Identification of Melanoma Skin Cancer Through Image Processing and DL

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Abstract

Melanoma is still the most deadly type of skin cancer among those that typically develop. Like other cancers, this one has a higher probability of survival if it is discovered early. Medical professionals find that computer-aided diagnostics is helpful in the detection of melanoma. In recent times, image processing, deep learning, and machine learning have emerged as the top options. The ABCDE rule is used to identify melanoma in most situations. Thus, the same technique is applied. The collected photographs or images from the database are transferred to the server via a local application. Features are extracted and segments are done using different image processing techniques. AlexNet, ResNet50 and EfficientNetB7 learning techniques. Various classifiers provide their outputs. The primary goal of this study is to compare the accuracy of different classifiers and use REST API to transmit the results to a local application. The study will be carried out using ISIC 2016 benchmark dataset.

Keywords-: Melanoma, Image Processing, Deep Learning, Machine Learning, CNN, AlexNet, Resnet50, EfficientNetB7

1.1 Introduction

Being the biggest organ in the body, the skin serves as the body's first line of protection. It has the functions of protecting, secreting, excreting and regulating body temperature. With the changes in lifestyle and environment, various skin diseases affect the normal life of human beings. There are more incidences of skin cancer than any other type of cancer, and skin illnesses affect a large number of individuals worldwide. As per [16], in the United States alone, there were 5.4 million new instances of skin cancer each year. As per [17], Melanoma accounts for only 5% of all skin cancer diagnoses, but 75% of those cases have the potential to be fatal. The factors for melanoma development are primarily UV radiation, which occurs in solar radiation. Other factors are signs on the skin or genetics. There is a good survival percentage for melanoma if it is identified early and treated appropriately. The prognosis for advanced melanoma remains poor. However, if detected during the earliest stages, the curative effect and prognosis are better.

Accurate screening for early identification of melanoma is a critical first step in lowering mortality and prolongation of patients' survival. In recent years, dermatologists around the world have devoted considerable attention to the study of dermoscopy. For accurate detection of melanoma, dermatologists use biopsy, which means the tissue or cells removal for analysis which is usually associated with pain, time and cost.

Dermoscopy is a non-invasive method of skin imaging that provides a bright, enlarged image of a specific area of skin to help make skin spots easier to see. Dermoscopy or dermatoscopy uses a tool named dermatoscope magnifying the lesions (usually x3-x10) and helps the dermatologists examine the skin more clearly. For melanoma detection, there are several ways that dermatologists use to avoid unnecessary biopsy, which ABCD rule is the most famous one. This was developed from the rule that dermatologists frequently apply to diagnose skin cancer. Asymmetry in the ABCD rule refers to two sides that do not match for symmetry but match for the other. This can help differentiate between skin lesions that are benign and those that are malignant.

In most situations, the border structure is irregular for malignant growth and even for benign growth. When it comes to benign conditions, the variegated color is usually only one, but in cases of malignancy, it is always two or more hues. When anything is benign, the overall dermatoscopical structure is always very small—about a quarter of an inch—while when something is malignant, it is always larger.

With the advancement of electronic devices and computers, diagnosis of diseases by them have become prevalent named Computer Aided Diagnosis or CAD. Recently, melanoma detection has also been evoked by CAD, which has reduced the number of unnecessary biopsies and detection has also been faster, although not as accurate as biopsy.

In order to diagnose skin cancer speedily at the earliest stage and solve some of the above-mentioned problems, there have been extensive research solutions by developing computer-based systems using image pre-processing and machine/deep learning algorithms.

As per [18], the average accuracy of diagnosis using machine/deep learning models is found to be approximately 98.89% and the best is 100%. The machine-assisted diagnosis developed system will overcome the problem of delay, accuracy, and scarcity of dermatologists in public health.

1.2 Motivation

Out of the generally occurring skin cancers, Melanoma remains to be the most dangerous type of skin cancer. Its detection in early stages is vital for survival, hence Computer Vision techniques are proved to be useful to detect Melanoma in early stages. Furthermore, any of the current attempts at automating the process have not been intuitive enough for actual use by Dermatologists in clinics and also there is a good survival percentage for melanoma if it is identified early and treated appropriately. Reducing mortality can be achieved in part by using accurate screening to detect melanoma early and prolongation of patients' survival. Hence, amalgamation of computer vision techniques is intended to be done along with Deep Learning to detect Melanoma in early stages to save life.

1.3. Problem Definition

Detection of Melanoma skin cancer using image processing techniques, deep learning algorithms like AlexNet, Resnet50 and EfficientNetB7 by taking images of lesions as input through local application.

2. Literature Review

According to Adegun and Viriri (2020) [2] until now, several computer-aided diagnosis and detection systems developed in the past. The complex visual qualities of the skin lesion photographs, such as jagged edges and uneven features, have impeded their effectiveness. To get beyond these restrictions and enable automatic melanoma lesion recognition and segmentation, a deep learning-based approach was put forth. A refined encoder-decoder network is suggested for effective feature extraction and learning. The system uses a multi-stage, multi-scale technique along with a softmax classifier to classify melanoma lesions pixel by pixel. They created a novel method known as Lesion-classifier, which uses the outcomes of pixel-wise classification to classify skin lesions as either melanoma or non-melanoma. Using the ISIC 2017 dataset, they obtained accuracy and dice coefficients of 95% and 92%. On PH2 datasets, accuracy and dice coefficients of 95% and 93% were attained.

