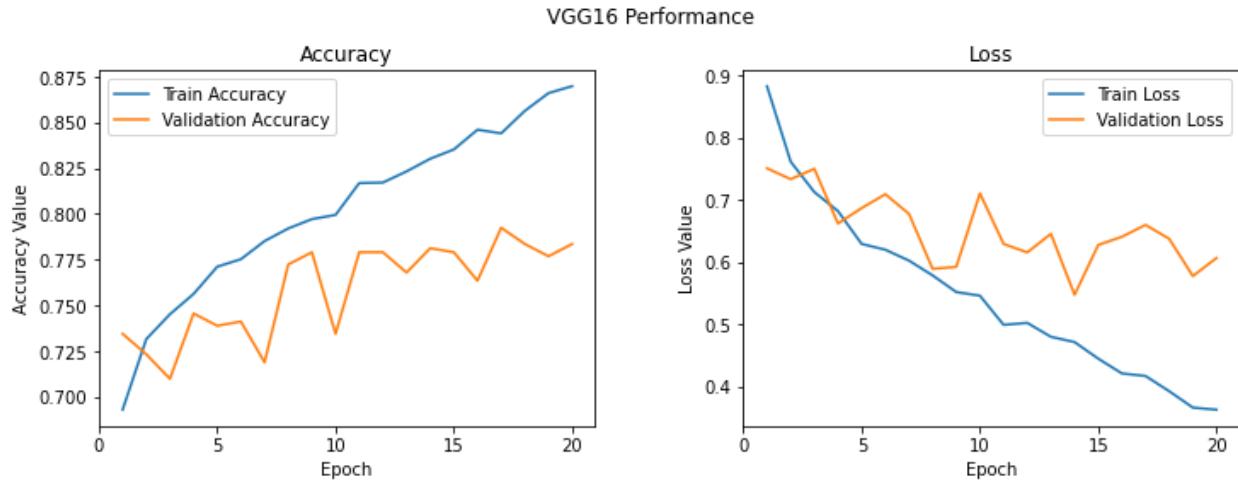
To fine-tune VGG16, the top fully-connected layers are removed, and new fully-connected layers (consisting of: one global max pooling layers, one fully connected layer with 512 units, one dropout layer with 0.5 rate, one softmax activation layer for 7 types of skin lesions) for our classification tasks are added. First, freeze all layers in VGG16, and perform feature

extraction for the newly added FC layers so that the weights for these layers aren't completely random and the gradient wouldn't be too large when we start fine-tuning. After 3 epochs of feature extraction, we unfreeze the final convolutional block of VGG16 and start fine-tune the model for 20 epochs. Throughout the training process, learning rate of 0.001 and Adam optimizer are used. The same data augmentation and learning rate decay strategy as in baseline model is used.

The model give training accuracy of 86% with loss 0.36 and test accuracy around 60% with loss 0.78

	loss	accuracy	val_loss	val_accuracy	lr
19	0.3622	0.8698	0.6061	0.7835	1.0000e
18	0.3656	0.8660	0.5770	0.7768	1.0000e
17	0.3919	0.8563	0.6369	0.7835	1.0000e
15	0.4205	0.8460	0.6402	0.7634	1.0000e
16	0.4164	0.8440	0.6593	0.7924	1.0000e
14	0.4443	0.8352	0.6270	0.7790	1.0000e
13	0.4709	0.8301	0.5469	0.7812	1.0000e
12	0.4794	0.8232	0.6449	0.7679	1.0000e
11	0.5018	0.8171	0.6150	0.7790	1.0000e
10	0.4986	0.8168	0.6287	0.7790	1.0000e

Show the changes in accuracy and loss training data and validation data during training process as the epochs progress

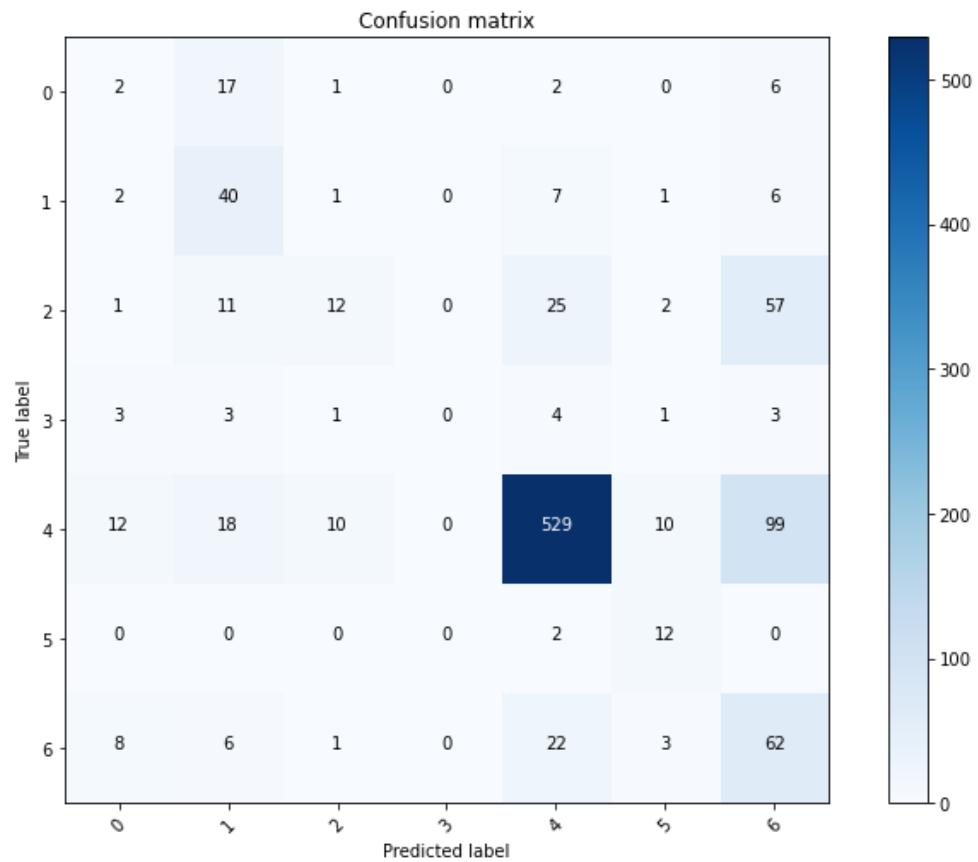


We find that the model with image augmentation is doing well with Training data having high accuracy but we have overfitting with validation data.

Showing the main classification metrics using classification report

	precision	recall	f1-score	support
0	0.08	0.07	0.08	28
1	0.42	0.68	0.52	57
2	0.44	0.10	0.17	108
3	0.00	0.00	0.00	15
4	0.90	0.77	0.83	678
5	0.41	0.86	0.56	14
6	0.27	0.61	0.37	102
micro avg	0.66	0.65	0.65	1002
macro avg	0.36	0.44	0.36	1002
weighted avg	0.71	0.65	0.66	1002
samples avg	0.65	0.65	0.65	1002

Computing confusion matrix to evaluate the accuracy of a classification.

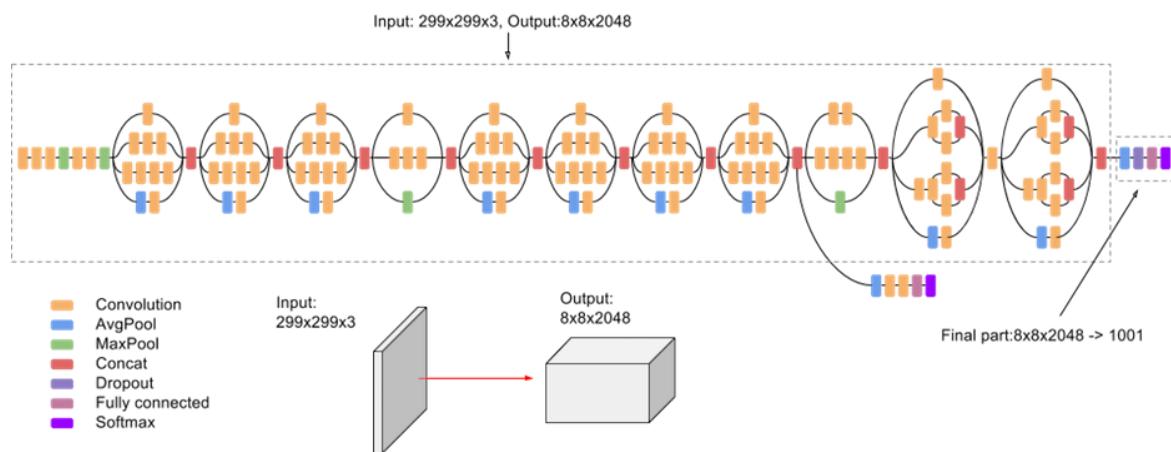


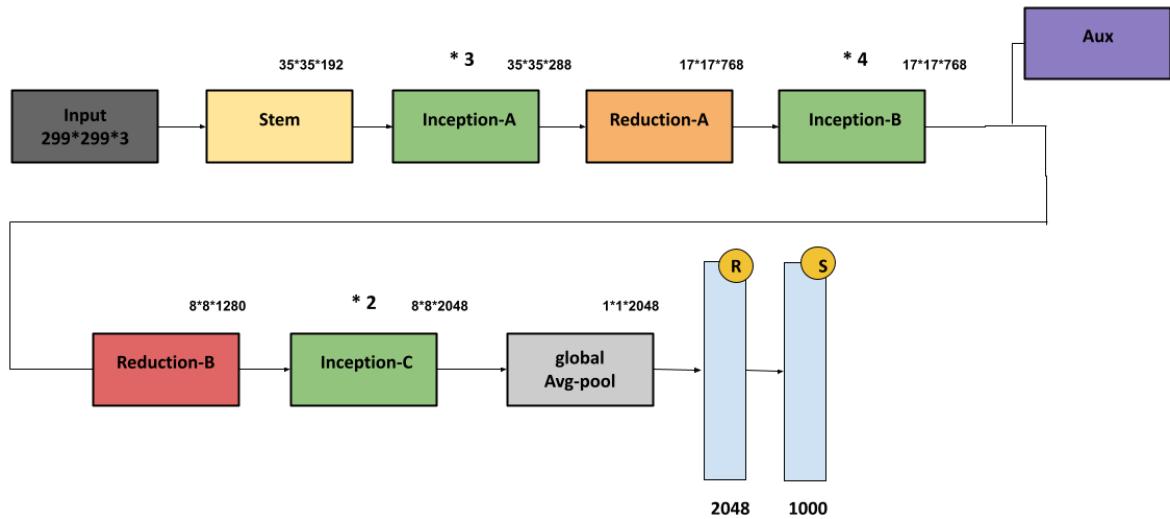
3.3.3 Inception V3

The namesake of Inception v3 is the Inception modules it uses, which are basically mini models inside the bigger model. The inspiration comes from the idea that you need to make a decision as to what type of convolution you want to make at each layer: Do you want a 3×3 ? Or a 5×5 ? The idea is that you don't need to know ahead of time if it was better to do, for example, a 3×3 then a 5×5 . Instead, just do all the convolutions

and let the model pick what's best. Additionally, this architecture allows the model to recover both local feature via smaller convolutions and high abstracted features with larger convolutions.

The larger convolutions are more computationally expensive, so [4] suggests first doing a 1×1 convolution reducing the dimensionality of its feature map, passing the resulting feature map through a Relu, and then doing the larger convolution (in this case, 5×5 or 3×3). The 1×1 convolution is key because it will be used to reduce the dimensionality of its feature map.

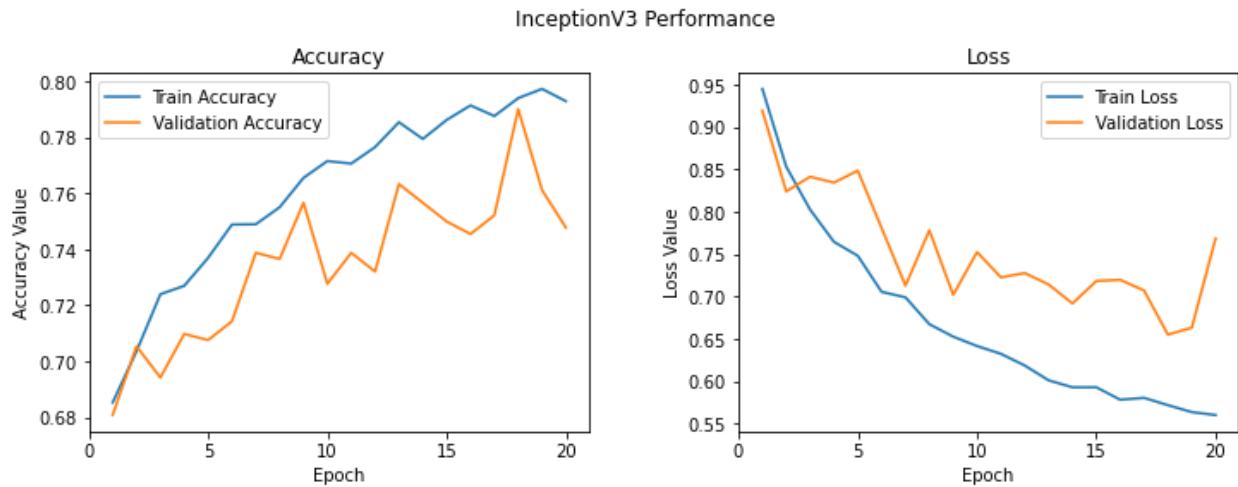




The model give training accuracy of 80% with loss 0.56 and test accuracy around 76% with loss 0.66

	loss	accuracy	val_loss	val_accuracy	lr
18	0.5634	0.7974	0.6630	0.7612	2.5000e
17	0.5716	0.7941	0.6549	0.7902	2.5000e
19	0.5599	0.7930	0.7685	0.7478	2.5000e
15	0.5780	0.7915	0.7196	0.7455	2.5000e
16	0.5802	0.7877	0.7070	0.7522	2.5000e
14	0.5927	0.7863	0.7182	0.7500	5.0000e
12	0.6009	0.7855	0.7141	0.7634	5.0000e
13	0.5927	0.7795	0.6917	0.7567	5.0000e
11	0.6184	0.7766	0.7276	0.7321	5.0000e
9	0.6414	0.7716	0.7524	0.7277	1.0000e

Show the changes in accuracy and loss training data and validation data during training process as the epochs progress

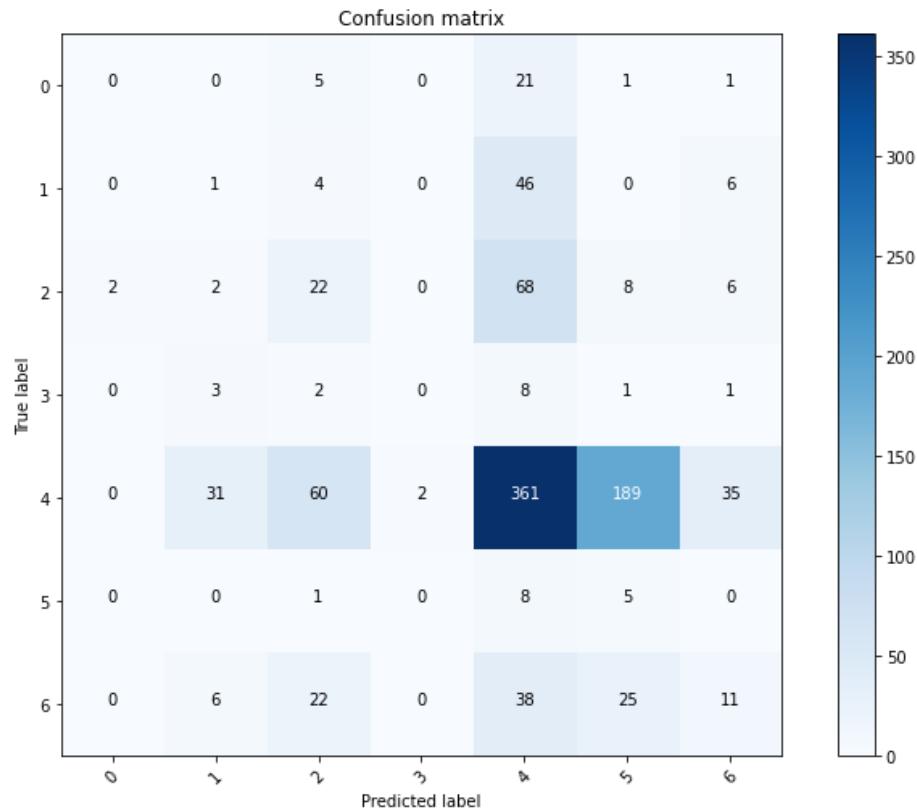


We find that the model with image augmentation is doing well with Training data having high accuracy but we have some overfitting with validation data.

Showing the main classification metrics using classification report

	precision	recall	f1-score	support
0	0.00	0.00	0.00	28
1	0.04	0.02	0.02	57
2	0.20	0.15	0.17	108
3	0.00	0.00	0.00	15
4	0.65	0.45	0.53	678
5	0.02	0.36	0.05	14
6	0.19	0.08	0.11	102
micro avg	0.41	0.33	0.37	1002
macro avg	0.16	0.15	0.13	1002
weighted avg	0.48	0.33	0.39	1002
samples avg	0.33	0.33	0.33	1002

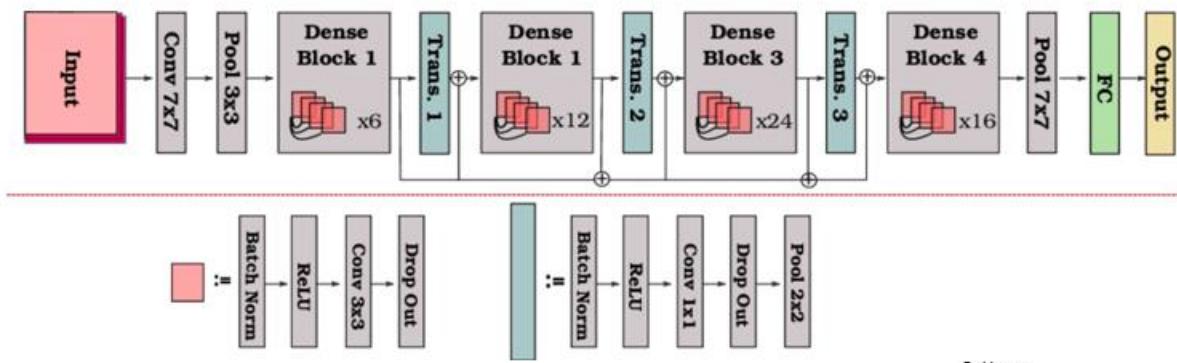
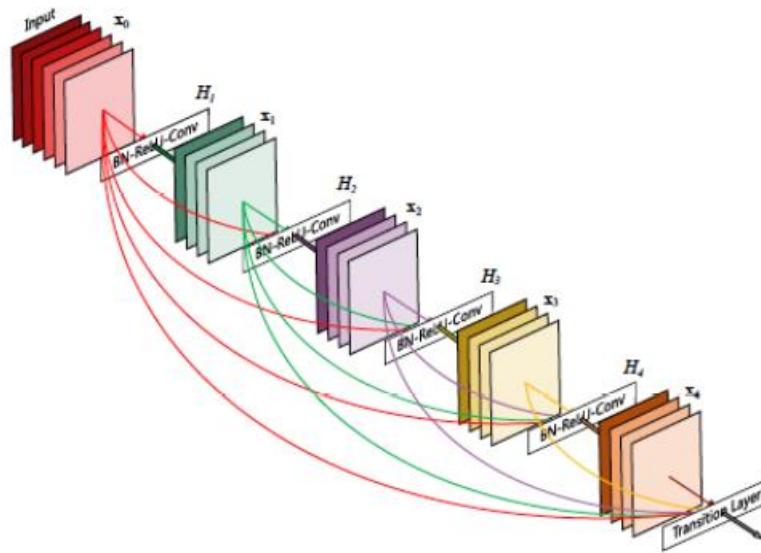
Computing confusion matrix to evaluate the accuracy of a classification.



