DETECTION OF SKIN CANCER USING DILATED RESIDUAL LEARNING NETWORKS

A PROJECT REPORT

Submitted in partial fulfillment of the requirement for the award of the Degree of

BACHELOR OF TECHNOLOGY
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by

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CERTIFICATE

This is to certify that the Project work titled "***Detection of skin cancer using dilated residual learning networks***" that is being submitted by ***Nagharjun M (18BLC1129), Gugan S Kathiresan (18BLC1089)*** and ***Anirudh M (18BLC1135)*** is in partial fulfillment of the requirements for the award of **Bachelor of Technology in Electronics and Computer Engineering**, is a record of bonafide work done under my guidance. The contents of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma and the same is certified.

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ABSTRACT

Skin cancer is one of the common forms of cancer. Early detection of skin cancer is essential to provide the right treatment to the patient affected by it. There is ample amount of research conducted to segment skin lesions and classify skin cancer using skin lesion images. Nevertheless, due to the high number of classes of various skin lesions, size and shape difference in lesions, and noise parameters such as hair and poor lighting hinder the performance of segmentation and classification. In this research, we propose a pipeline of both segmentation and classification with noise removal in the preprocessing stage. First, the image undergoes preprocessing where unwanted hair in the images is being removed using appropriate filters. Second, the image is being segmented using Dilated Residual Networks. Third, the segmented images are used for classification of skin cancer. Performance comparisons of our segmentation method has been done with other popular models such as UNet, PSPNet, LinkNet. After segmentation our proposed model achieves a Dice Score of 89.69% and IoU Score of 82.11%. Our classification accuracy, precision, recall, and F1 Score are 88%, 88.28%, 88.29%, and 88.29%.

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LIST OF ABBREVIATION

ABBREVIATION	TITLE	PAGE NO.
AKIEC	Actinic Keratoses and Intraepithelial Carcinoma/Bowen Disease	18
BCC	Basal Cell Carcinoma	18
BKL	Benign Lesions of the Keratosis Type	18
DF	Dermatofibroma	18
MEL	Melanoma	18
NV	Melanocytic Nevi	18
VASC	Vascular Lesions	18

CHAPTER 1
INTRODUCTION

A study conducted by the Indian Council of Medical Research (ICMR) in the year 2021, reported that over the recent years vulnerability to skin cancer has increased in people belonging to specific regions of the India [1]. One of the causes of skin cancer is attributed to occupations that spend more time in the outdoor environment [2]. In 2021, skin cancer was considered the most common form of cancer in the United States of America [3]. It has also been estimated that non-melanoma skin cancer is the leading cancer in terms of cases among men in Oceania, Australia, and North America and among women in Oceania and Australia [4]. While skin cancer is characteristically harmful to European skin profiles, recent studies report increasing cases and severity of skin cancer in other parts of the world as well.

Skin cancer can be broadly classified in two types, non-Melanoma skin cancer (NMSC), and Melanoma skin cancer (MSC). MSC is comparatively less prevalent in developing countries than the common NMSC. However, the health risk and mortality rate in MSC is much higher [3]. It is expected that, the deaths caused by melanoma is expected to increase by 6.5% from 2021 to 2022. The causes behind skin cancer vary in source, but are common in terms of its composition of radioactive and radiation compounds. Ultraviolet radiation, Plutonium, Arsenic and Cigarettes are considered as group 1 skin cancer-causing agents. Agricultural workers are susceptible to compounds like arsenic due to its presence in pesticides used regularly in farms [2]. This leaves farmers who work for long hours in the sun and exposed to pesticides at a higher risk.

Detection of skin cancer in its preliminary stages is of vital importance. Early detection of melanoma indicates a positive 5-year survival rate is 99% [4]. Of the existing methods, skin biopsy is the most recommended method to detect the presence of skin cancer cells [5]. It involves a procedure to remove skin cells and samples, and testing them under laboratory conditions for detecting the presence of skin cancer. Skin biopsies are of three types: Shave Biopsy, Punch Biopsy, and Excisional Biopsy. These biopsies vary in terms of the instrument used and the requirement of the epidermis, dermis, and superficial fat. If diagnosis and treatment is not started withing the first 30 days the risk of death increases by 5%, and further increases by 41% after the first 119 days [6]. As a result, without initial diagnosis of the disease, patients are more likely to experience problems such as bleeding, bruising, scarring, infection, and allergic responses.