The automatic skin lesion analysis of dermoscopy images is still a difficult problem, according to Song et al (2020) [8].

An end-to-end multi-task deep learning system for autonomous skin lesion analysis was proposed in this research. The suggested framework is capable of concurrently completing tasks for segmentation, classification, and skin lesion detection.

Data preparation is the first step in the proposed framework, where dermoscopy images with arbitrary sizes are fed as the inputs. It is then divided into: - Image Size Organization and zero-center Normalization. After data preparation, the processed images are sent to the deep learning model architecture. Feature pyramid network (FPN), region proposal network (RPN), and three convolution subnets make up the suggested model architecture. These subnets are utilized independently for segmentation, detection, and classification. The framework accepts images of any size as input and directly provides the melanoma kind, position, and boundary without requiring any additional post-processing activities.

Given that manual dermoscopy detection is heavily reliant on physicians' clinical experience and that the intricacy of dermoscopic images presents significant challenges for categorization, Gong, Yao, and Lin (2020) [4] suggested a decision-making technique in this model. Based on multiple pre-trained CNNs, the study combined many CNNs using block ideas, and then used multiple blocks to make decisions. The research used a total of 3 algorithms namely Decision fusion, StyleGANs and CNN. With the method proposed by the paper it was able to alleviate the uneven distribution of dermoscopic images, along with automatically classifying the dermoscopic images.

In this study, Naemm et al. (2020) [3] compares the accuracy of CNN classifiers when evaluated on unpublished datasets and analyze the classifiers. Out of the 5112 studies that were found, 55 reputable studies were chosen. This study's primary goal is to compile the most recent information from these studies and examine the available approaches for deep learning-based melanoma detection diagnosis. Furthermore, this research also proposed a taxonomy for melanoma detection.

According to Alizadeh and Mahloojifa (2018) [12] traditional Melanoma detection techniques, dermatologists use the biopsy method. This method has its own limitations as it involves pain, time and cost. It involves tissue removal and analysis. The main motive of this paper is that it introduced an application for Melanoma detection which is available on Android as well as iOS. The application used two methods for classification. SVM and Naive Bayes were the algorithms used. The accuracy and sensitivity of both the algorithms was quite high. On the other hand, the application was user friendly too. The final results were displayed on the smart- phone for the dermatologists to see.

According to Ashraf et al (2020) [10], deep learning algorithms are hampered by the restricted number of images available. Based on this line of inquiry, this work suggests an intelligent Region of Interest (ROI) based system that uses the transfer learning technique to distinguish between nevus cancer and melanoma. This paper proposed a fully automated transfer learning-based improved CAD solution to detect melanoma accurately. And also designed an augmentation-based CAD for melanoma to handle class imbalance The Kmean, CNN, and AlexNET algorithms were employed. The suggested method applies augmentation after using ROIs taken from the upgraded K-mean algorithm. After that, a transfer learning technique is used to classify these photos, producing very good results. Images based on Region of Interest were employed in the suggested approach to assist in extracting only discriminative characteristics.

According to Ali, Li, and Yang (2020) [1], early melanoma identification is critical for survival and subsequent therapy. The task involves categorizing the photographs as either positive or negative. With the aid of the ABCD (Asymmetry, Border, Colour, Diameter) rule and the application of several algorithms for the segmentation of provided image. Multilevel Otsu Thresholding was employed in this paper to achieve segmentation. Solution efficiency is raised via dynamic thresholding.

According to Yang et al. (2018) [7], 75% of people with melanoma die from the disease when it is discovered later on. Additionally, it may spread to other bodily parts. Regional Average Pooling, a weighted global average pooling operation, was proposed in this study. Classifiers can better focus on the region of interest with the use of this regional average pooling technique. RankOpt was utilized for the CNN model's post-processing. It strengthens the CNN model's resilience. A CNN of 50 layers deep, called ResNet 50, was employed. The picture can be divided into more than 100 categories by the pretrained network. ResNet 50 increased the model's accuracy.

Ahn et al. (2017) [6] addressed in this study the challenges that traditional segmentation techniques encounter in situations such as blurry lesion borders, uneven background, etc. This study presented a computer-aided diagnosis method that uses the RSSLS framework and saliency-based lesion segmentation technique on dermoscopic pictures to detect and classify melanoma skin cancer. For accurate detection, they employed the Robust-Saliency based skin lesion segmentation (RSSLS) framework. To put it briefly, a computer application-based approach was created to accurately classify skin cancer via image segmentation.

Walaa Gouda and others [13] used deep learning models such as CNN, Resnet50, Inception Net v3 and Inception Resnet for classifying skin images into melanoma or benign. The authors used ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) as a pre-processing step for improving the quality of images before classification. The authors achieved 83.2% accuracy rate from CNN, 83.7% from Resnet50, 85.8% from InceptionV3, and 84% from Inception Resnet on ISIC 2018 dataset.