3.3.4 Dense Net

Dense Net is competitive to Inception V3, but Dense Net has less parameters (approximately 20M compare with approximate 23M of Inception V3). Dense Net 201 has 4 dense blocks. In a dense block, the l th layer has l inputs, consisting of the feature-maps of all preceding convolutional blocks, and its own feature-maps are passed on to all subsequent layers $L - l$. Each layer reads the state from its preceding layers and writes to the

subsequent layer. It changes the state but also passes on information that needs to be preserved. Dense Net architecture explicitly differentiates between information that is added to the network and information that is preserved by concatenating features instead of summing features as in Res Net.

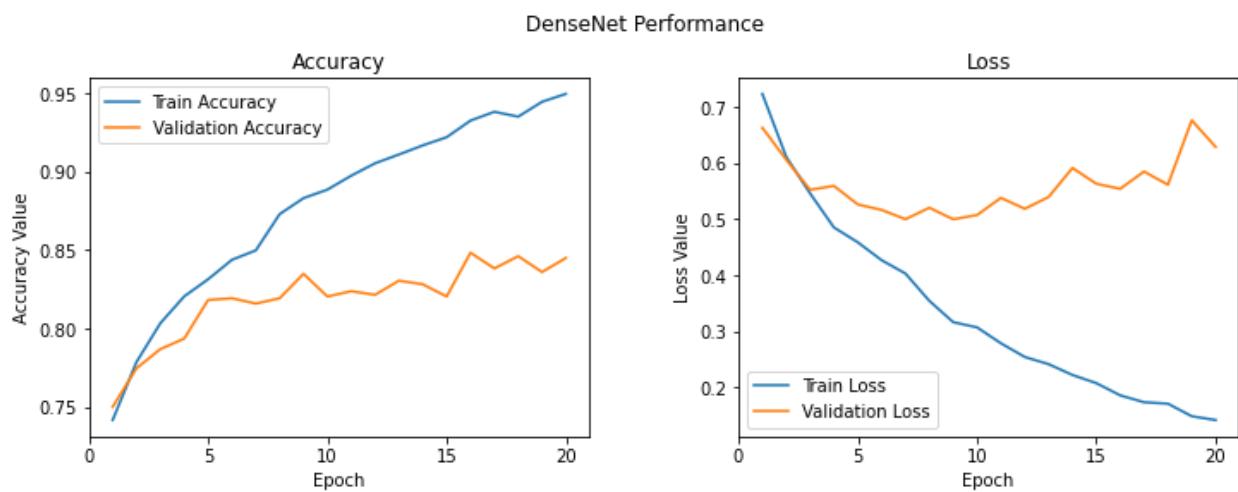


G. Huang

The model give training accuracy of 95% with loss 0.1 and test accuracy around 85% with loss 0.6

	loss	accuracy	val_loss	val_accuracy	lr
19	0.1422	0.9494	0.6285	0.8449	1.0000e
18	0.1490	0.9444	0.6759	0.8359	1.0000e
16	0.1739	0.9380	0.5847	0.8382	1.0000e
17	0.1714	0.9349	0.5612	0.8460	1.0000e
15	0.1862	0.9324	0.5539	0.8482	1.0000e
14	0.2079	0.9218	0.5629	0.8203	1.0000e
13	0.2224	0.9166	0.5911	0.8281	1.0000e
12	0.2417	0.9108	0.5394	0.8304	1.0000e
11	0.2545	0.9052	0.5183	0.8214	1.0000e
10	0.2789	0.8973	0.5379	0.8237	1.0000e

Show the changes in accuracy and loss training data and validation data during training process as the epochs progress

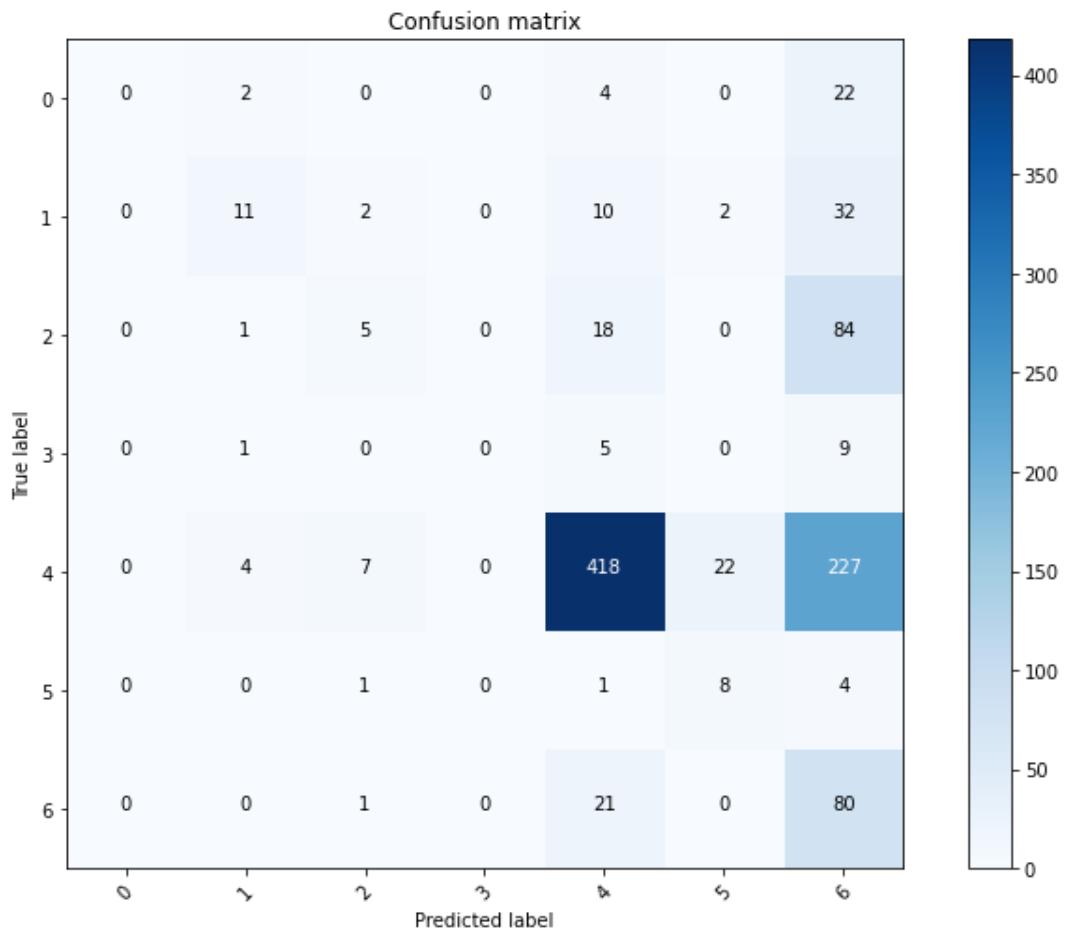


We find that the model with image augmentation is doing well with Training data having high accuracy but we have overfitting with validation data.

Showing the main classification metrics using classification report

	precision	recall	f1-score	support
0	0.00	0.00	0.00	28
1	0.58	0.19	0.29	57
2	0.36	0.05	0.08	108
3	0.00	0.00	0.00	15
4	0.88	0.61	0.72	678
5	0.27	0.57	0.36	14
6	0.18	0.78	0.29	102
micro avg	0.52	0.51	0.52	1002
macro avg	0.32	0.31	0.25	1002
weighted avg	0.69	0.51	0.55	1002
samples avg	0.51	0.51	0.51	1002

Computing confusion matrix to evaluate the accuracy of a classification.



3.4 Results

Model	Accuracy	Loss	Test accuracy	test loss	Depth	Params
Baseline Model	78%	0.56	76%	0.61	11 layers	2,124,839
VGG16	87%	0.36	78%	0.60	23 layers	14,980,935
Inception V3	80%	0.56	76%	0.66	315 layers	22,855,463
Dense Net 201	95%	0.14	85%	0.62	711 layers	19,309,127

When a model is underfit, we are oversimplifying the problem. If you have pegs with the following shape: square, circle, triangle, star, and hexagon, making the hole too big such that all of them fit through would be an example of underfitting. This is also considered error due to bias. Underfit learning curves are often indicated by a flat or decreasing training loss until the end of training, as well as a high training and validation loss.

When a model is overfit, we are overcomplicating the problem. If you have a hole that only allows for the star shape to pass through, that would be one way of thinking about overfitting. Overfit learning curves are often indicated by training loss

continuing to decrease with epochs and validation loss decreases and increasing again, where there is an increasing difference between the training and validation loss. In other words, high validation and low training error.

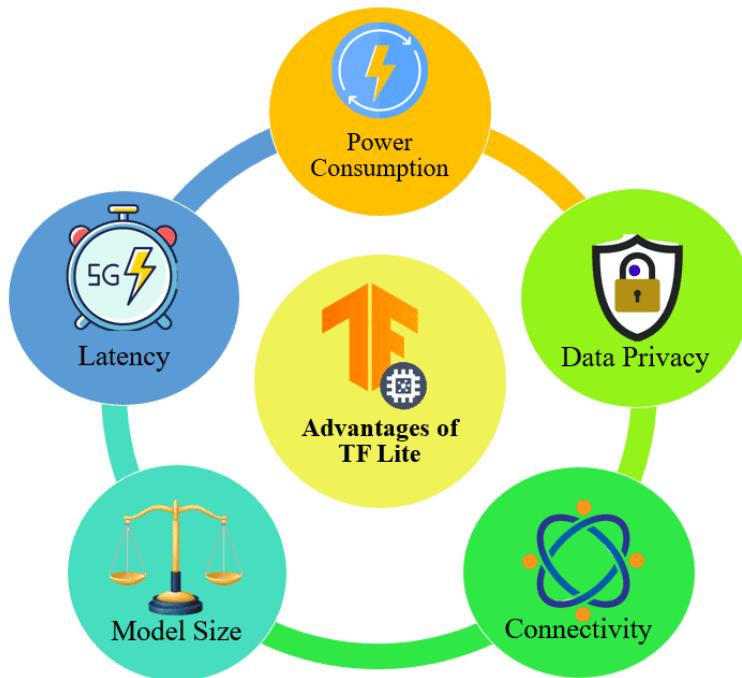
Noisy movements around training loss can be indicative of an unrepresentative validation dataset or one that has too few examples compared to the training dataset.

Best models were decided by lowest validation loss, which ensures that the model is not already overfitting such that the training and validation loss start diverging.

Some of the models looked like they could still be further trained as the training loss was still continuing to decrease through the end of the epochs.

3.5 Save and convert model

We saved model with best accuracy in H5 format so to used model in real product like mobile application not in terminal we decided to convert the saved model to tflite format



Advantages of using a TensorFlow Lite Model for on-device Machine-Learning:

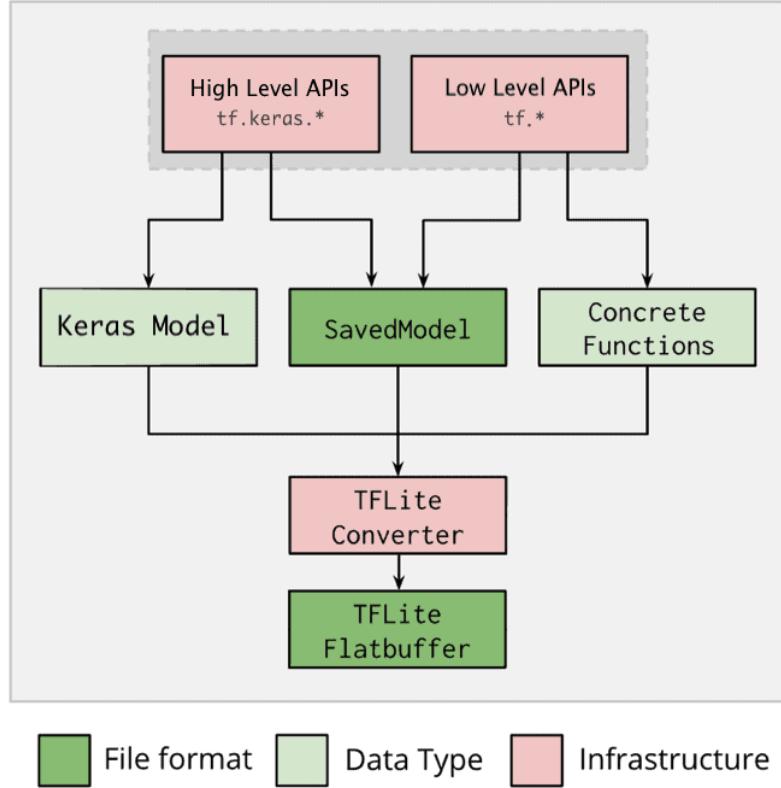
Latency: As inference is taken on the edge, there's no round-trip to a server resulting in low latency.

Data Privacy: Due to inference at edge, the data is not shared across any network. So the personal information doesn't leave the device resolving any concerns to the data privacy.

Connectivity: As no internet connectivity is required, there are no connectivity issues.

Model Size: Tensor Flow Lite models are lightweight as the edge devices are resource-constrained.

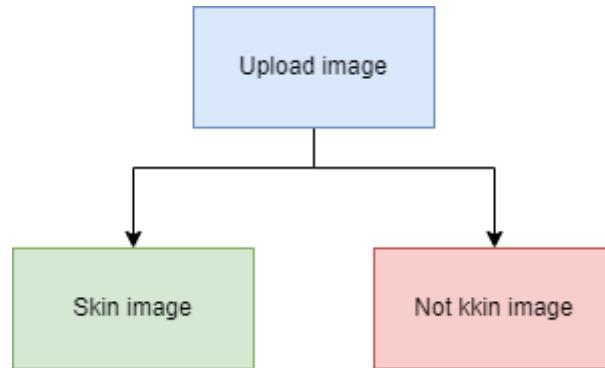
Power Consumptions: Efficient inference and lack of network connectivity lead to low power consumption.



3.6 Validation model

To make sure that the photos entered are skin lesion images we made a small model based on classification images to skin image or not skin image. The dataset we used consisted of 8k images of skin images and a random images of everything

(dogs, cats, trees, sky, wood... etc.). We can develop it using mode data and better algorithm



We got that idea from an Alveoli application for Sreyom Sresaan Indian engineer who helped us a lot.

<https://github.com/sreyom31>

3.7 Developing results and their quality

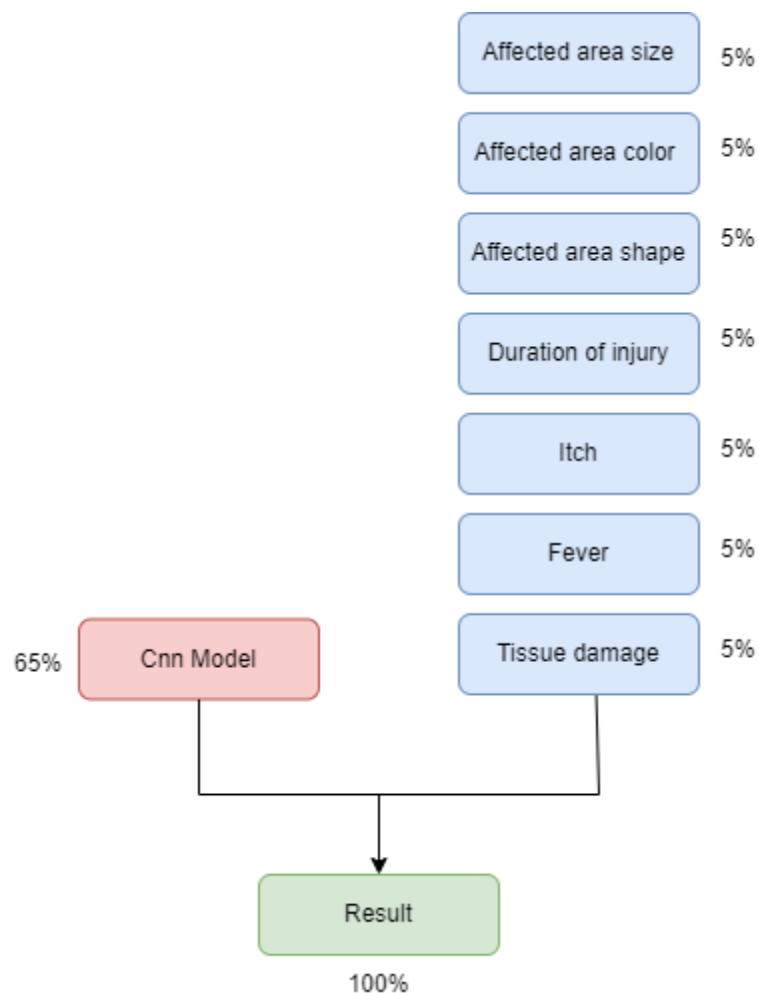
Combination of the patient's metadata can prevent overfitting that occurs in the CNN model using dermoscopic images only.