In addition, skin biopsies are prone to human error as well. Skin biopsy pathways and wrong-site surgeries are such common errors. In the whole process of skin biopsy, it has been estimated that there are 20 steps approximately. Each of the steps has an error rate of >0. Even if each step is 99% accurate in its tasks, the overall accuracy comes down to 82% [7]. With these risks and delays in mind, automated detection and classification of skin lesions would be pivotal to improving diagnostic performance.

In this case, leveraging the power of deep learning can potentially act as a viable diagnostic assistant, eliminating the need for the risk involved in skin biopsy. Image based detection is a solution to both the risks involved, and can save valuable time. Thus, a computerized model can provide a much faster and more accurate prediction and detection of skin cancer. It can relieve the pressure mounted on medical officials and focus on only the essential steps in diagnosis.

In this study, we propose a novel pipeline to provide accurate and precise classification of skin lesions for dermoscopy images. The proposed model is tested on real-world datasets that are verified by experienced dermatologists. The goal behind this research is to provide a solution to precisely classify multiple classes of skin lesions with high precision. By creating a precise automated solution, reliable early diagnosis can be achieved with low-risk.

CHAPTER 2

RELATED WORKS

The task of classifying skin lesions from dermoscopy images has been attempted in various studies. These studies have been categorized based on the employed approaches that are similar to our proposal. The majority of works reviewed utilized real-world skin dermoscopy datasets that are concurrent with the data used in the proposed work. The categories include works that have employed classification [10-27] and segmentation techniques [28-31].

2.1 Classification techniques

The classification approaches can be further categorized into transfer learning and pretrained approaches [10-16], custom architectures and federated learning [17-19], hybrid and multi-stage models [20-25], RCNN architectures [26-27].

Transfer learning is a popular approach employed in deep learning research for their benefits in computational efficiency and performance. Modified transfer learning models have been commonly used to leverage these benefits. The MobileNet architecture is a popular implementation, as seen in studies by Anand et al. [10], Agrahari et al. [11], and Sae-Lim et al. [12]. Calderón et al. proposed a novel bilinear CNN architecture in an attempt to improve the classification performance by two-fold [13]. The two models combine ResNet-50, and VGG-16 networks.

Residual networks are generally employed for their robustness against the vanishing gradient problem. The ResNet architecture and its variants are popular in this regard. Khan et al. employed a pretrained ResNet-50 and ResNet-101 models in collaboration with Support Vector Machine classifiers and achieved an overall classification accuracy of 89.8% [14]. In an attempt to enhance diagnostic accuracy, Thomas et al. combined patient metadata along with the classification performance of pretrained models [15]. The GoogleNet, DenseNet-201 and Inception-Resnet-v2 architectures reported a 10% increase in accuracy when patient metadata was included to image features. In their study, Karthik et al. proposed a novel implementation of the EfficientNetV2 architecture with an attention-block. This proposed Eff2Net allowed for a model with lower parameters, and improved overall performance [16].

Deployable and explainable solutions are part of a recent trend in deep learning research. Waweru et al. employed the pretrained DenseNet-201 architecture [17] where their solutions are customized and crafted for deployment as web services or mobile applications. However, custom architectures are often employed as novel approaches to solve specific facets of a larger problem statement. Huo et al. introduced a fully deployed solution that employs a customized CNN architecture, classifying skin lesions at an accuracy of 75% [18]. Polap et al. proposed a federated learning approach that combines a range of deep learning-based classifiers [19]. These classifiers include, custom CNN architectures, and state-of-the-art models like MobileNet.