According to Qasim Gilani, S., Syed, T., Umair, M [15], spiking neural networks are widely used for classification of skin cancer. They employed deep spiking neural networks using the surrogate gradient descent method to classify images into melanoma/non-melanoma on ISIC 2019 dataset. An overall accuracy of 89.57% and an F1 score of 90.07% was achieved using the proposed spiking VGG-13 model.

T. Imran and others [14] used a pre-trained CNN with ACO (Ant-Colony Optimization) for the feature selection phase. The authors also used a variety of pre-processing steps such as histogram equalization, gamma correction, and white balance adjustment, to enhance visibility, quality, and make color corrections. The highest accuracy of over 98% was attained in addition to training time being reduced and prediction speed maintained.

After reviewing fifteen studies, our study found that only one or two of them used a local application to identify melanoma skin cancer. Furthermore, machine learning or deep learning were employed in the majority of the studies. As a result, this gap is located and closed by employing local application and machine learning and deep learning techniques in this study. It would be more user-friendly in this approach.

3. Methodology

It was a local application which can be easily used by doctors and patients. It classified skin into either Non-melanoma Lesion or Melanoma Lesion by internally using image classification algorithms. User uploaded the image of the skin on application and after classification, user got the result on the application. Eg-It differentiated between lesions of same structure by detailed analysis of images and by some data. Local application took input images either through camera or directly from local storage (e.g. Gallery). Local application differentiated images into 2 classes Melanoma or Non-Melanoma affected skin. And finally the output was shown to the user on screen.

Features-:

i) Login-:

The login feature allowed registered users to login to the app to access all of the features that their account gives them access to. The login screen contained a textbox to enter login credentials such as username and password. The login screen also contained a buttons named as register, login and forgot passwords.

ii) Registration-:

If the user wanted to create a new account then the user used this feature. With the help of this feature, system got all necessary information of the user which is required for future use. In this feature there was textbox for name, email address, mobile number, birth date and password for taking input data. There was also one button named register information.

iii) Select Image from Device-:

Select image from device feature is for selection of image which is present in device where application is running to upload this image on server to get result from server. In this feature there is one button named as select image from device.

iv) Preprocessing of Image-:

This is server-side feature. This feature includes intensity adjustment, brightness thresholding and detecting edges. This feature is using OpenCV library to fulfill these requirements. This feature also includes hair removal sub-feature. With Otsu's method or any other approach, such as "local thresholding" or even "local histogram equalization and then global thresholding," this feature uses adaptive local thresholding to discover the hair region.

v) Segmentation of Image-:

This segmentation feature takes input image from pre-processing model and performs segmentation on image using OpenCV library. Segmentation divide image into various part called segments (like background of lesion and actual part of lesion). For this segmentation feature uses thresholding methods like Otsu's thresholding method for segmentation of image.

vi) Classification of Image-:

This feature is responsible for classification of a given input image from segmentation model into two classes (melanoma positive / melanoma negative). This feature uses AlexNet, ResNet 50 and EfficientNetB7 for classification of images. This network uses ISIC 2016 dataset for training of model.

vii) Get Result-:

Get result feature is for getting result to user from server whether result of input is positive or negative. This feature has one single get result feature button

The system architecture diagram is depicted in the following Fig 1.

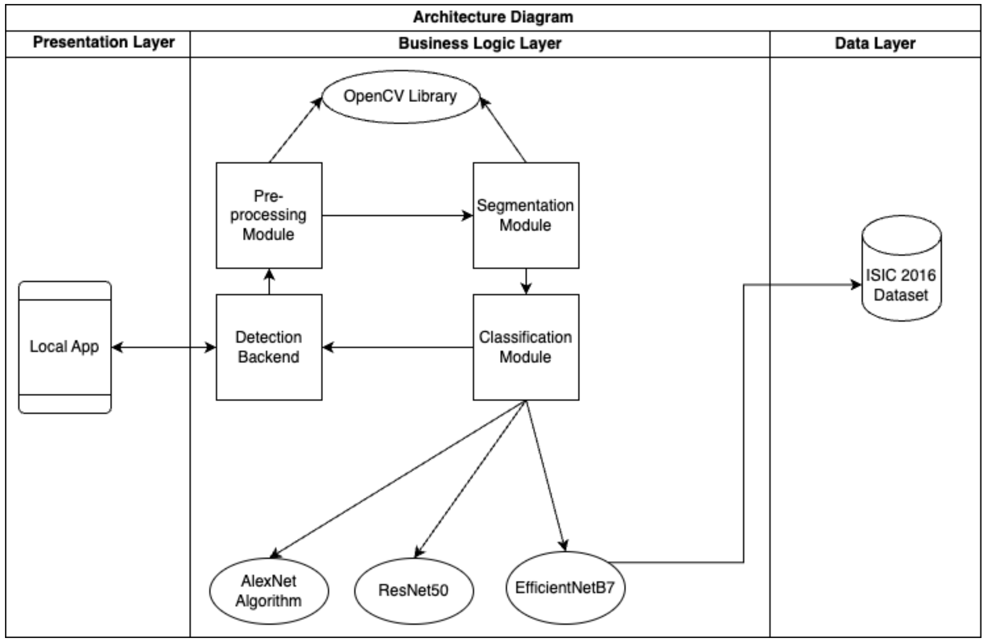


Fig. 1 System Architecture Diagram

The use diagram for the system is given in following Figure 2.