We did research to find out the questions about symptoms that if we ask the patient, it can lead to a better result. We created this excel fill sheet with help of Dr Mostafa Mahmoud Eid

(Dermatologist at the Oncology Institute in Cairo) and Skin cancer foundation <https://www.skincancer.org/skin-cancer-information/>

Test	Benign Keratosis	Vascular Lesion	Melanoma	Melanocytic Nevus	Dermatofibroma	Actinic Keratosis	Basal Cell Carcinoma
Affected area position							
Head	✓	✓	✓	X	X	✓	✓
Chest	✓	X	✓	✓	✓	X	X
Upper Limb	✓	X	✓	X	✓	X	X
Abdominal area	X	X	✓	✓	✓	X	X
Lower Limb	X	X	✓	X	✓	X	X
Affected area size							
Single lesion	✓	X	✓	✓	✓	✓	✓
Limited area	✓	X	✓	X	X	✓	X
Widespread	X	✓	✓	X	X	X	X
Duration injury							
Minutes to Hours	✓	X	X	X	X	X	X
Days to Weeks	X	X	X	X	✓	X	X
Weeks to Months	X	X	✓	✓	X	✓	✓
Months to Years	X	✓	X	✓	X	X	X
Recurring Episodes	X	X	X	X	X	X	X
Itch							
Yes	X	✓	✓	✓	X	✓	X
No	✓	X	✓	✓	✓	X	✓
Fever							
Yes	X	✓	X	X	X	X	X
No	✓	X	✓	✓	✓	✓	✓
Affected area shape							
Raised or Bumpy	✓	✓	✓	✓	X	✓	✓
Flat	X	X	✓	✓	✓	✓	X
Skin loss or Sunken	X	X	✓	X	X	X	X
Affected skin color							
Patch or Mucule	✓	X	✓	X	X	✓	✓
Broad area of color	X	✓	✓	✓	✓	X	X
Tissue damage							
Thinning or Atrophy	✓	✓	✓	X	✓	X	✓
Fissures or Cracking	✓	X	X	X	X	✓	X
Scarring	X	X	X	X	X	X	X
Ulcers or Erosion	✓	X	✓	✓	X	X	X

The accuracy for CNN model 95% in training and 85% in test. Combination of the patient's metadata prevents the overfitting that occurs in the CNN model using dermoscopic images only and achieve better results.



Chapter 4

Deployment & Technology

4.1.1 Tools

Software

Visual code: frame work of the implemented code

Firebase: cloud services from google used to save data

Languages:

Flutter: used in design user interface in mobile apps

Dart programming language: used in developing mobile apps on multi platforms

Libraries:

Google maps: Google API to add maps to mobile app

Tflite: Flutter plugin for accessing TensorFlow Lite API.
Supports image classification

Image_picker: A Flutter plugin for iOS and Android for picking images from the image library, and taking new pictures with the camera.

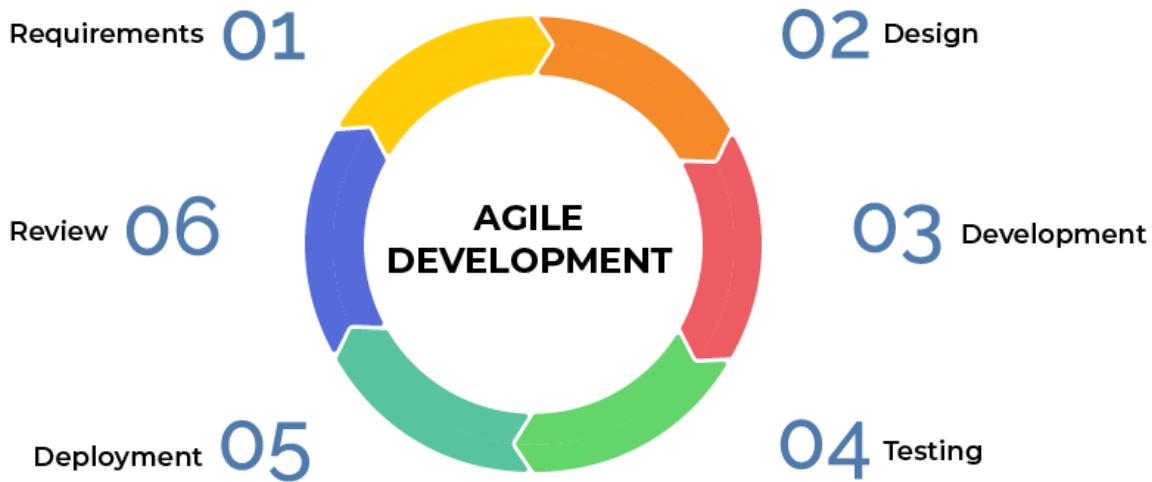
Firebase_auth: Flutter plugin to allow use of firebase authentication to
register and login users

Location: Flutter plugin to get current location of the user

4.1.2 Environment

CPU: We used CPU because the mobile application didn't focus on graphics or rendering images or videos

4.2 Methods



The agile lifecycle is a structured series of stages that a product goes through. It consists of six phases:

Requirements

Stakeholders conduct an overall project assessment to determine the time and resources required for the development process. At the same stage, the owner assesses the risks and prioritizes the various functions depending on their business value.

Design

The software owner meets with the software development team and introduces them to the requirements outlined in the first step. The group then discusses the sequence for introducing functions and identifies the essential tools – the programming language, syntax libraries, and basic frameworks. At the same stage, software development teams can prototype the expected user interface.

Development and coding

After agreeing on the plan with the customer, the team develops the product itself. The product is delivered in stages, in separate sprints, each designed to improve the current version of the product. The initial release is likely to undergo many changes to provide improved functionality and new features.

Each cycle includes testing, and the final product must also undergo final testing. For this phase, you can use Scrum and the Kanban methodology, the development process based on individual tasks.

Integration and testing

At this point, the product becomes available to consumers, so the team must conduct a series of tests to ensure that the software is fully functional. If potential bugs or flaws are found,

the developers will fix them immediately. At this stage, they also collected consumer feedback.

Implementation and deployment

The software is now fully deployed and available to customers. This action puts him in the maintenance phase. During this phase, the software development team provides ongoing support to keep the system running smoothly and fix any new bugs. Over time, further iterations are possible to update an existing product or add other functionality.

Review

That is the last stage of the agile development cycle. After completing all the previous stages of development, the development team presents to the owner the result achieved in meeting the requirements. After that, the agile software development phases start over – either with a new iteration or moving to the next stage and scaling Agile.

Advantages of Agile Project Management

- You can deploy software quicker, so your customer can get value sooner rather than later
- You waste fewer resources because you always work on up-to-date tasks

- You can better adapt to change and respond faster
- Faster turnaround times
- You can detect and fix issues and defects faster
- You spend less time on bureaucracy and busywork
- There's a big community of Agile practitioners with whom you can share knowledge
- You can get immediate feedback (which also improves team morale)
- Developers can improve their skills based on QA feedback
- You don't have to worry about premature optimization
- You can experiment and test ideas because its costs are low

Disadvantages of Agile Project Management

- Documentation tends to get sidetracked, which makes it harder for new members to get up to speed
- It's more difficult to measure progress than it is in Waterfall because progress happens across several cycles
- Agile demands more time and energy from everyone because developers and customers must constantly interact with each other
- When developers run out of work, they can't work on a different project since they'll be needed soon
- Projects can become ever-lasting because there's no clear end
- Scope creep and experience rot
- Clients who work on a specified budget or schedule can't know how much the project will actually cost, which makes

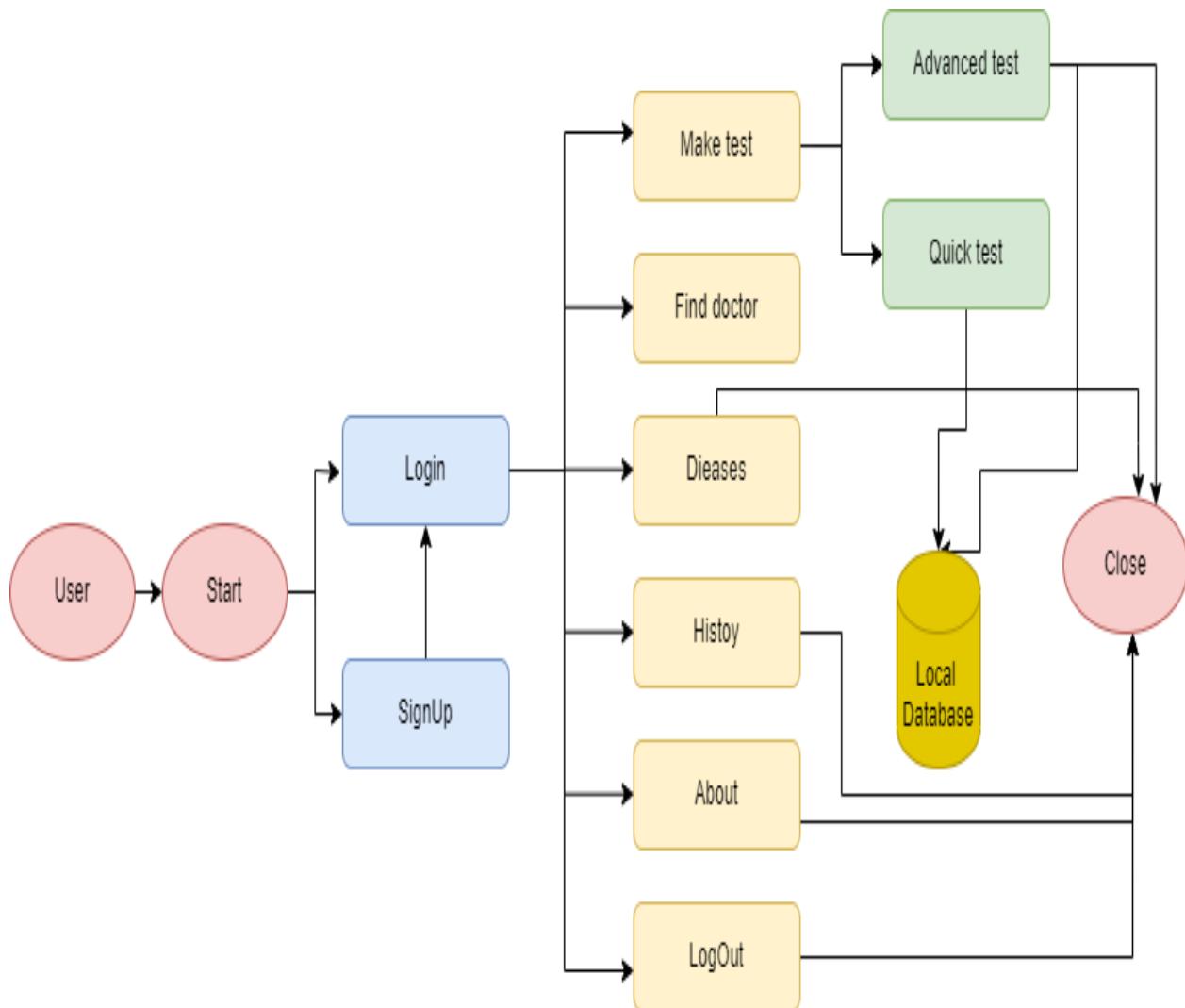
for a very complicated sales cycle ("Until iteration ends," is not something clients like to hear)

- The product lacks overall design, both from a UX and architecture point of view, which leads to problems the more you work on the product
- Teams can get sidetracked into delivering new functionalities at the expense of technical debt, which increases the amount of unplanned work
- Features that are too big to fit into one or even several cycles are avoided because they don't fit in nicely into the philosophy
- You need a long-term vision for the product and actively work on communicating it
- Products lack cohesion, and the user journey is fragmented because the design is fragmented. The more time passes, the more disjointed the software ends up becoming
- Short cycles don't leave enough time for the design thinking process, so designers have to redevelop the experience over and over due to negative feedback

4.3 App architecture

In the following example, the specification will display the range of activity for program users (patient) and how any of them works for the framework and what the local database does. Architecture Diagram is extremely relevant for any organization or program, particularly in organizations that use architecture

diagrams to make a judgment or to take decisions that are not decided upon by all managers of that business.



Chapter 5

System requirements & Designs

5.1 Functional Requirements

Functional Requirement is a summary of the function that the program will deliver. Describes the software program or its portion. Function is the input to the software system, its behavior and outputs. It can be a measurement, data processing, business method, user experience, or some other unique feature that determines what role the program is likely to execute.

5.1.1 Login:

The system provides security features through username-password matching where only authorized user can access the system. We use firebase authentication to provide maximum security.

Input:-Username, Password

Output: - Invalid or successfully logged in

5.1.2 Register:

This allows healthy public to register as donor, seeker or blood Bank itself.

Input: Name, Email Address, Password, Contact Number

Output: - Successfully Registered.

5.1.3 Make Test

This function is for patient, in this function the user can make request for making skin cancer test using his personal image and metadata. Once he click this Tflite library make classification using model which is pretrained

5.1.4 Find Doctor

This function is for patient, in this function the user can send request for the find doctor in his location. Once he click this request the google API use his location to search for the nearest doctors in local area.

5.2 Non-Functional Requirements

The quality attribute of the software system is defined by a non-functional requirement.

We reflect a collection of criteria used to determine the basic function of the method. Example, how fast is the website loaded? In order to maintain the reliability and productivity of the whole operating program, a non-functional necessity is necessary. Failure to meet non- functional specifications can make systems that fail to meet user needs. Non-functional Specifications enable you to place constraints or limits on the architecture of the device.

5.2.1 Availability

The app are available at all times, meaning the user can access it using application.

5.2.2 Reliability

As the app provide the right tools for problem solving it is made in such a way that the app is reliable in its operations and for securing the sensitive details

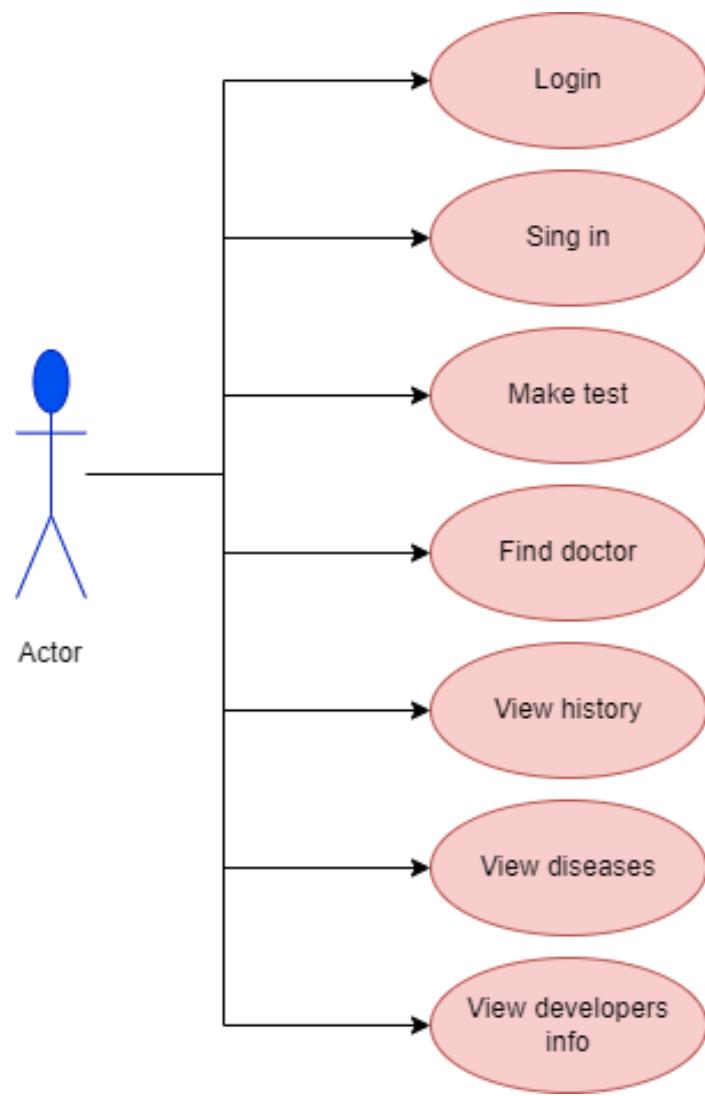
5.2.3 Performance:

Our App didn't take more than few seconds if there is a good internet connection.

5.3 System Design:

5.3.1 Use Case Diagram:

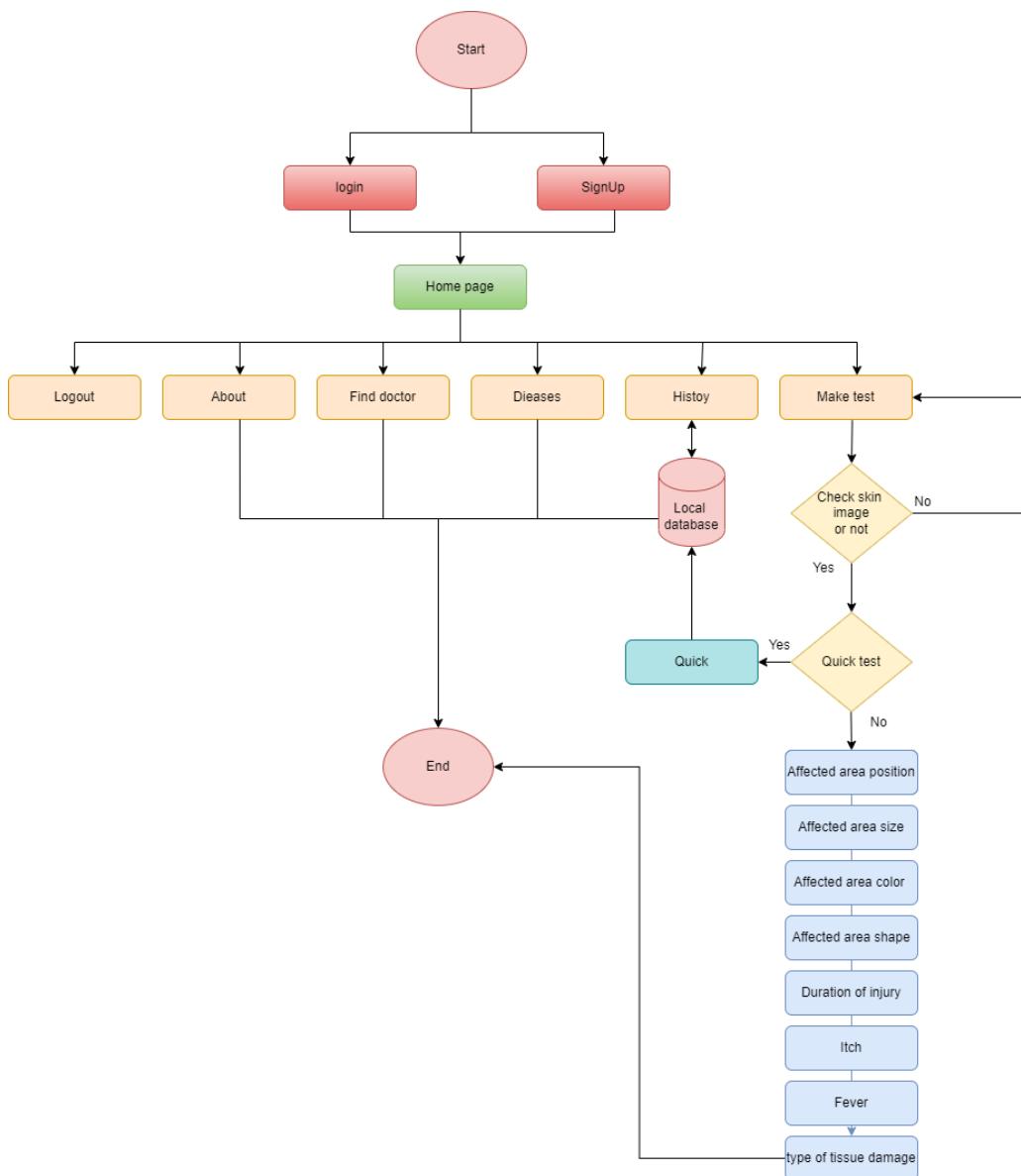
Use case diagram shows a graphical representation of the interaction of device components with users. It helps to identify the requirements of the system and to provide clearness of understanding.