Hybrid and muti-stage models are often employed to harness the power of combining multiple architectures and their benefits. These combinations can span across other domains as well. For example, the study by Khan et al. introduced a IoT based framework with multi-modal skin lesion classification capabilities [20]. The model included dedicated custom segmentation and classification stages. Similarly, Mahbod reported a maximum classification accuracy of 89.8% by combining images that were pre-processed by subtracting manually created masks [21]. Khan et al. took a novel high dimension contrast transform (HDCT) based saliency segmentation stage to segment skin lesion images [22]. These segmented images were further classified by a pretrained DenseNet model stage. In their proposed hybrid model, Cengil et al. combined paradigm machine learning classifiers with pretrained deep learning architectures [23]. The best performance of accuracy 77.80% was reported by an AlexNet-SVM hybrid.

Fusion-based and extreme learning machine approaches make up a small niche in skin lesion classification techniques. Employing a fusion-based approach, Khan et al. proposed two stages with pretrained DenseNet and MobileNet models [24]. The extracted features were combined using a multimax coefficient correlation method and further classified using a multiclass extreme learning machine classifier. Similarly, the correlation and extreme learning techniques were also employed in the work by Khan et al., combined with an improved moth flame optimization (IMFO) algorithm [25]. The IMFO algorithm extracted the dominant features from images segmented by Deep Saliency Segmentation method.

RCNN architectures are effective in bounding box and pixel-wise localization tasks with classification as well. In their study, Khan et al., utilized a Mask-RCNN architecture with a ResNet-50 backbone and softmax classifiers [26]. The model yielded an accuracy of 86.5%. Goyal et al. proposed an ensemble approach that adds the features extracted by Mask-RCNN and DeeplabV3+ to generate a combined segmentation mask [27]. The employed ensemble reported an accuracy of 94.1%.

2.2 Segmentation techniques

Of the collected works that have taken an exclusively segmentation approach, a wide range of techniques have been employed. While these works vary in datasets used, they are common in their attempts to accurately segment skin lesions from dermatoscopy images. Mainly proposed as an assistive mechanism to doctors in real world medical scenarios, these works can be further categorized based on the methods employed. These categories include attention-based techniques [28-29], pretrained and paradigm architectures [30-31].

In the study by Sarker et al., the proposed SLSNet model aimed to be lightweight solution designed for emergency medical applications. The model applied channel attention mechanisms to improve localization, similar to previous works. By employing a Generative adversarial network (GAN) model and a multiscale aggregation mechanism, the overall effects of noise were reduced [28]. In a very similar approach with a GAN based model that combines multiscale aggregation and 1-D channel filtering. Singh et al. proposed the FCA-Net [29]. The FCA-Net reported a better IoU score than the SLSNet, however trained with a larger dataset.

Employing pretrained and paradigm architectures allow for enhanced performance and quicker computation times. There are a range of works that customize popular architectures like UNet and UNet++. For example, Yang et al. proposed the EfficientUNet++ that combine the UNet++ architecture with an EfficientNet backbone [30]. By introducing more skip connections, the retention of information is achieved across all layers, improving overall segmentation. Another such architecture is the YOLO architecture, popularized by its single shot learning technique. This attributes to its fast computation, suitable for real world medical emergencies. In the model proposed by Unver et al., the YOLOv3 model was combined with the GrabCut algorithm [31s]. In an overall four stage implementation, the GrabCut algorithm improved the localization in the post-processing phase along with morphological operations as well.

CHAPTER 3
RESEARCH GAPS AND CONTRIBUTIONS

This research aims to address the following research gaps in skin lesion localization and classification.

- Skin lesion can be categorized into multiple types. The discriminative features of each lesion type present themselves in varying shapes and sizes. However, the color scheme and texture are similar. Thus, there is a considerable risk of false positives. Balanced performance between classes may not be the case in simple CNN architectures and transfer learning methods.

- A majority of the works employed the dataset without performing initial augmentation. However, pixel-wise augmentation has been used scarcely. This augmentation could possibly be beneficial to improving inter-class accuracy with large number of dataset categories.