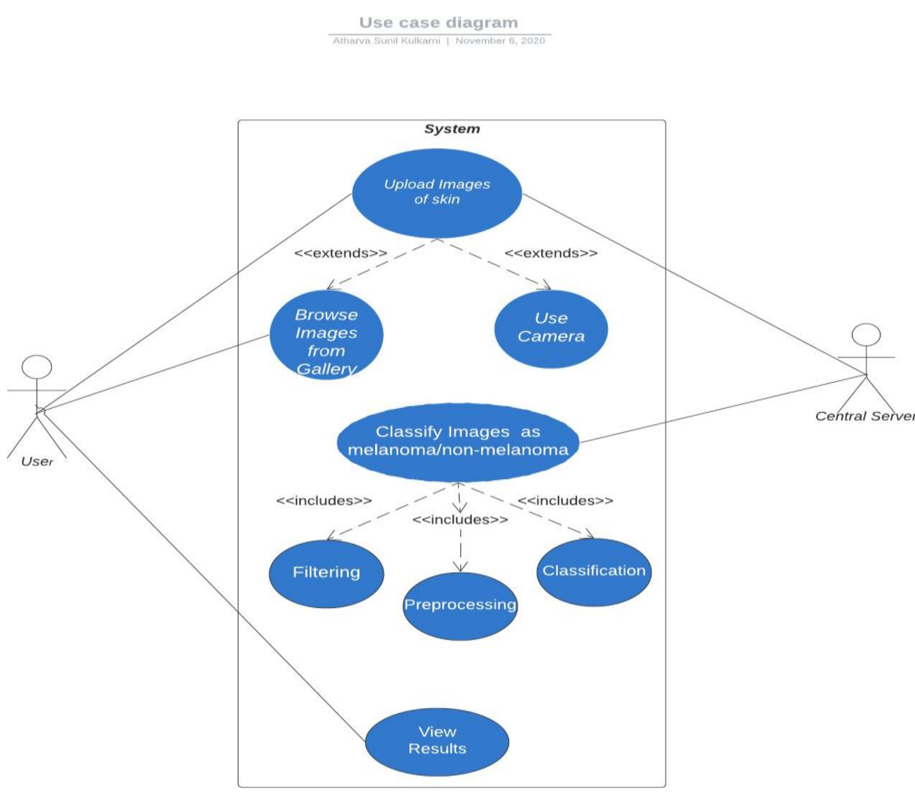


Fig. 2 Use Case Diagram

4. Implementation

OpenCV was used to preprocess the images, segment the images to feature of interest and then ML algorithms such as AlexNet, Resnet50 and EfficientNetB7 were used to classify these images into Melanoma/non-melanoma. The results were displayed to the user through the UI.

The implementation is carried out from scratch without using any open-source libraries.

5. Results and Discussion

The following test case table shows the different scenarios tested for our application-:

Test Case No	Test Case	Actions	Expected Outcome
1	Login with valid credentials	1. The user will first be taken to the login page. 2. The user must input their password and user name in the designated textbox. 3. At last, he or she will press the submit button.	He or she will be taken to the home page for the right credentials after clicking the submit button.
2	Login with invalid username and valid password	1. The user will first be taken to the login page. 2. The user must input their password and user name in the designated textbox. 3. At last, he or she will press the submit button.	When one hits the submit button, an error message stating that your username is wrong will appear on the login page.
3	Login for valid username and invalid password	1. The user will first be taken to the login page. 2. The user must input their password and user name in the designated textbox. 3. At last, he or she will press the submit button.	When one hits the submit button, an error message stating that your password is wrong will appear on the login page.
4	Login for invalid username and invalid password	1. The user will first be taken to the login page. 2. The user must input their password and user name in the designated textbox. 3. At last, he or she will press the submit button.	When one hits the submit button, an error message stating that your username and password are wrong will appear on the login page.
5	Register with all details validated	1. The user will first be taken to the login page. A link for new users will be available here. 2. The user will be taken to the registration page after clicking the link. 3. Entering the essential user information here, he or she will press the register button.	All of the fields will be evaluated in accordance with their respective rules after the register button is clicked. In this instance, registration will be accepted, and the user will be taken to the login screen.
6	Register with invalid username	1. The user will first be taken to the login page. A link for new users will be available here. 2. The user will be taken to the registration page after clicking the link. 3. Entering the essential user information here, he or she will press the register button.	All of the fields will be evaluated in accordance with their respective rules after the register button is clicked. In this instance, registration will not be accepted, and the user will be shown an error window saying username as invalid.