L

5.3.2 Activity Diagram:

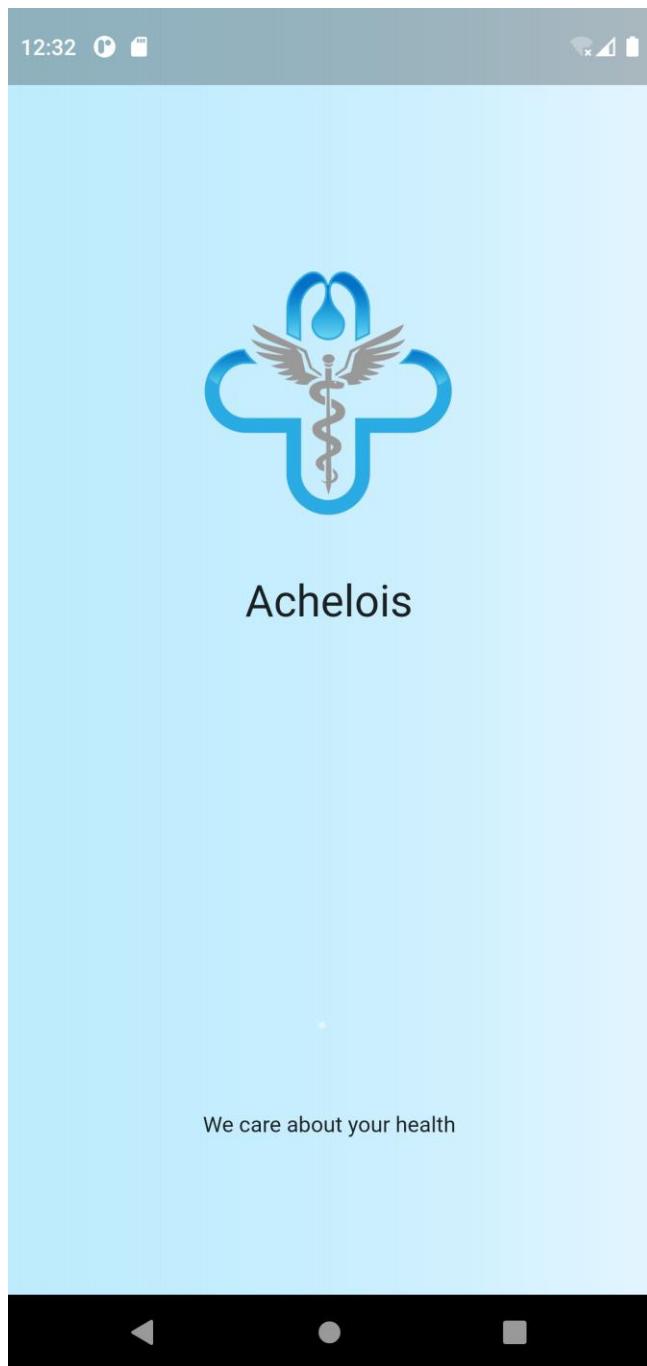
Activity diagram is structure step-by - step process. Comprising system flow and user interaction with system is helpful. The diagram shows how user enters the system interface and executes actions. This minimizes the risk of in-process duplication



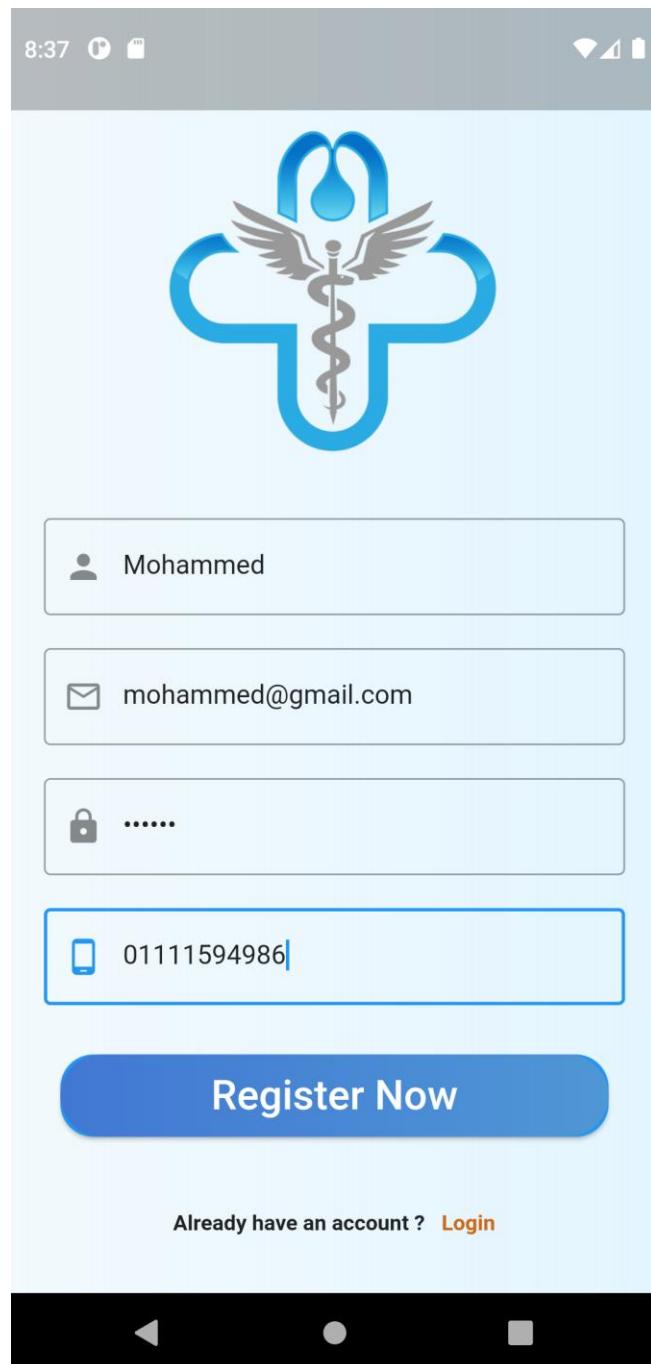
Chapter 6

Application Design

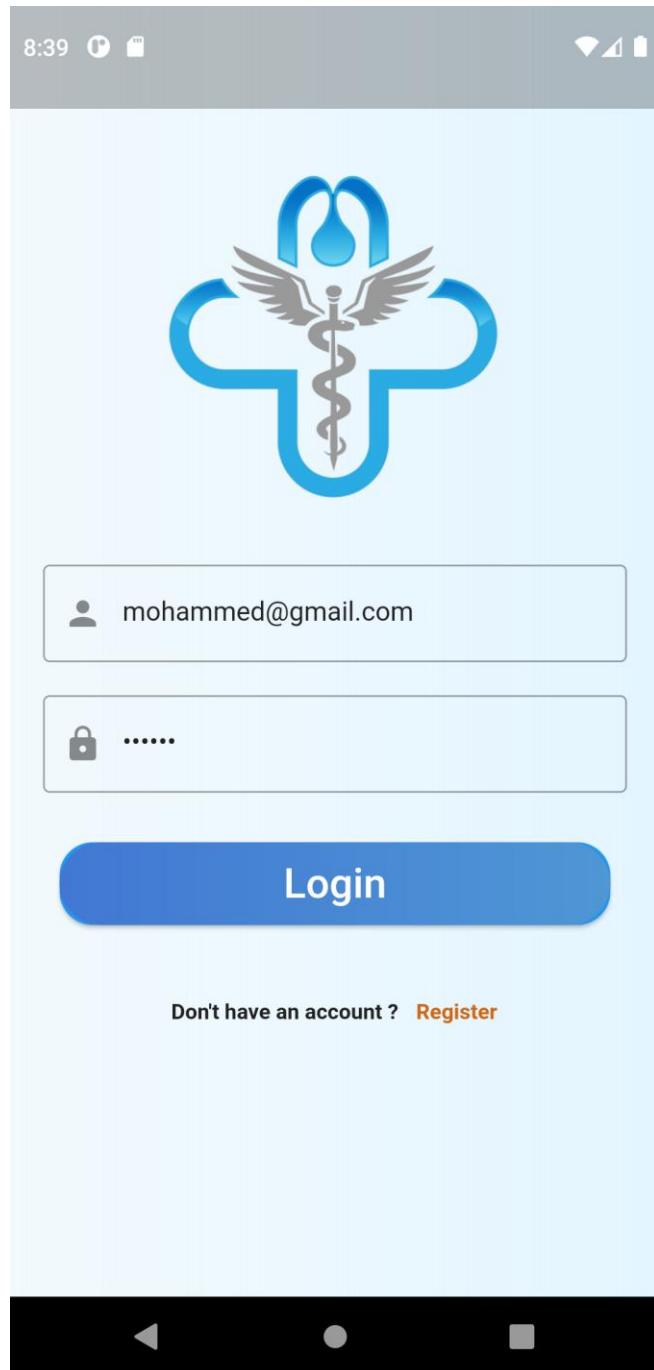
6.1.1 Splash screen



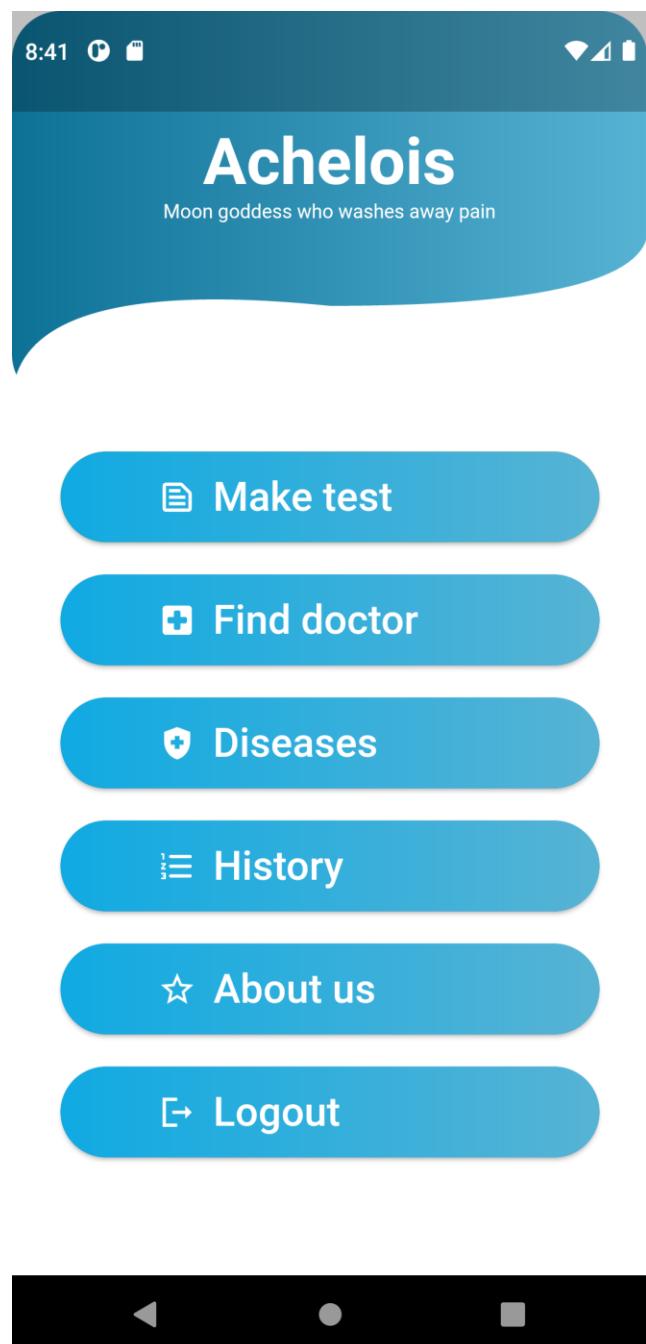
6.1.2 Signup



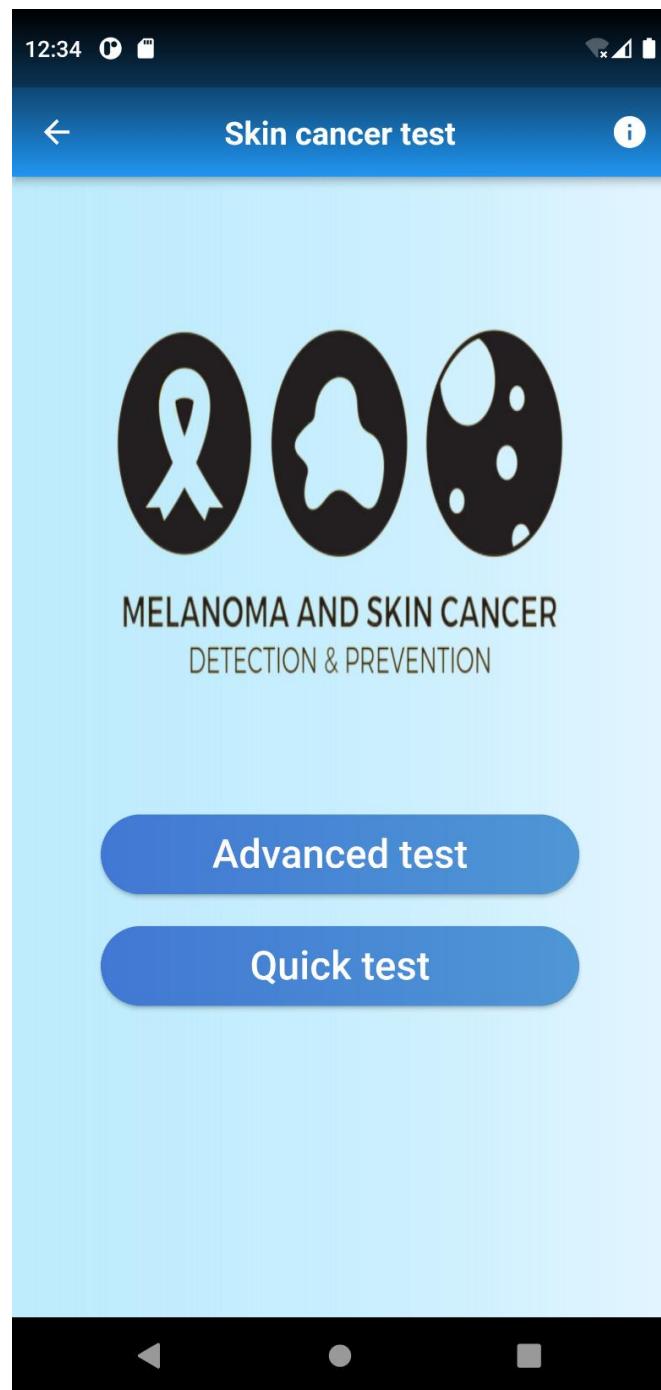
6.1.3 Login



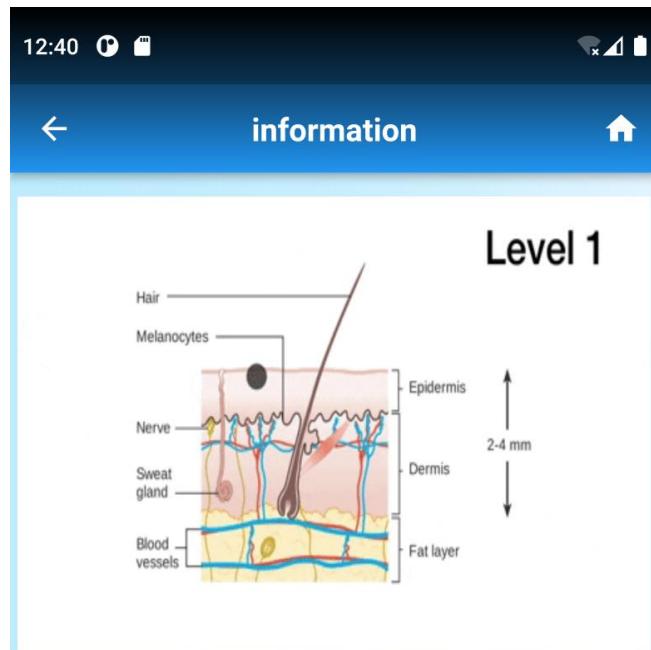
6.2.1 Main page



6.2.2 Test main page



6.2.3 Info for using app



This app can diagnose pigmented skin lesions via machine learning by classifying your case in these 7 important categories. For better result we recommende using medical knowlodge informations