- Of the observed studies, the focus dedicated to accurately detecting the morphology in the lesion is less. Comparatively there is much focus dedicated to semantic classification of the lesions. While classification is the end goal, automated classification is driven by accurate feature extraction. Hence, accurate segmentation of the features is essential to the classification process.

- Most works employ binary classification or tasks with lesser number of classes of lesions. This is also done to ensure low-complexity models for easy deployment. In real-world scenarios, simple binary classification is not a holistic assistance to healthcare workers. In fact, it requires further human intervention to classify the specific category of the lesion. More focus must be granted to classifying specific classes of skin lesions, while maintaining moderate model complexity.

The research gaps that have been identified from the literature survey serve as the basis for this research. The proposed work looks to address these challenges, and provide solutions to it. The proposed solutions can be generalized as the following contributions,

- This study presents a three-stage pipeline for the classification of skin lesions. The stages include a pre-processing, segmentation, and classification stage.
- The pre-processing stage includes a custom combination of pixel-wise transformations (CLAHE Filter and Hue-Saturation Transform) and hair-filtering. By removing the occluding hairs and increasing the discrimination of lesion features, the overall precision of segmentation and classification is improved.
- The segmentation stage accurately localizes the edges and corners of the lesion. The segmented output acts as a precise basis for further classification. By performing this stage, only the necessary features are taken into learning for the classification task. For this, a novel residual dilated architecture is constructed with customized layers for best feature extraction.
- The proposed classification stage employs a noise robust loss function. The proposed function looks to reduce the impact of noise during the training of the classification stage.

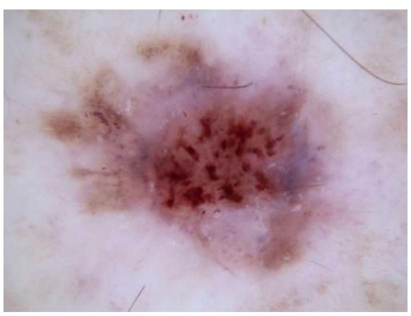
CHAPTER 4
PROPOSED WORK

4.1 Dataset Details

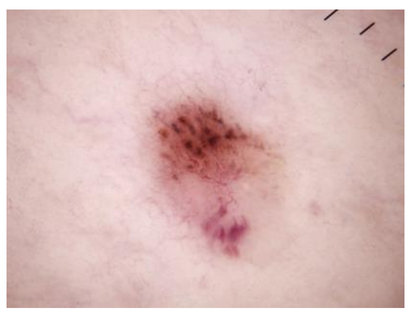
The dataset used for training is the HAM10000 dataset from the Harvard Dataverse. The dataset consists of multi-source dermascopic images of common pigmented skin lesions. The dataset contains a total of 10,015 Dermoscopic Lesion images that are in JPEG format. Additionally, binary segmentation masks are provided along with the images. The dataset consists of seven classes of skin lesions, which indicate the diagnosis of each of the input lesion images.

The classes are ‘MEL’ (Melanoma), ‘NV’ (Melanocytic Nevus), ‘BCC’ (Basal Cell Carcinoma), ‘AKIEC’ (Actinic Keratosis / Bowen’s Disease), ‘BKL’ (Benign Keratosis), ‘DF’ (Dermatofibroma), ‘VASC’ (Vascular Lesion).

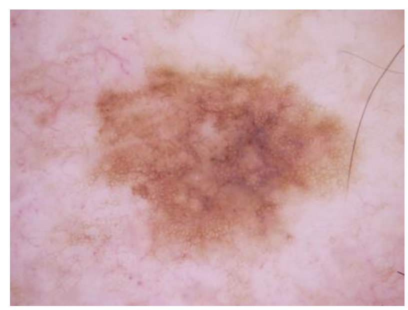
Samples from the dataset are visualized in Figure 4.1. and the dataset distribution per class is also shown in Figure 4.2. This figure also contains details about the balanced dataset employed. While the original dataset consisted of 10,015 images, the balanced dataset was of 46,489 images. Dataset balancing was performed to improve the overall classification performance. This ensured that there is equal representation of each label to the model. Balancing was performed by creating multiple variations of the images using geometrical image transformations.