7	Register with invalid password	1. The user will first be taken to the login page. A link for new users will be available here. 2. The user will be taken to the registration page after clicking the link. 3. Entering the essential user information here, he or she will press the register button.	All of the fields will be evaluated in accordance with their respective rules after the register button is clicked. In this instance, registration will not be accepted, and the user will be shown an error window saying password as invalid.
8	AlexNet, Resnet50 and EfficientNetB7 for image classification on training data.	1. Using AlexNet, Resnet50 and EfficientNetB7 on train data, ML classification algorithms will identify the image as melanoma/non-melanoma after applying preprocessing and image segmentation. 2. The back-end will perform the classification, and the front-end will get the results.	Expected Train Accuracy: 89% for AlexNet, 100% for Resnet50, and 83% for EfficientNetB7.
9	AlexNet, Resnet50 and EfficientNetB7 for image classification on test data.	1. Using AlexNet, Resnet50 and EfficientNetB7 on test data, ML classification algorithms will identify the image as melanoma/non-melanoma after applying preprocessing and image segmentation. 2. The back-end will perform the classification, and the front-end will get the results.	Expected Test Accuracy: 78% for AlexNet, 82% for Resnet50, 83% for EfficientNetB7.
10	Receive an Unselected Image in the Result	1. Upon successful login, the user will see an image upload button on the main page. 2. The user will be presented with two choices: gallery or camera. 3. The user will not upload a picture; instead, they will click the "get result" button.	An error message indicating "image not selected" will appear when you click the "Get Results" button.
11	Receive a selected Image in the Result	1. Upon successful login, the user will see an image upload button on the main page. 2. The user will be presented with two choices: gallery or camera. 3. The user will not upload a picture; instead, they will click the "get result" button.	The user will get results after clicking the "get result" button, with the status of skin cancer being "melanoma/benign."