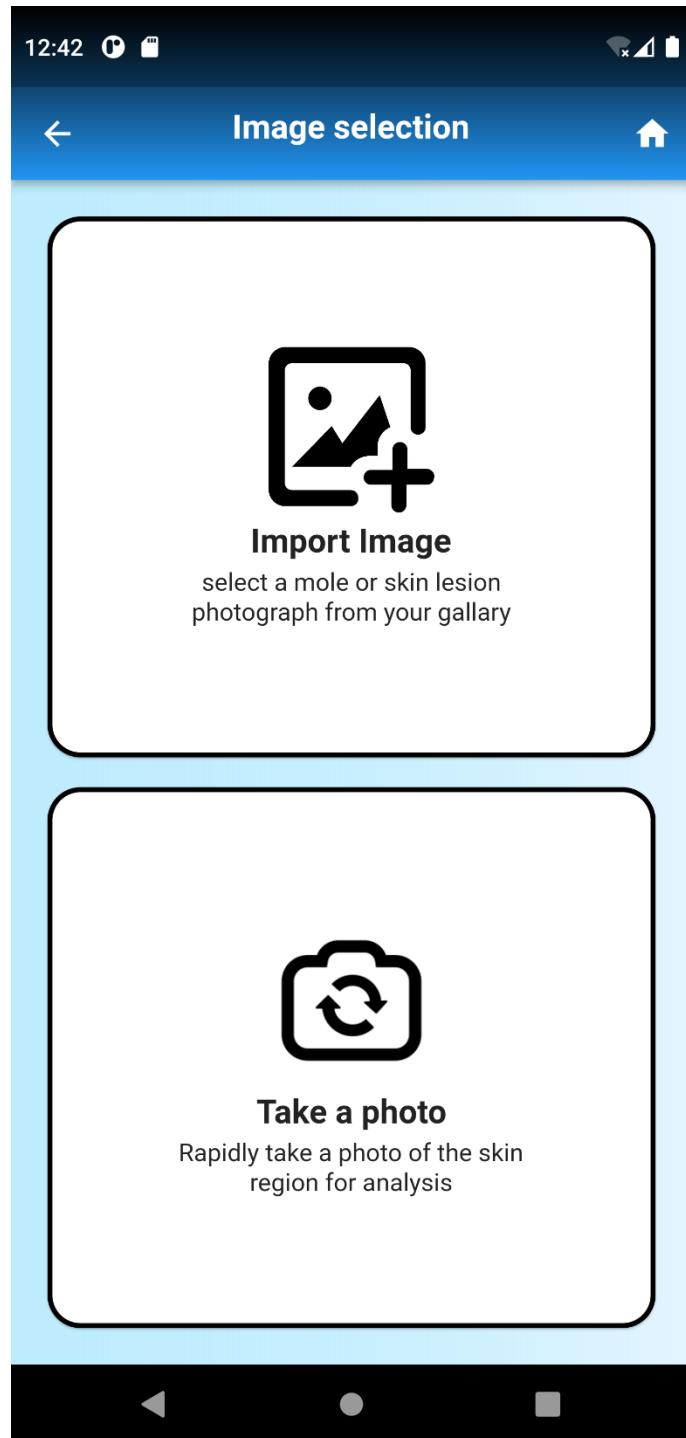
Benign tumors

Malignant tumors

- Melanocytic nevi
- Melanoma
- Benign keratosis-like lesions
- Basal cell carcinoma
- Actinic keratoses
- vascular lesions