AKIEC

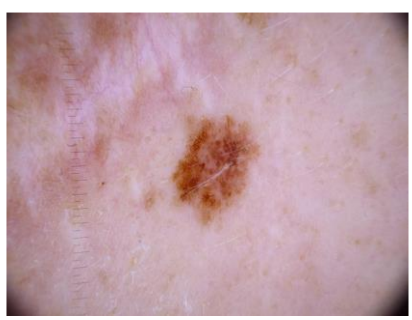


BCC



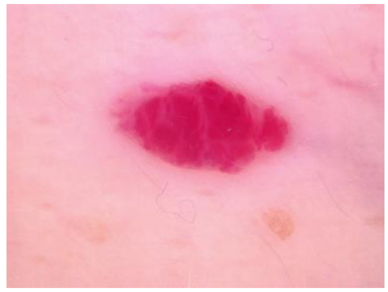
BKL

DF



MEL

NV



VASC

Fig 4.1. Examples of samples belonging to each class of the HAM10000 dataset

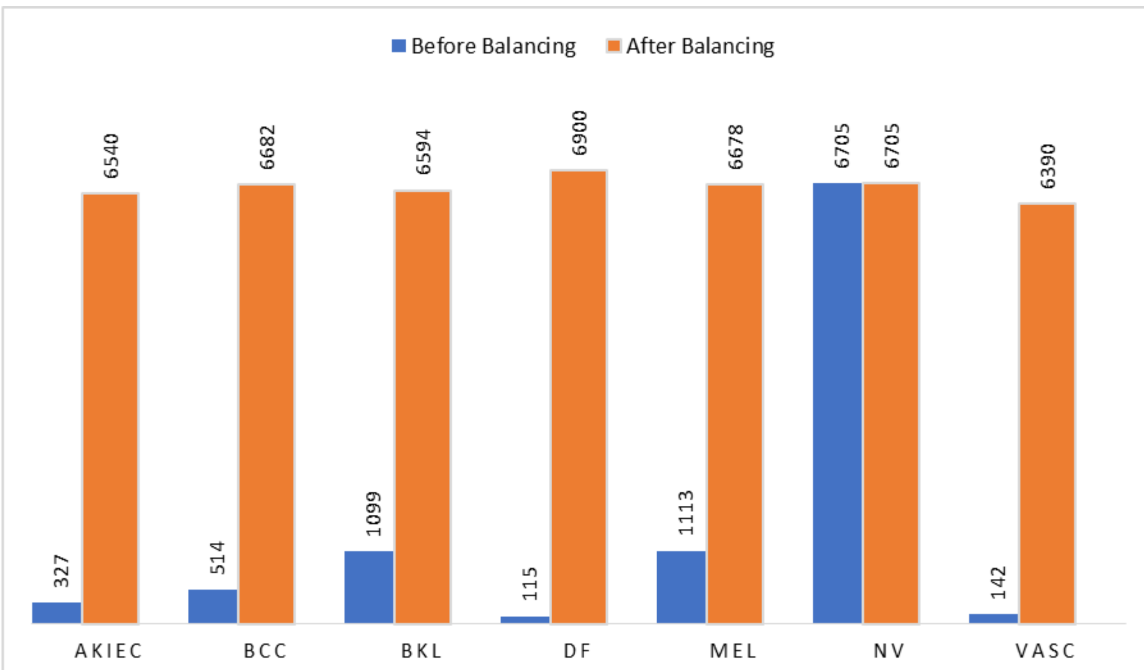
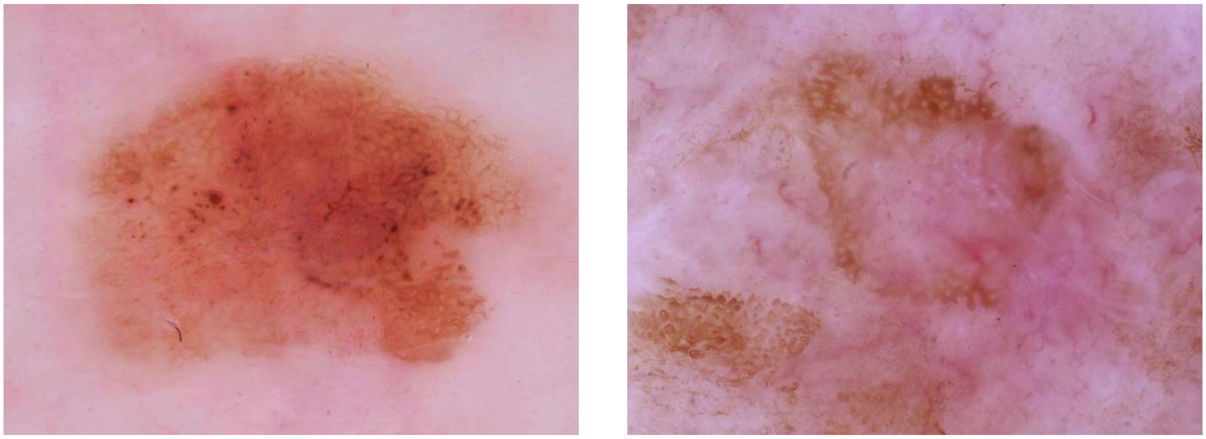