6. Screenshots of the application

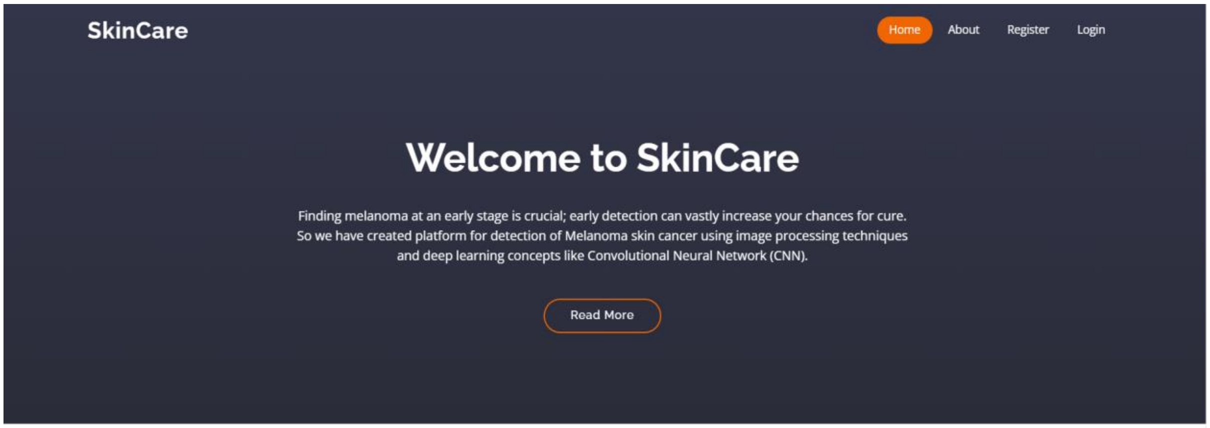


Fig. 3 Home Page

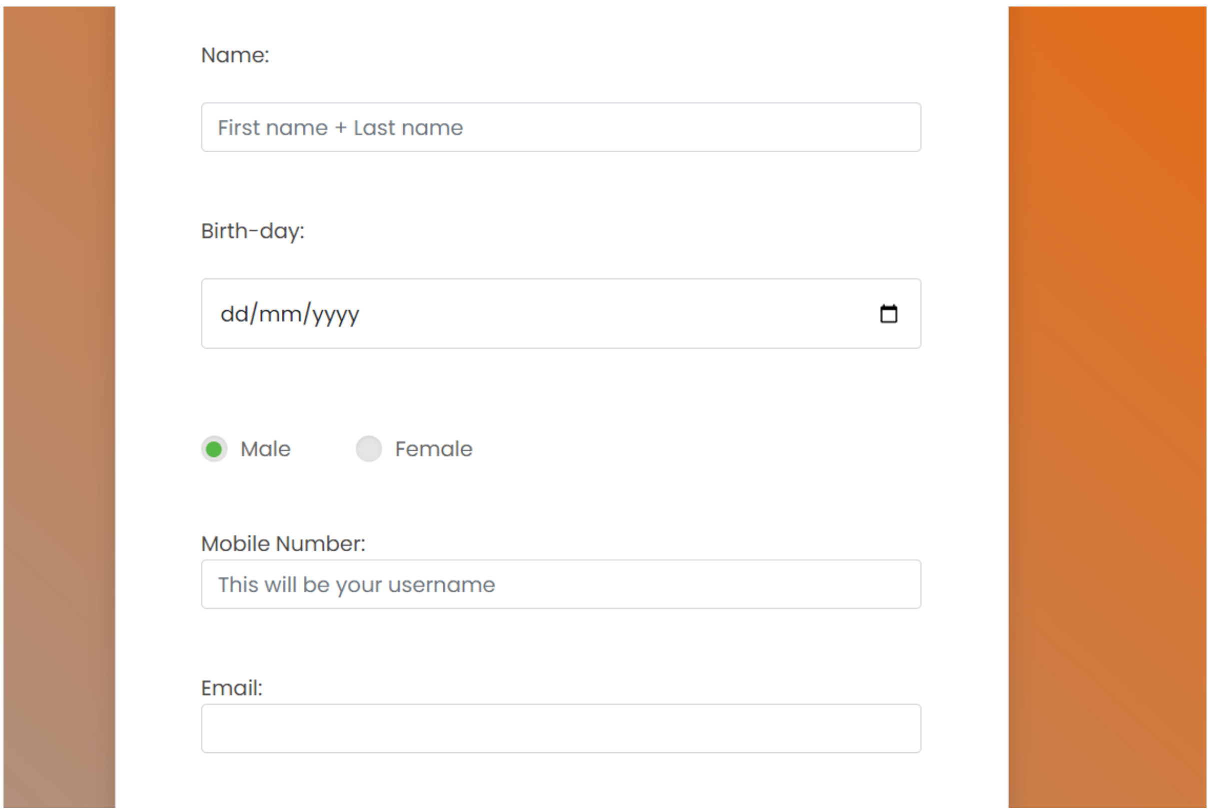


Fig. 4 Registration Page

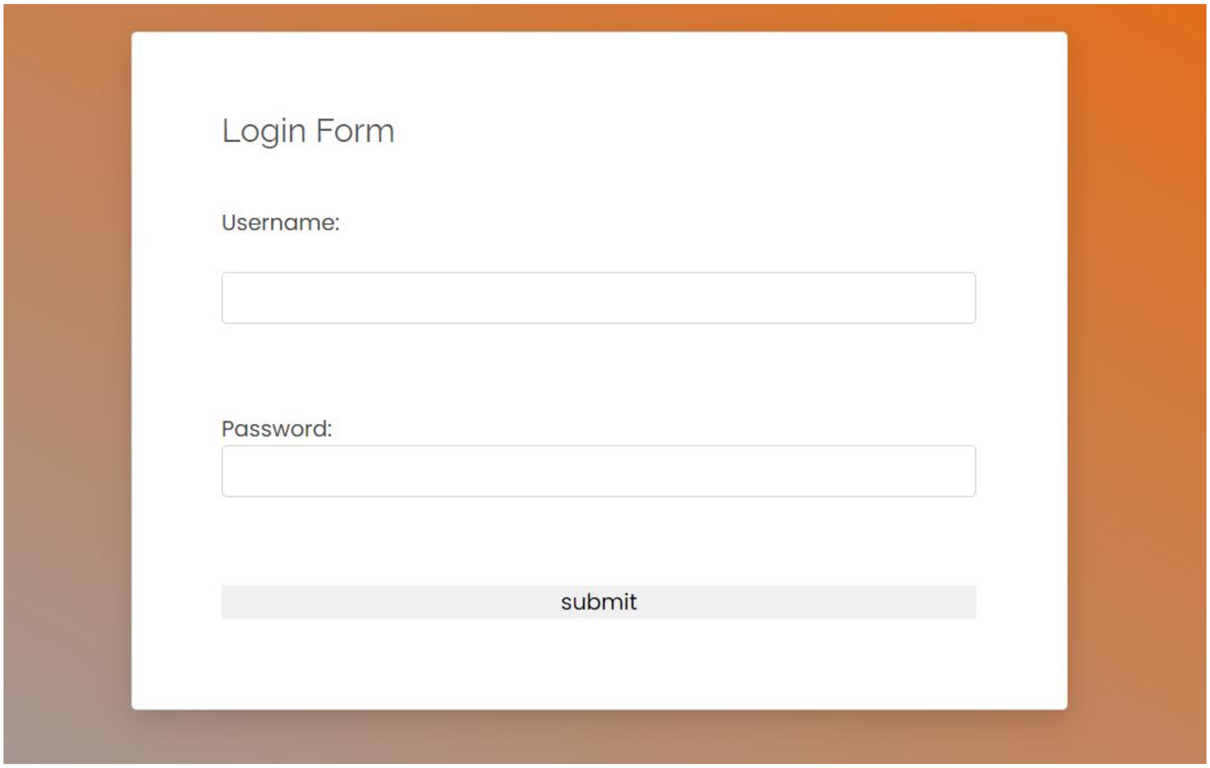


Fig. 5 Login Page