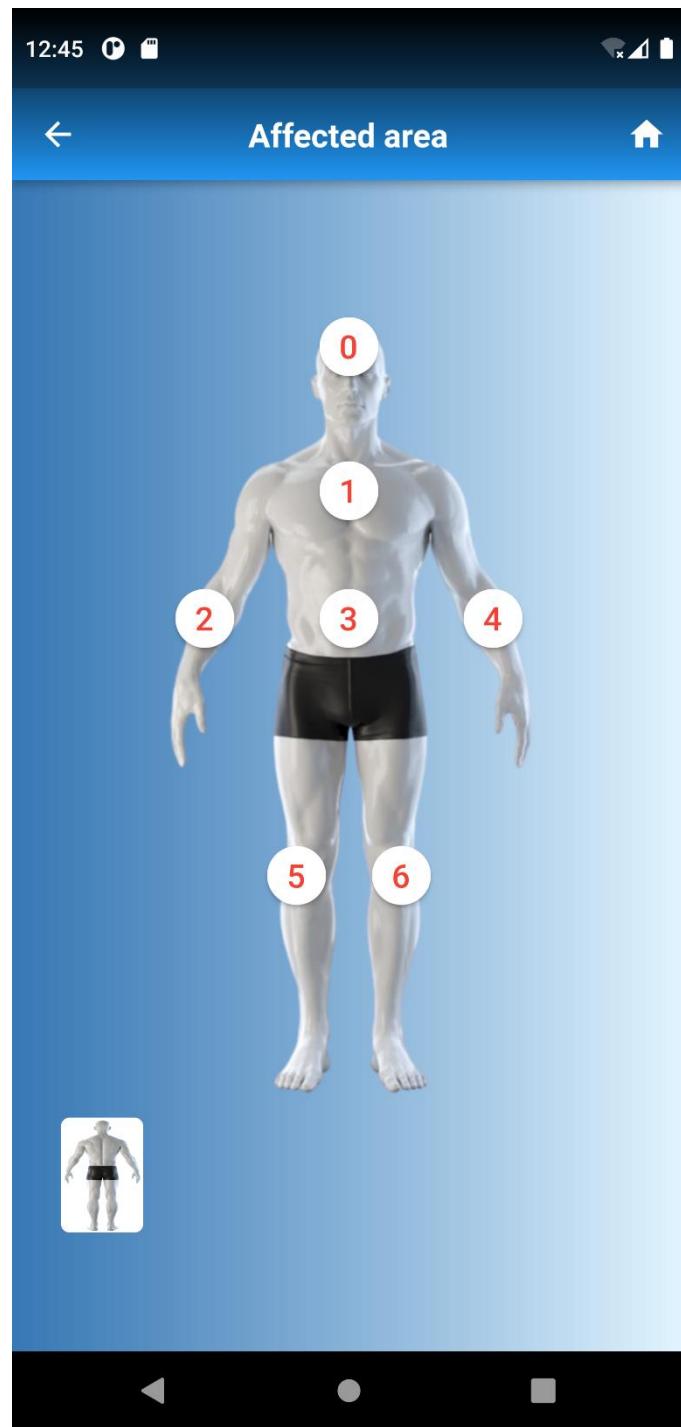
6.2.4 Image selection



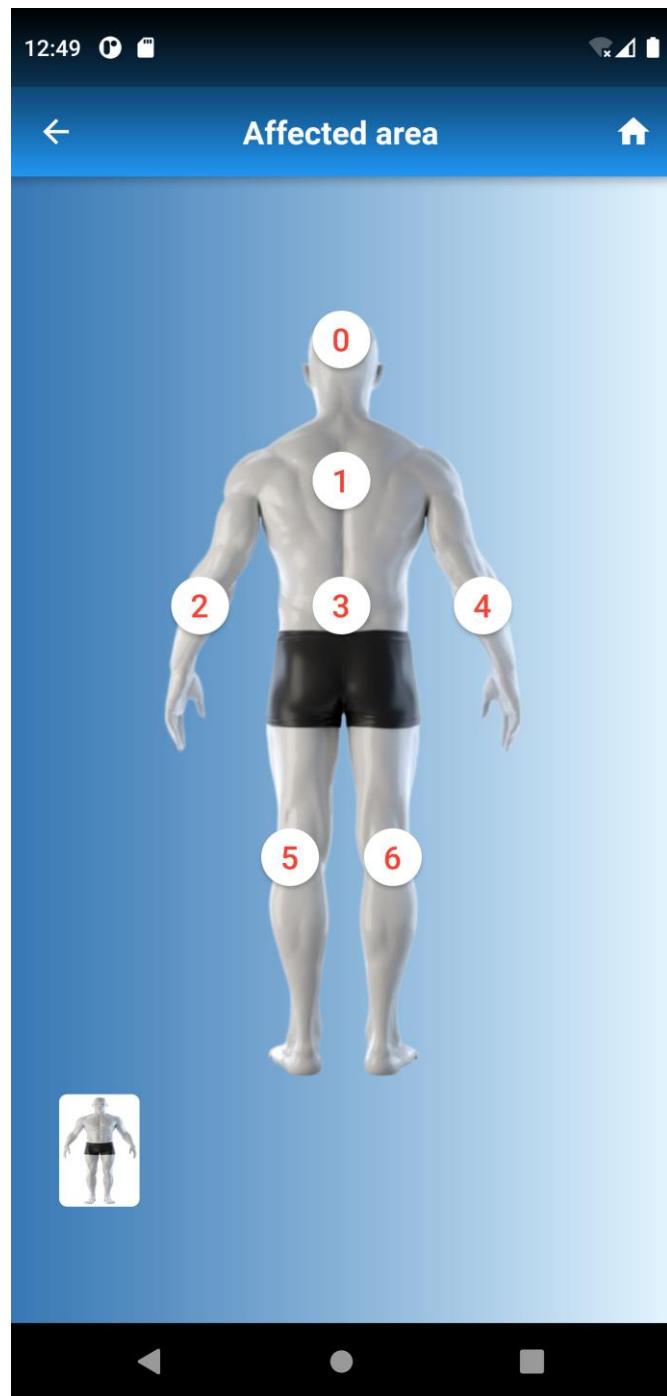
6.2.5 Display selected image



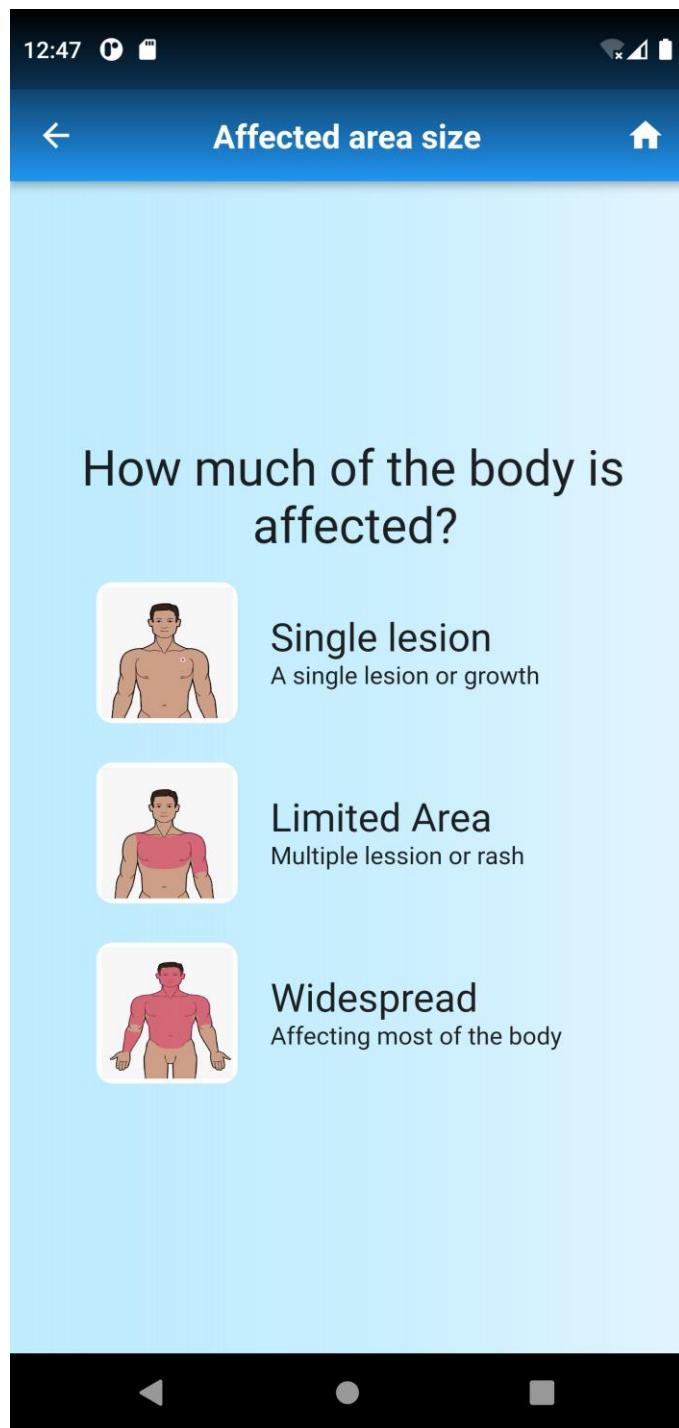
6.2.6 Select affected area position



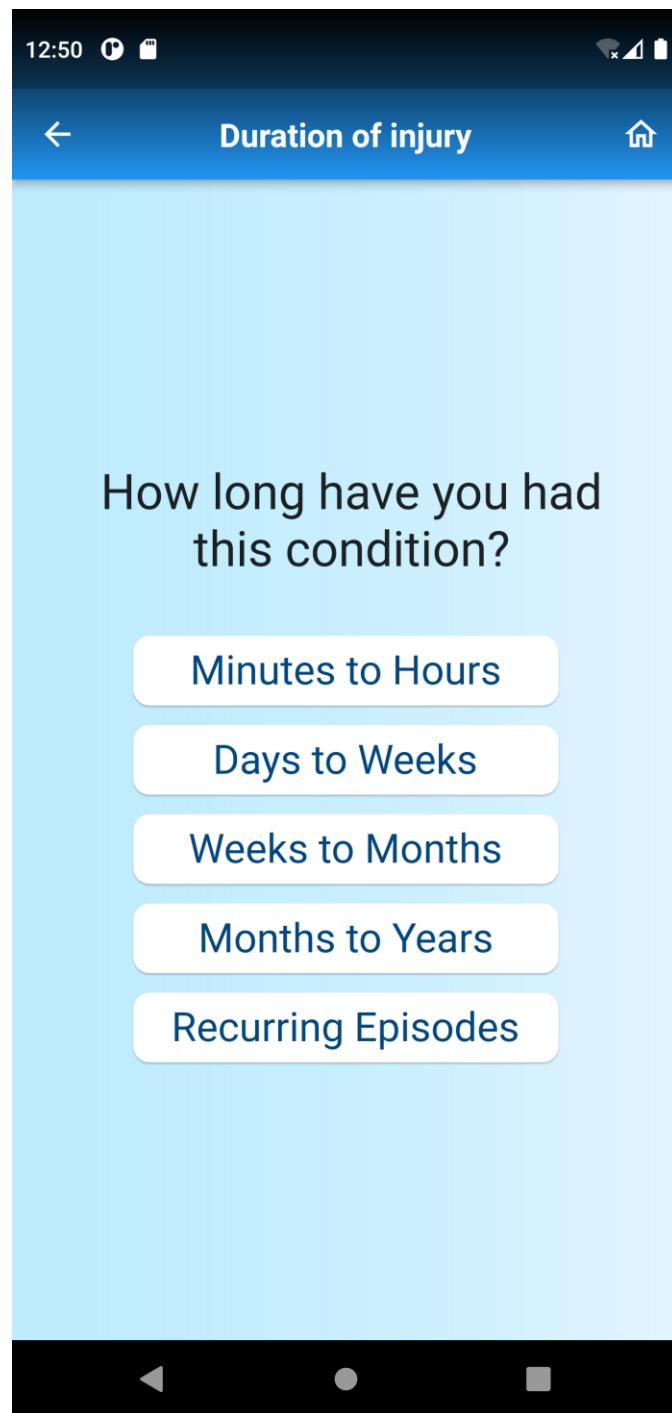
6.2.7 Select affected area position



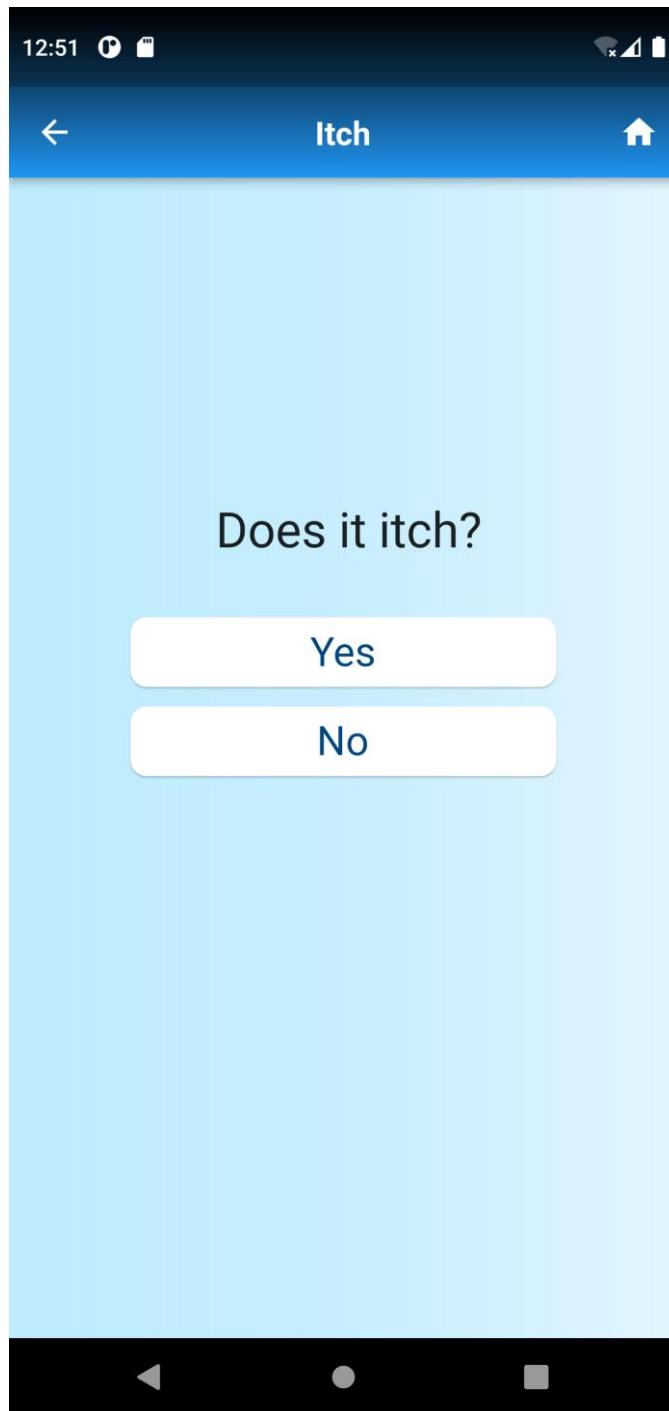
6.2.8 Select affected area size



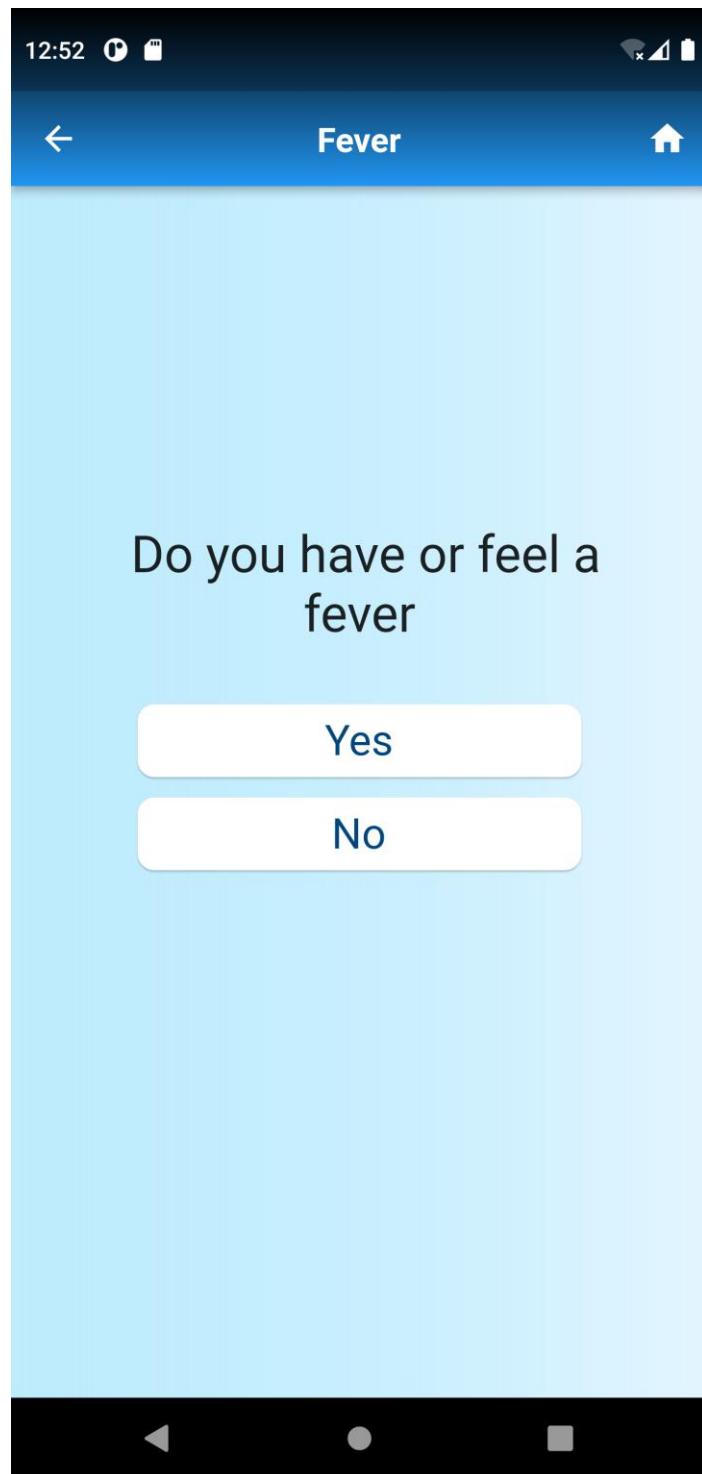
6.2.9 Select duration of injury



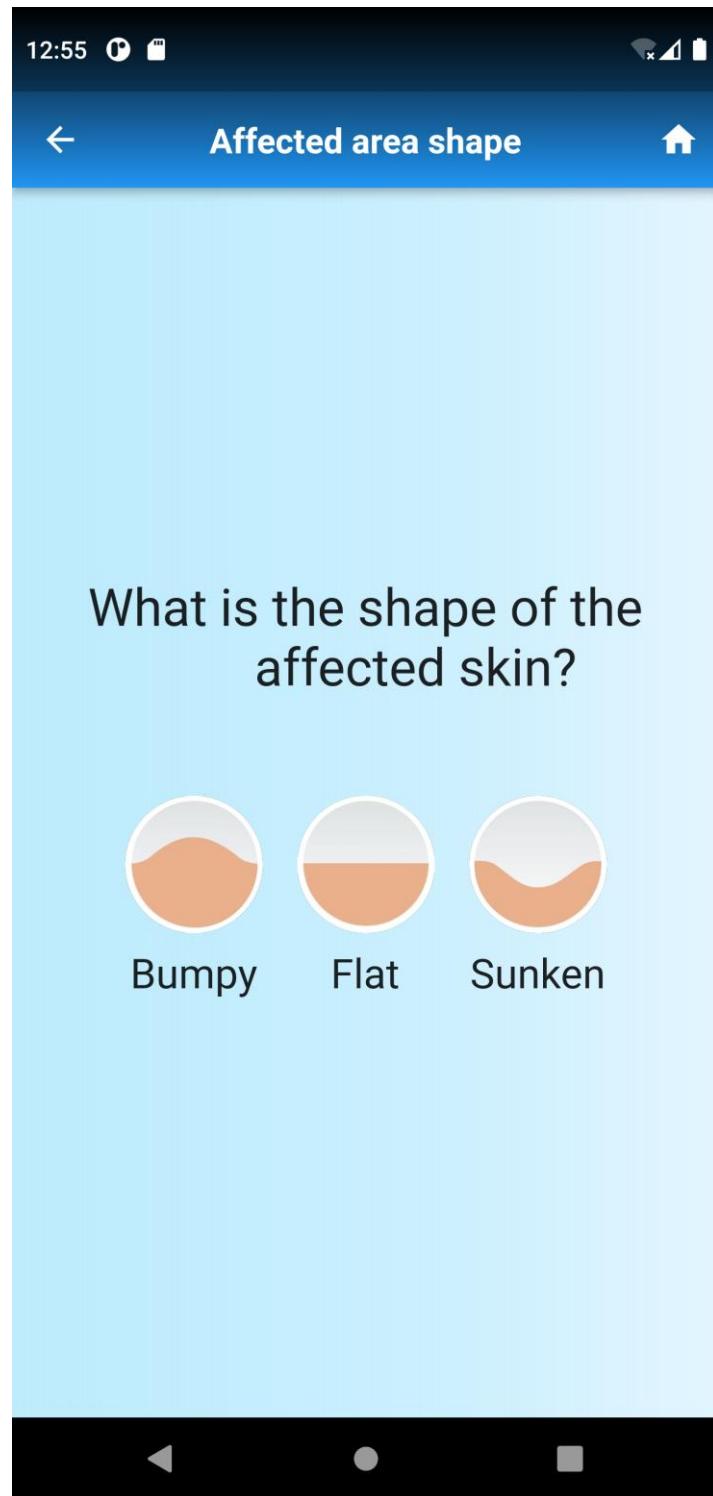
6.2.10 Select if it is itch or no



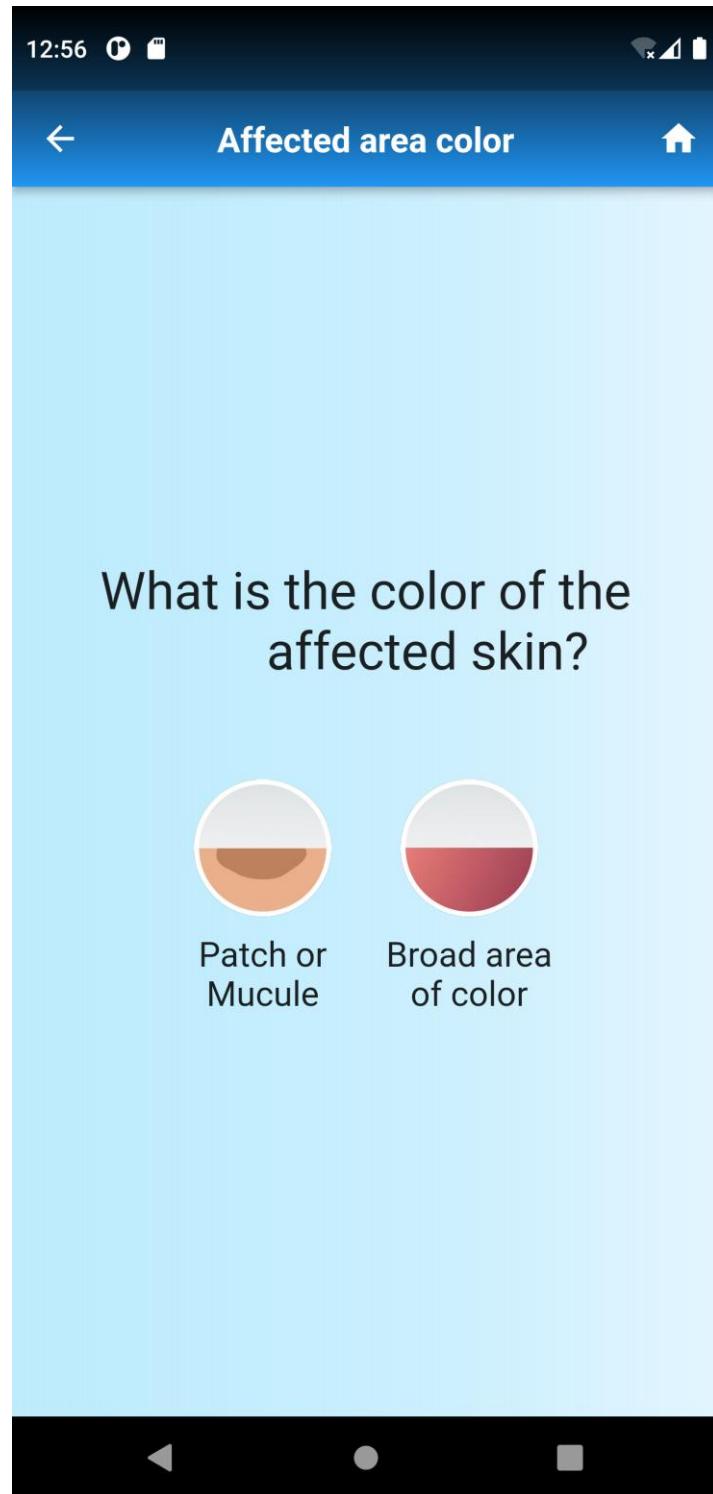
6.2.11 Select if having fever or not



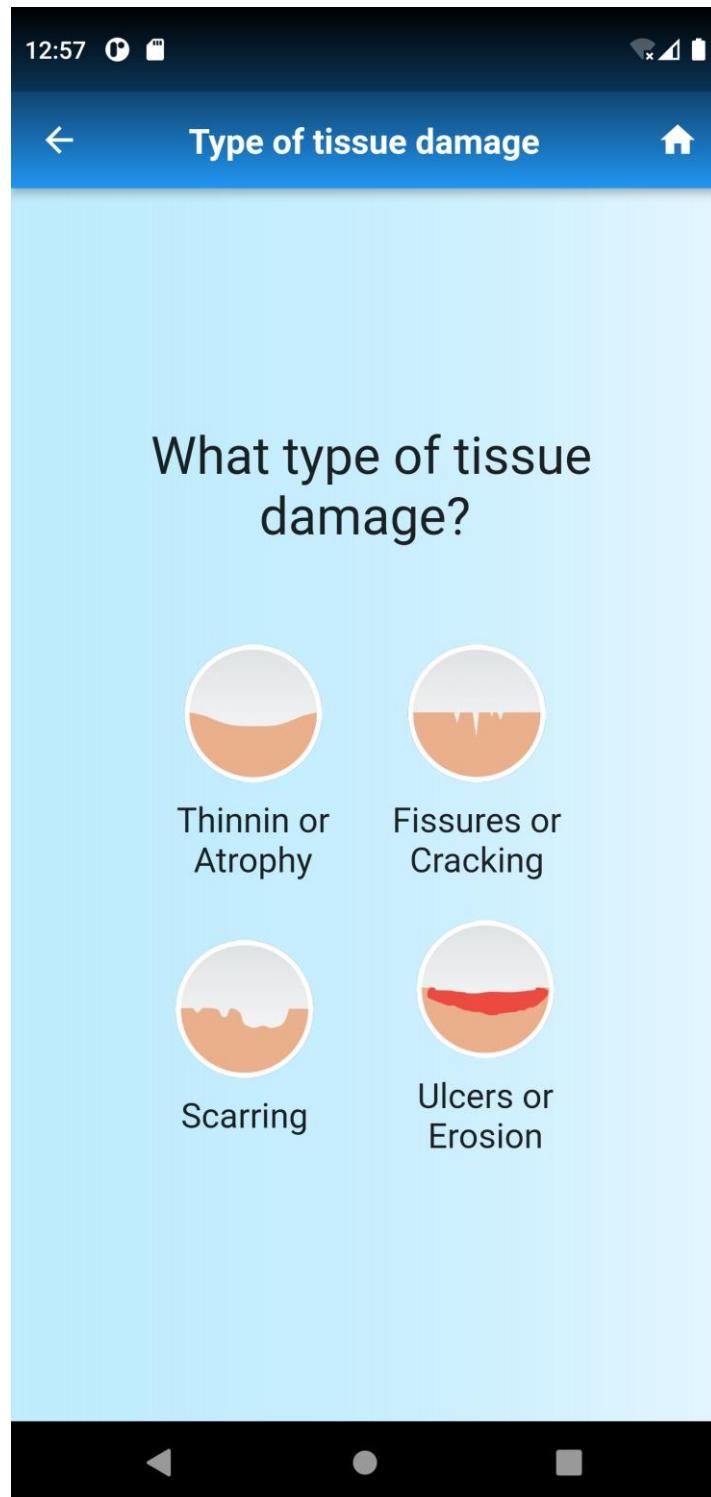
6.2.12 Select affected area shape



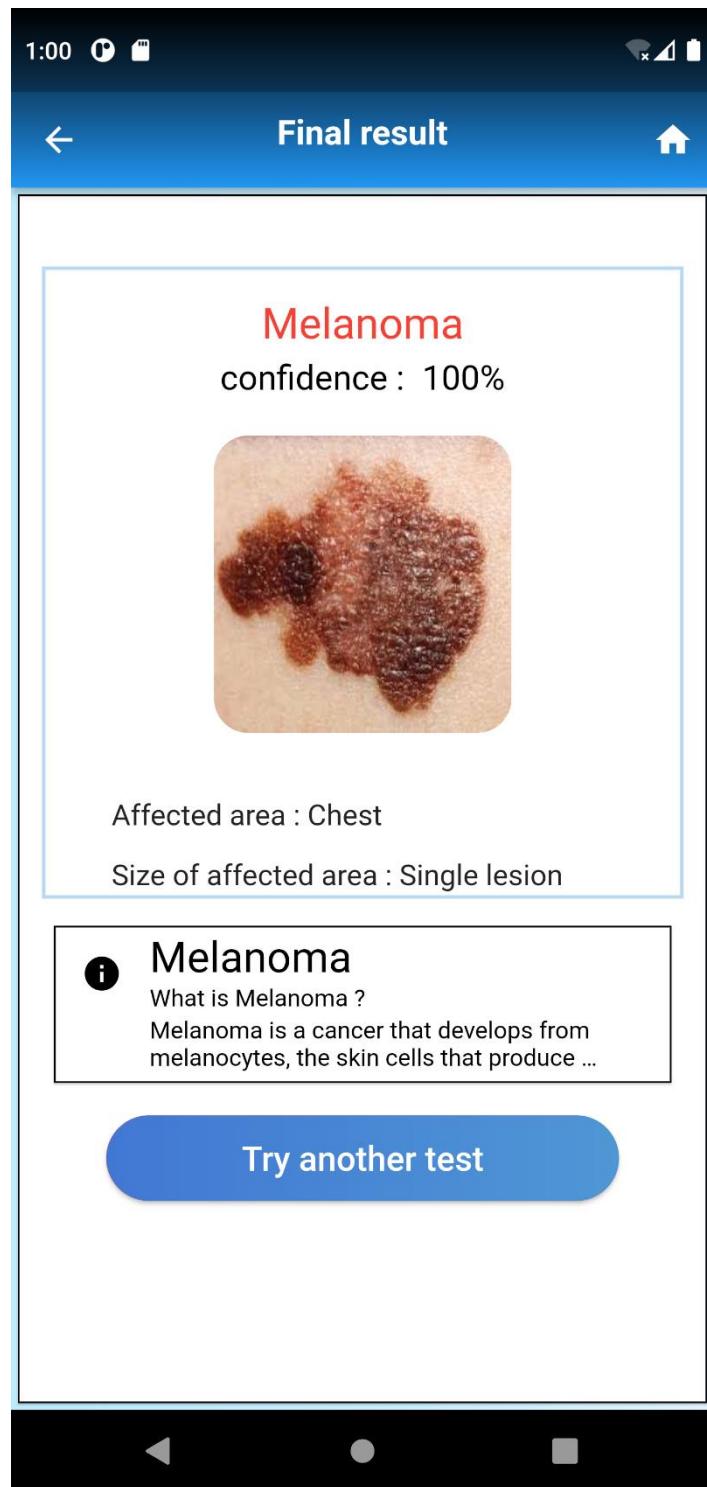
6.2.13 Select affected area color



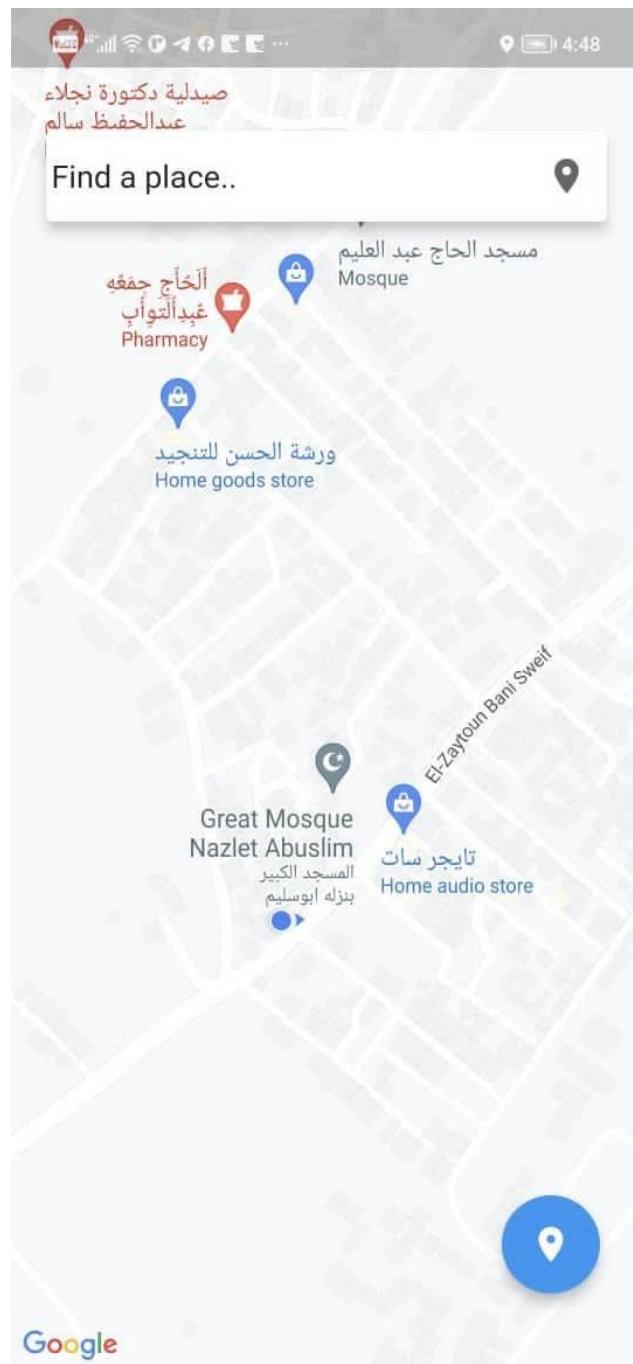
6.2.14 Select type of tissue damage



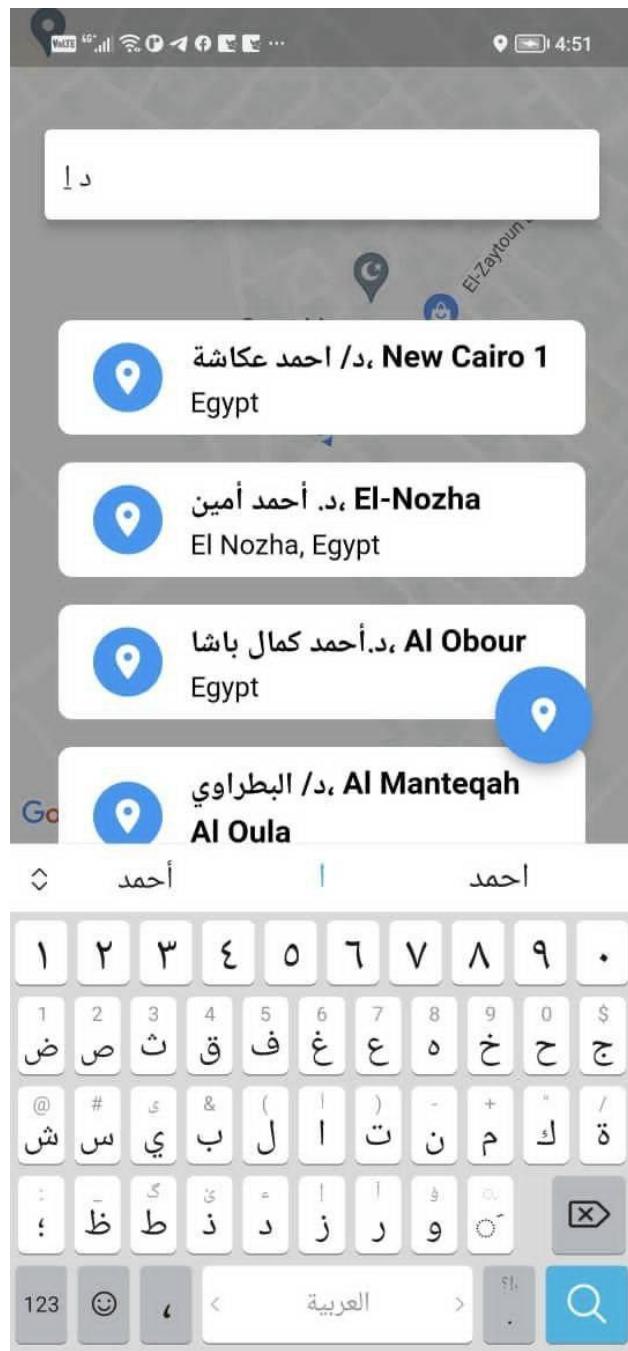
6.2.15 Final result



6.3.1 Find doctor



6.3.2 Find doctor



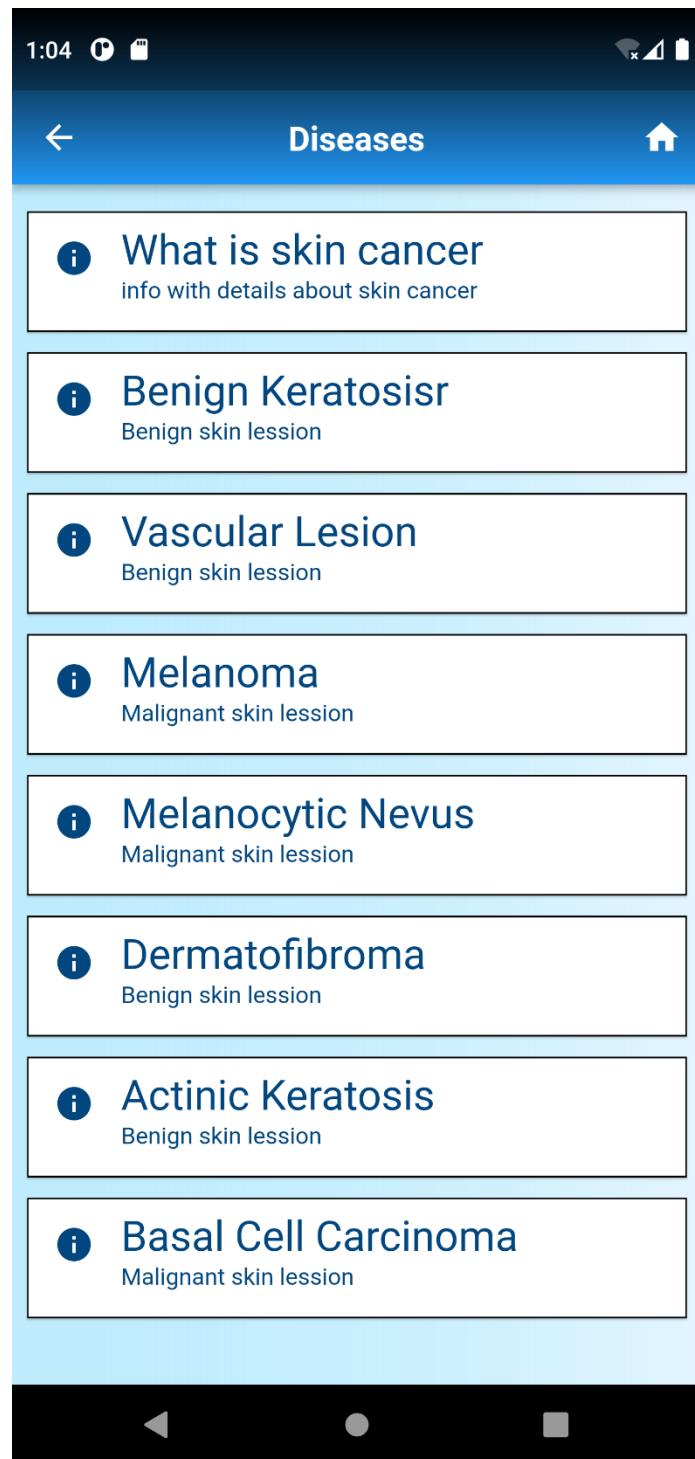
6.3.3 Find doctor



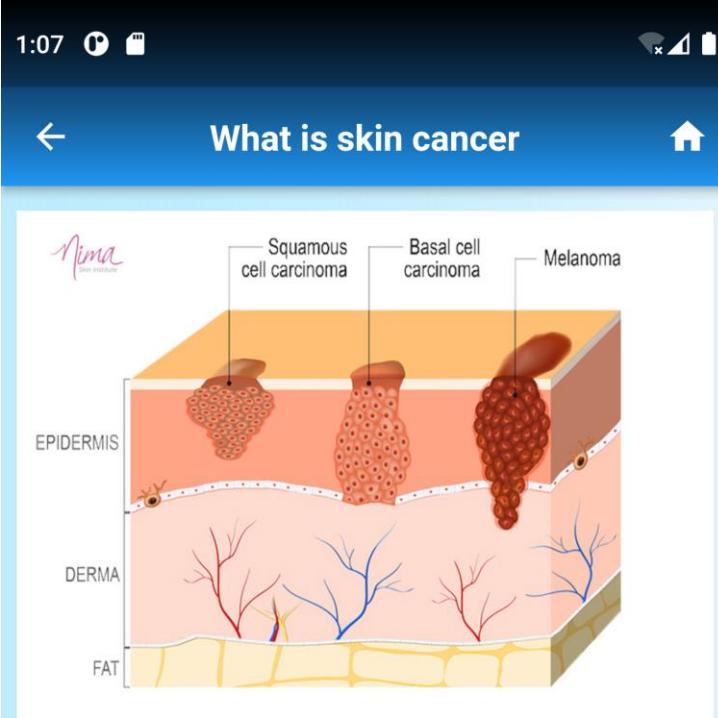
6.3.4 Find doctor



6.4.1 Diseases main page



6.4.2 Skin cancer info page



The screenshot shows a mobile application interface titled "What is skin cancer". At the top, there is a navigation bar with a back arrow, the title "What is skin cancer", and a home icon. Below the title is a diagram of the skin cross-section. The diagram labels the "EPIDERMIS" (outer layer) and "DERMA" (inner layer). Within the epidermis, three types of cancer are shown: "Squamous cell carcinoma", "Basal cell carcinoma", and "Melanoma". The derma layer contains blood vessels. The bottom of the diagram is labeled "FAT". On the left side of the main content area, there is a section titled "What Is Skin Cancer ?" followed by a detailed description of skin cancer. At the very bottom of the screen, there is a black navigation bar with standard Android icons for back, home, and recent apps.

What Is Skin Cancer ?

Skin cancer is the out-of-control growth of abnormal cells in the epidermis, the outermost skin layer, caused by unrepaired DNA damage that triggers mutations. These mutations lead the skin cells to multiply rapidly and form malignant tumors. The main types of skin cancer are basal cell carcinoma (BCC), squamous cell carcinoma (SCC), melanoma and Merkel cell carcinoma (MCC).

What Causes Skin Cancer ?

The two main causes of skin cancer are the sun's harmful ultraviolet (UV) rays and the use of UV tanning beds. The good news is that if skin cancer is caught early, your dermatologist can treat it with little or no scarring and high odds of eliminating it entirely. Often, the doctor

6.4.3 Benign Keratosis info page

What is seborrheic keratosis ?
A seborrheic keratosis is a type of skin growth.
The term keratosis refers to a knobby
overgrowth of keratinocytes. The keratinocyte is
the most common type of skin cell in the
epidermis (the outer layer of the skin).

Location ?
Multiple lesions may appear, although at the
beginning there might be just one. Growths can
be found anywhere on the body except the
soles of the feet, palms, and mucous
membranes.
Some places they may show up include the:
scalp ,face ,chest ,shoulders ,abdomen, back

6.4.4 Vascular Lesion info page

The image shows a smartphone screen with a blue header bar. The header contains the text "Vascular Lesion" in white, flanked by a back arrow icon on the left and a home icon on the right. The time "1:11" and signal strength icons are also visible at the top. Below the header is a large photograph of a reddish-brown vascular lesion on a person's skin. The main content area is a white box containing text. The text begins with the question "what is vascular lesions ?" followed by a detailed explanation of vascular lesions as relatively common abnormalities of the skin and underlying tissues, specifically birthmarks. It mentions three major categories: Hemangiomas, Vascular Malformations, and Pyogenic Granulomas. The text continues to describe the variations in origin and treatment for these lesions. At the bottom of the content box, there is a note from SSM Health Cardinal Glennon Children's hospital about their commitment to creating individualized care plans for vascular lesions. The bottom of the screen features a black navigation bar with standard Android icons for back, home, and recent apps.

what is vascular lesions ?

Vascular lesions are relatively common abnormalities of the skin and underlying tissues, more commonly known as birthmarks. There are three major categories of vascular lesions: Hemangiomas, Vascular Malformations, and Pyogenic Granulomas. While these birthmarks can look similar at times, they each vary in terms of origin and necessary treatment.