Fig 4.2. Native vs Balanced Dataset distribution across all classes

4.2 Pre-processing and Augmentation Used

Skin lesions manifest on the visible layer of the skin. They vary in terms of their shape, color and texture. However, the distinction between these lesions on dermatoscopy images is low, due to the minimal differences in color, and similar shape. A representation of this similarity can be seen in Figure 4.3 a and 4.3 b, of the “Melanoma” class and “Actinic keratoses” class respectively. It is notable to mention that Melanoma are cancerous lesions, while Actinic keratoses are not cancerous. This reiterates the significance of having distinct features between classes.



a) b)

Fig 4.3. a) Melanoma Sample and b) Actinic keratoses Sample

In addition to this, dermatoscopy images often have lesions occluded by the hair on the patient's skin. Occluding hair can impact the overall features of the lesion and its extraction. This can be seen in an example in Figure 4.4.

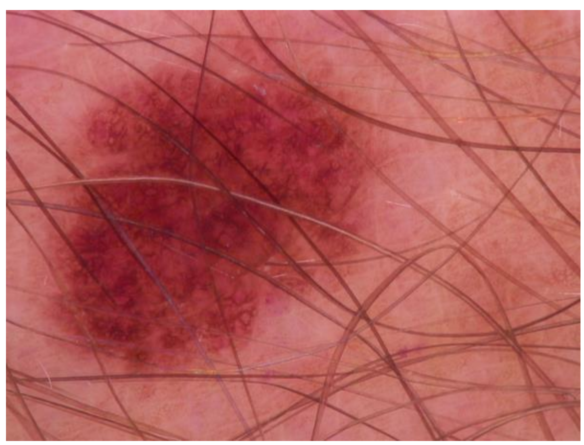


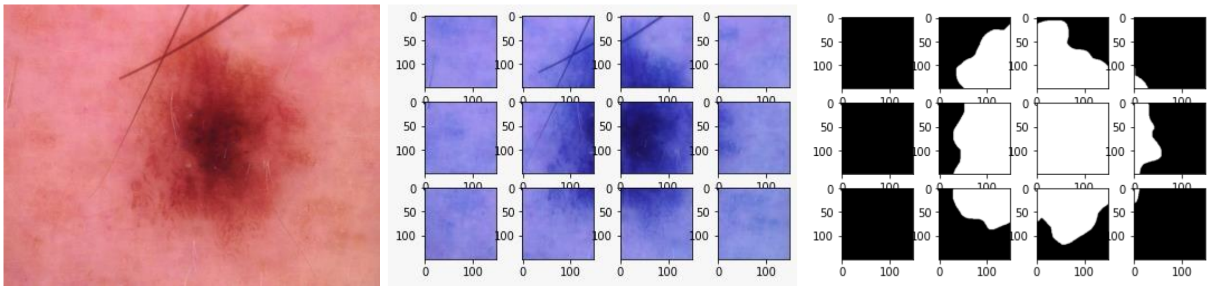
Fig 4.4. Melanocytic Nevus Sample with occluding hair