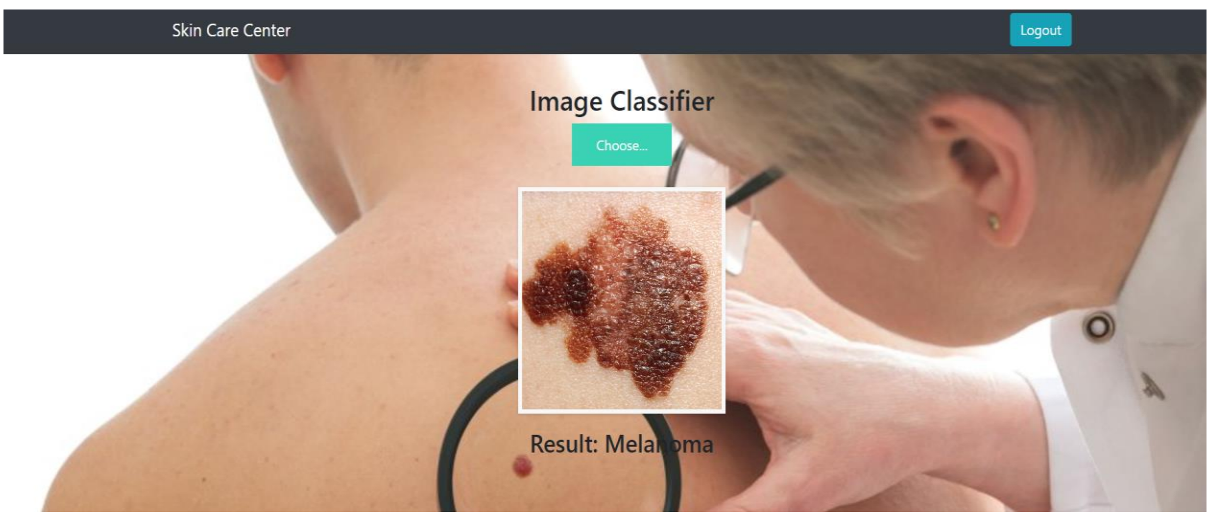


Fig. 6 Melanoma Classification of an input image

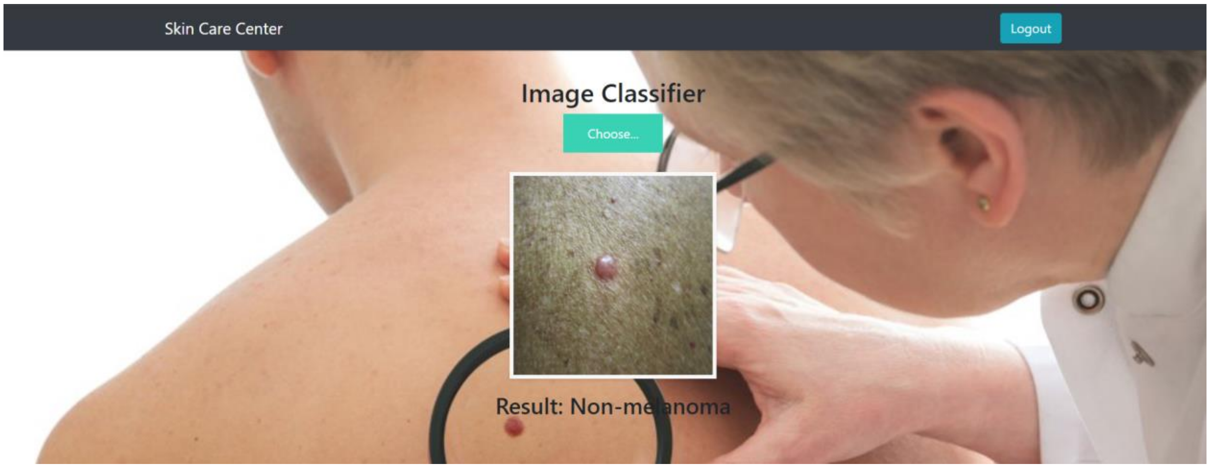


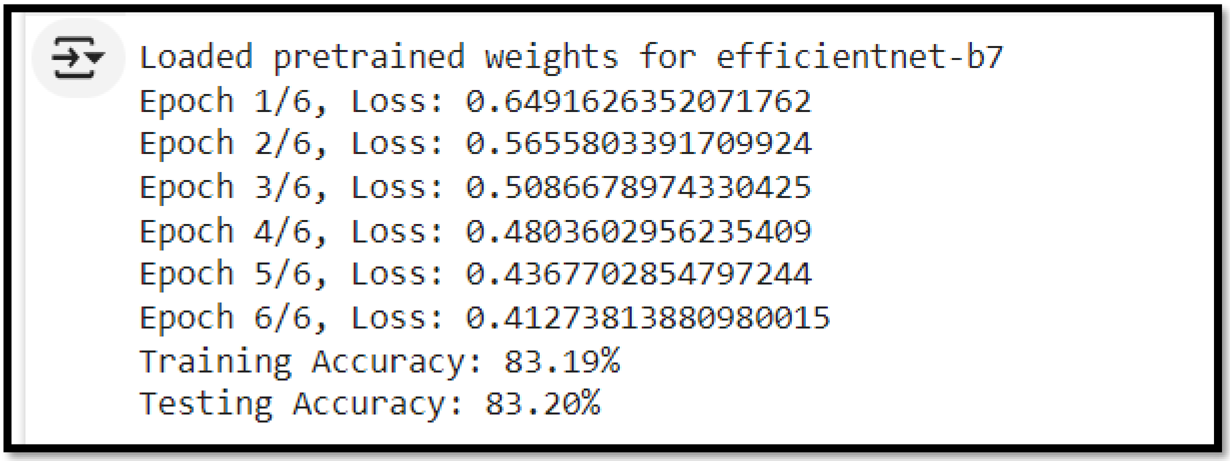
Fig. 7 Non-Melanoma Classification of an input image