At SSM Health Cardinal Glennon Children's hospital, the SLUCare Physician Group pediatric plastic surgery team is committed to creating an individualized care plan for vascular lesions that improves the physical and emotional well-being of your child.

6.4.5 Melanoma info page

The image shows a mobile application interface titled "Melanoma". At the top, there is a navigation bar with a back arrow, the title "Melanoma", and a home icon. Below the title, the section "Stages of Melanoma" is displayed. The diagram illustrates the progression of melanoma through four stages based on skin depth:

- Stage 0:** Melanoma confined to epidermal region of skin.
- Stage I:** Localized disease, only in skin and very thin.
- Stage II:** Localized disease, thicker than Stage I.
- Stage III:** Spread to lymph nodes.
- Stage IV:** Spread to other organs.

Labels indicate the layers of skin: Epidermis, Dermis, and Subcutaneous Tissue. The diagram shows melanoma cells increasing in size and depth from Stage 0 to Stage IV.

What is Melanoma ?
Melanoma is a cancer that develops from melanocytes, the skin cells that produce melanin pigment, which gives skin its color.

Where is it usually found ?
Melanomas often resemble moles and sometimes may arise from them. They can appear on any area of the body, even in areas that are not typically exposed to the sun.

What causes it ?
Melanoma is often triggered by the kind of intense, intermittent sun exposure that leads to sunburn. Tanning bed use also increases risk for melanoma.

6.4.6 Melanocytic Nevus info page



The image shows a screenshot of a mobile application. At the top, there is a blue header bar with the text "Melanocytic nevus" in white. On the left side of the header is a back arrow icon, and on the right side is a home icon. Below the header is a photograph of a dark brown, irregularly shaped skin lesion on a light-colored, textured skin surface. The lesion has a mottled appearance with darker and lighter areas. At the bottom of the screen is a black navigation bar with three white icons: a triangle pointing left, a circle, and a square.

Melanocytic nevi are benign neoplasms or hamartomas composed of melanocytes, [1] the pigment-producing cells that constitutively colonize the epidermis. Melanocytes are derived from the neural crest and migrate during embryogenesis to selected ectodermal sites (primarily the skin and the CNS), but also to the eyes and the ears. Ectopic melanocytes have been identified at autopsy in the gastrointestinal and genitourinary tracts. Congenital melanocytic nevi are thought to represent an anomaly in embryogenesis and, as such, could be considered, at least in a sense, malformations or hamartomas. [2] In contrast, most acquired melanocytic nevi are considered benign neoplasms. Compare the images below. Melanocytic nevi occur in all mammalian species and are especially common in humans, dogs, and horses.

6.4.7 Dermatofibroma info page

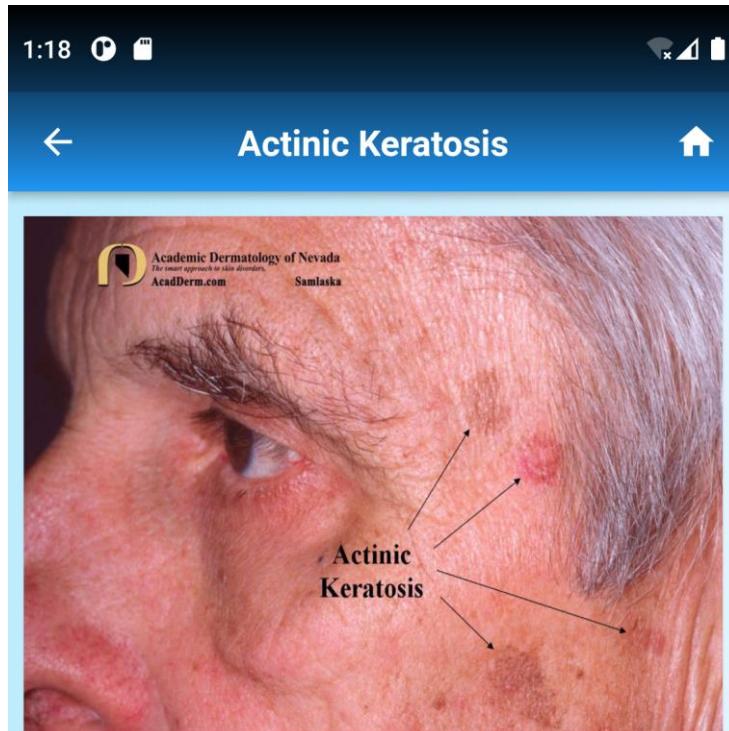
The image shows a smartphone screen with a mobile application interface. The top status bar indicates the time as 1:15 and shows signal strength and battery level icons. Below the status bar is a blue header bar with a back arrow on the left, the title "Dermatofibroma" in the center, and a home icon on the right. The main content area features a large, close-up photograph of a skin lesion, which is a reddish-brown, raised nodule on light-colored skin, characteristic of a dermatofibroma. Below the image is a white text box containing the following information:

What is a dermatofibroma ?
A dermatofibroma is a common benign fibrous nodule usually found on the skin of the lower legs.
A dermatofibroma is also called a cutaneous fibrous histiocytoma.

Who gets a dermatofibroma ?
Dermatofibromas are mostly seen in adults. People of every ethnicity can develop dermatofibromas. Ordinary dermatofibromas are more common in women than in men, although some histologic variants are more commonly identified in males.

At the bottom of the screen is a black navigation bar with three white icons: a left arrow, a circular dot, and a square.

6.4.7 Actinic Keratosis info page



Actinic keratoses (AKs) and Bowen's disease are common forms of sun-damage where abnormal cells have developed in the top layer of the skin (the epidermis) from excessive sun exposure. They appear as scaly patches. These usually occur on areas of the body which catch the sun such as the face and ears, scalp in balding men, back of the hands, forearms, and lower legs in women.

Actinic keratoses (also called solar keratoses) are dry scaly patches of skin that have been damaged by the sun.

The patches are not usually serious. But there's a small chance they could become skin cancer, so it's important to avoid further damage to your skin.