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and ma
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights
  warnings.warn(msg)
Epoch 1/6, Loss: 0.5313665103167295
Epoch 2/6, Loss: 0.4191095223650336
Epoch 3/6, Loss: 0.3759641223587096
Epoch 4/6, Loss: 0.3467765301465988
Epoch 5/6, Loss: 0.3207173948176205
Epoch 6/6, Loss: 0.3021239209920168
Training Accuracy: 89.44%
Testing Accuracy: 78.52%
```

Fig. 8 Accuracy of the model for AlexNet

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and m
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights
  warnings.warn(msg)
Epoch 1/6, Loss: 0.5811197785660625
Epoch 2/6, Loss: 0.37781568337231874
Epoch 3/6, Loss: 0.26911873277276754
Epoch 4/6, Loss: 0.16484620585106313
Epoch 5/6, Loss: 0.07768207765184343
Epoch 6/6, Loss: 0.03624134580604732
Training Accuracy: 100.00%
Testing Accuracy: 82.81%
```

Fig. 9 Accuracy of the model for Resnet50



```
Loaded pretrained weights for efficientnet-b7
Epoch 1/6, Loss: 0.6491626352071762
Epoch 2/6, Loss: 0.5655803391709924
Epoch 3/6, Loss: 0.5086678974330425
Epoch 4/6, Loss: 0.4803602956235409
Epoch 5/6, Loss: 0.4367702854797244
Epoch 6/6, Loss: 0.41273813880980015
Training Accuracy: 83.19%
Testing Accuracy: 83.20%
```

Fig. 10 Accuracy of the model for EfficientNetB7

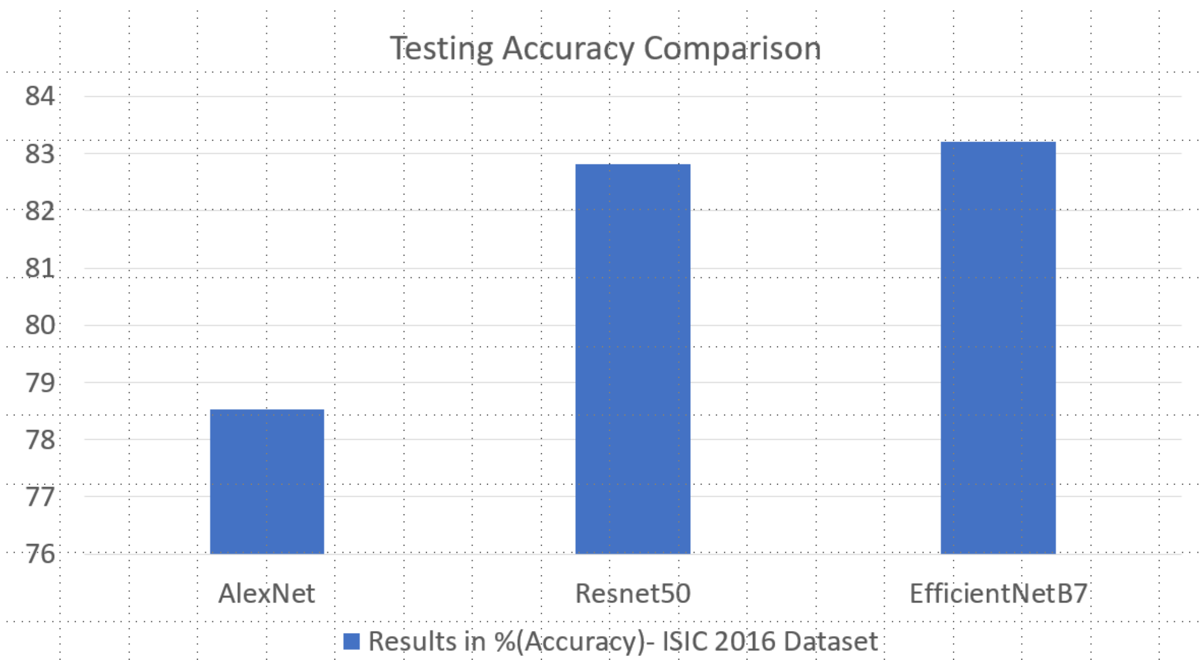


Fig. 11 Testing Accuracy Comparison Chart

The above figure shows the performance of 3 models on testing data. It can be seen that EfficientNetB7 is the winner with 83% testing accuracy followed by Resnet50 and AlexNet. This is quite evident given the extra number of hidden layers and the use of compound scaling method in EfficientNetB7 to optimize the network's depth, width, and resolution simultaneously.

7. Conclusion

Detection of melanoma cancer in the early stage is very important for further treatment of cancer. The solution proposed was for classification of melanoma cancer images by using deep learning algorithms like AlexNet, Resnet50 and EfficientNetB7 along with image pre- processing with the help of OpenCV module. An overall testing accuracy of 83.2% was achieved for EfficientNetB7 Algorithm which was a considerably high accuracy given the overall complex task of cancer detection. The other algorithms such as Resnet50 achieved testing accuracy of 82% and AlexNet of 78% was quite good given the complex nature of image classification.

8. Limitations

1. The application requires good internet connectivity. Slow internet can increase delay in outcome.
2. Users can only upload one image at a time, no more than that.

9. Future Work

1. Accuracy can be improved by experimenting with the hyperparameters, learning rate and optimizer and hence reduce the number of false positives/negatives.
2. Feature of uploading multiple images at a time can be added since there can be multiple areas on the skin where cancer can be caused.
3. Features can be extracted from a pre-trained neural network and then classification models like SVM can be trained on it.

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