6.4.8 Basal Cell Carcinoma info page

1:20 100% 100%

Basal Cell Carcinoma

CANCER OF THE SKIN
BASAL CELL CARCINOMA

SQUAMOUS CELL CARCINOMA

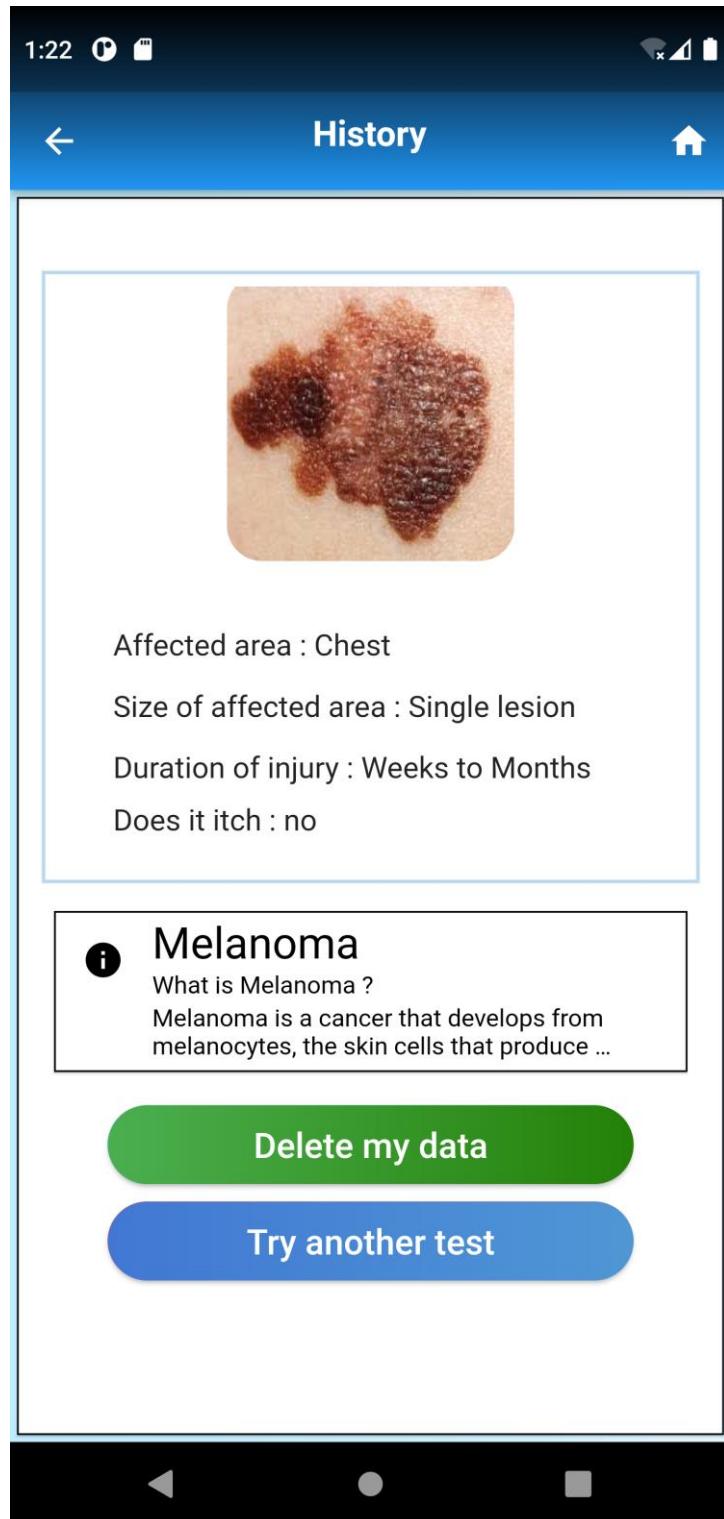
MELANOMA

What is it ?
Basal cell carcinomas (BCCs) are abnormal, uncontrolled growths that arise from the skin's basal cells in the outermost layer of skin (epidermis).

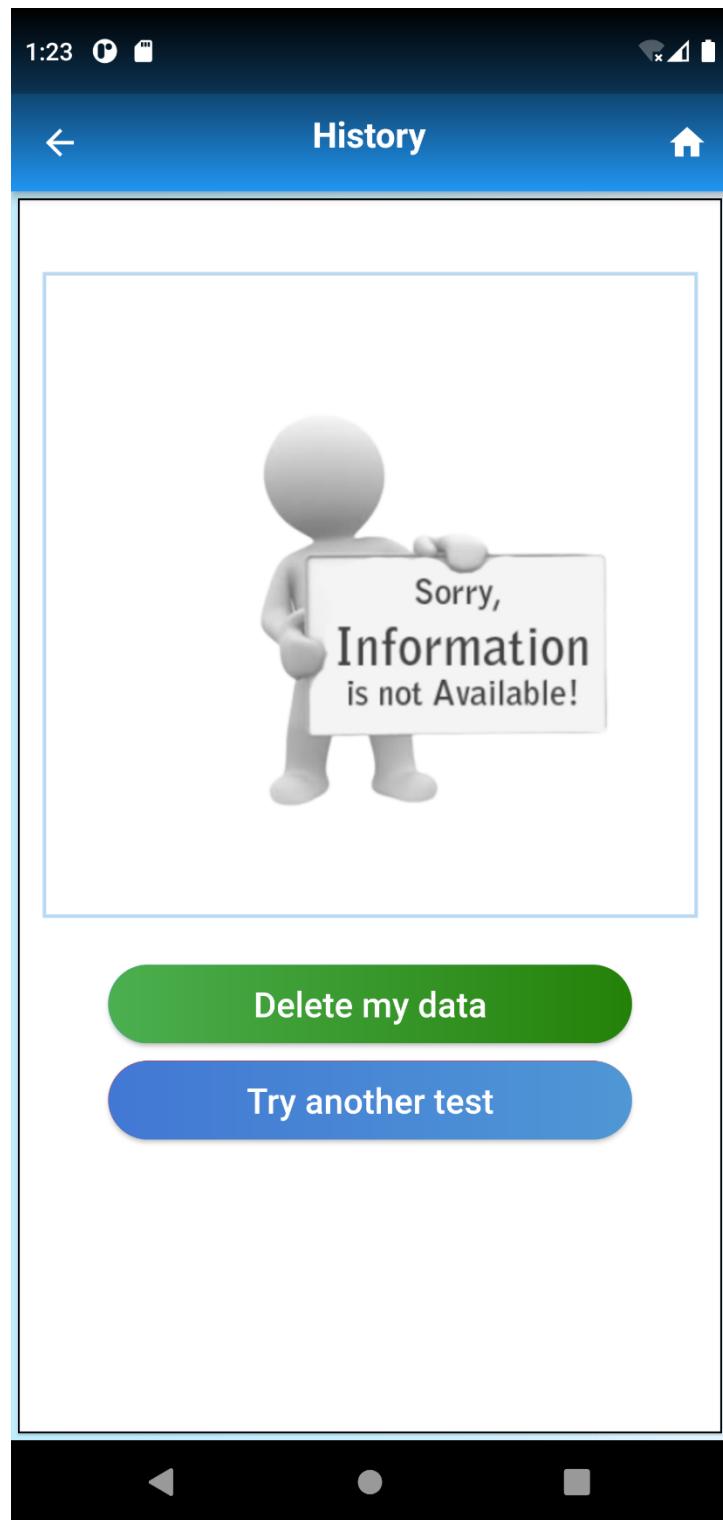
Where is it usually found ?
These cancers most often develop on skin areas typically exposed to the sun, especially the face, ears, neck, scalp, shoulders and back.

What causes it ?
Most BCCs are caused by the combination of intermittent, intense exposure and cumulative, long-term exposure to UV radiation from the sun.

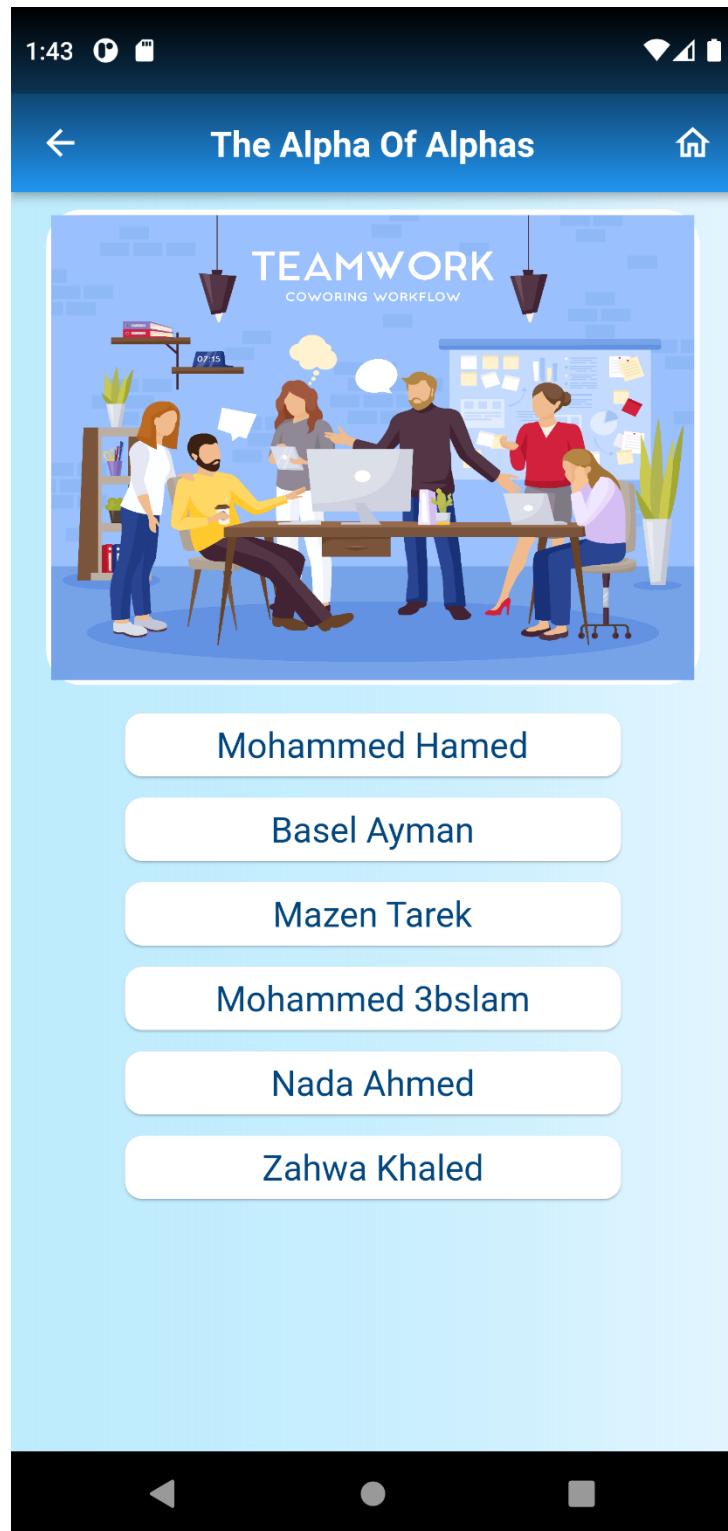
6.5.1 History page



6.5.2 History page



6.6 About developer's page



Chapter 7

Testing & evaluation

7.1 Testing & Evaluation

Testing is an essential step in this program as we can find issues in testing, and our framework in general has problems. We checked every step in our application, and we would check each step, as I described before to achieve the project goal, our strategy was gradual and iterative. There are various check forms that you can use to ensure that code changes function as intended. However, not everyone's testing is the same.

7.1.1 Unit testing

Unit testing is very weak, near to the application's source. You check specific methods and features of the software's classes, elements or modules. Unit tests are typically cheap to carry out with a continuous integration system and can be performed quite quickly.

7.1.2 Integration testing

Integration testing ensure that the program fits together well with various components or utilities. For example, the relationship with the database can be checked. Such kinds of experiments are more difficult to conduct, because certain parts of the code are required for them to function.

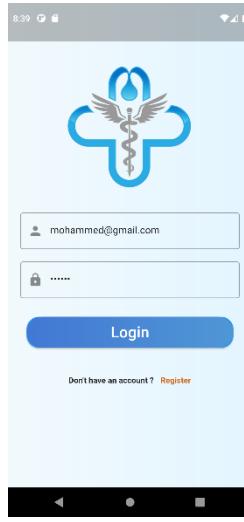
7.1.3 Functional testing

Functional testing rely on the application's market specifications. You just test the results of an operation and do not track the system intermediate state during this operation. Sometimes there is a discrepancy between integration testing and functional tests, as they both tend to communicate with multiple elements. The distinction is that an integration test will only verify whether the database can be queried while a practical test is required to derive a particular value from the database as specified by the software specifications.

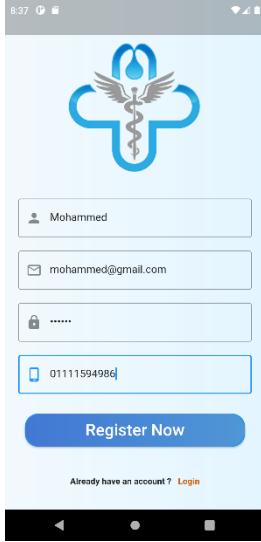
7.1.4 End-to-end tests

End-to -end testing in a full program environment replicates the device experience of the applications. It verifies that different user flows work as expected and can be just as simple as downloading a website, logging into or verifying email alerts in more complicated situations.

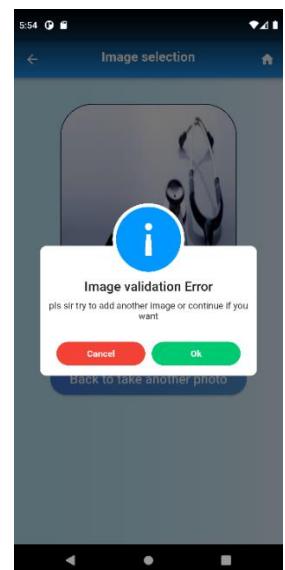
7.2.1 Login

Test Name	Login
Test Scenario	Login page form
Test Case Description	Empty email or password field
Pre-requisites	Email:am@gmail.com Password:1234567
Test Input	Nothing to write
Execution	click on (sign in) button Message show “please enter email”, Password must at least 7 digits will appear. check the empty fields in email
Expected behavior	An error toast message contains “Empty Fields” will appear
Assumptions	Null
Actual Result	 A screenshot of a mobile application's login screen. At the top, there is a logo consisting of a blue caduceus symbol (a staff with two snakes entwined and wings at the top). Below the logo are two input fields: one for email with the placeholder "mohammed@gmail.com" and one for password with the placeholder ".....". A large blue "Login" button is positioned below the fields. At the bottom of the screen, there is a link "Don't have an account ? Register" and a navigation bar with three icons.

7.2.1 Register

Test Name	Register
Test Scenario	Register page form
Test Case Description	Missing fields
Pre-requisites	Null
Test Input	Nothing to Entered
Execution	<p>Click “next” button</p> <p>Errors on the empty fields will appear with red text.</p> <p>Start checking empty fields and fill them with information needed.</p>
Expected behavior	<p>Focused errors on the empty fields will appear with red labels.</p>
Assumptions	<p>Design GUI will be tested in alone Scenario or as a test scenario.</p>
Actual Result	

7.2.1 Make test

Test Name	Make test
Test Scenario	Make test page form
Test Case Description	Enter an image for no human skin body
Pre-requisites	Valid image for skin
Test Input	Nothing to write
Execution	<ul style="list-style-type: none"> - Click on processed button. - Warning dialog show “Please enter an valid image for human skin body or continue anyway”
Expected behavior	An error toast message contains “Invalid image”
Assumptions	Null
Actual Result	

7.2.2 Find doctor

Test Name	Find doctor
Test Scenario	Find doctor page form
Test Case Description	Enter an invalid location
Pre-requisites	Valid location
Test Input	Nothing to write
Execution	Click on processed button. Warning dialog show “Please enter an valid location for”
Expected behavior	An error toast message contains “Invalid location”
Assumptions	Null
Actual Result	

Chapter 8

Conclusion & Future Work

8.1 Conclusion

This work involved a novel method involving deep learning algorithm for skin lesion type identification based on image data. This introduces a new method to identify lesion type before medical diagnosis and helps the medical staff to diagnose the type predicted by the model first. This reduces a lot of time and effort. This model uses a Convolution Neural Network (CNN) within a Tensor flow framework. For the specific cancer types the accuracy ranges from 88% to 100%. And the overall accuracy of the model is 95%.

Compared to traditional medical diagnosis this method is better in two ways. First. This method will not be influenced by diagnostic medical instruments that is error in the instruments can occur during medical diagnosis and this will not have any effect in this method if the images are of good quality. With more and more cancer cases our model becomes more and more powerful unlike medical instruments which has wear and tear.

Second, this method does not depend on stage of cancer and the cancer can be detected even in an early stage. But some medical diagnosis can detect some types of skin cancer only when it reaches advanced stage and this does not occur with this model. If among seven types, we add one more class which is non-malignant cancer type and then train the model, our model can even detect whether it is malignant or not and also tells the type of cancer.

This model may have some limitations like the prediction probability cannot be 100%. But it provides a good basis for further diagnosis and will be very helpful. The CNN model with metadata can increase the accuracy of classification in skin cancer detection even with limited data and is promising for development as a screening device in remote and low resources health care.

8.2 Future work and other ideas

In many of the image classification projects correct results depends mostly on dataset. Our dataset contains 10,015 images, but most of those images are of only one class Melanocytic Nevi. It is important to collect a balanced data for better predictions. Also our dataset has only seven different lesion types whereas in practical there are many more different types of skin cancer. One of the future work is to collect a better dataset with more balanced data with more lesion types. Also our data only contains cancer images of patients. This model can only tell different types of cancer, but cannot tell whether the lesion itself is malignant or not. Along with the 7 classes if we can get images of non-malignant lesions and add them to our data and then train the model, we can also detect cancer and also tell the type of cancer.

The skin cancer detection app places the control in the palm of your hand to save lives. To developing our app and make it accessible and more efficient we target a lot of plans:

- 1- Connect the application to a cloud database so that we can see a large amount of data and improve the accuracy
- 2- Allows you to contact the doctor directly from the application
- 3- Sending the patient's data to the personal doctor on an ongoing basis
- 4- Send alerts to the patient to perform a periodic examination to ensure his safety
- 5- Make our own application that supports different social groups
- 6- Adding more diseases and not just 7 to get better results

References

<https://github.com/datascisteven/Melanoma-Image-Classification>

<https://github.com/ashishpate126/Skin-Lesions-Detection-Deep-learning>

<https://www.kaggle.com/code/jagdmir/siim-melanoma-classification-modelling/notebook#Some-insights-about-the-training-and-testing-data>

<https://www.kaggle.com/code/sid321axn/step-wise-approach-cnn-model-77-0344-accuracy#Step-11:-Model-Building>

<https://www.kaggle.com/code/jagdmir/all-you-need-to-know-about-cnns>

<https://github.com/Geeky-star/Skin-Cancer-Detection-App>

<https://github.com/MoatazMaher1998/Skin-Cancer-Detection-Mobile-App>

<https://github.com/DefineDan/ml-skin-cancer-classification-app>

<https://github.com/datascisteven/Melanoma-Image-Classification>

https://github.com/ruoyzhang/Skin_Cancer_Detection_with_GradCam

<https://github.com/Tirth27/Skin-Cancer-Classification-using-Deep-Learning>

https://github.com/sj-singh/DL_Melanoma_Detection

<https://github.com/SwagatSBhuyan/Skin-Cancer-Classification-Using-CNN-Deep-Learning-Algorithm>

https://github.com/AakashKumarNain/skin_cancer_detection

<https://www.skincancer.org/skin-cancer-information/>

<https://www.skincancerpractice.com.au/skin-cancer/introduction>

<https://towardsdatascience.com/building-a-skin-lesion-classification-web-app-16fd2c422b9d>

https://www.medrxiv.org/content/10.1101/2020.05.03.20072454_v1.full.pdf

THANK

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