Hence, there is scope for improvement in terms of the distinctiveness of features, and the occluding hair. By applying specific pre-processing techniques to improve the distinctness of the features and to remove the occluding hair, better performance is expected. This is tested in the proposed work in Stage 1.

Stage 1 involves pixel-wise augmentation and morphological filtering to achieve this performance improvement.

4.2.1 Patching of Images

The images are split into 12 different patches of equal size before feeding it into the segmentation model. After the patched images undergo segmentation seperately, it is repatched to get the final segmented image. Figure 4.5 a represents the original image which is being patched which is represented by Figure 4.5 b. Finally, Figure 4.5 c is the output of the segmentation model which will be repatched to get the whole segmented image.



a) b) c)

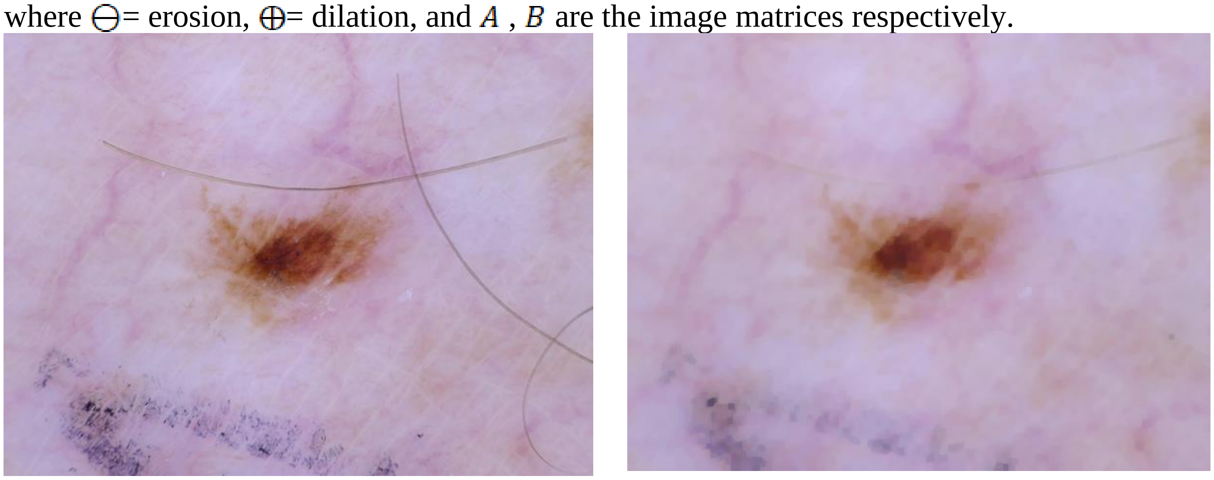
Fig 4.5. a) Original Image b) After Patching c) After Segmentation

4.2.1 Hair Filtering

A combination of morphological operations was applied on the native dataset. The combination included “closing” and “opening” operations in the order that yielded images without occluding hairs. A customized filter was employed for the operations. The relations for “closing” and “opening” operations can be found in Eq. 1 and 2 respectively. An example for the proposed combination can be found in Figure 4.6 for the “Melanocytic Nevus” class.

$$A \cdot B = (A \oplus B) \ominus B \qquad \textbf{(Eq 1)}$$
$$A \circ B = (A \ominus B) \oplus B \qquad \textbf{(Eq 2)}$$

where $\ominus$= erosion, $\oplus$= dilation, and A , B are the image matrices respectively.



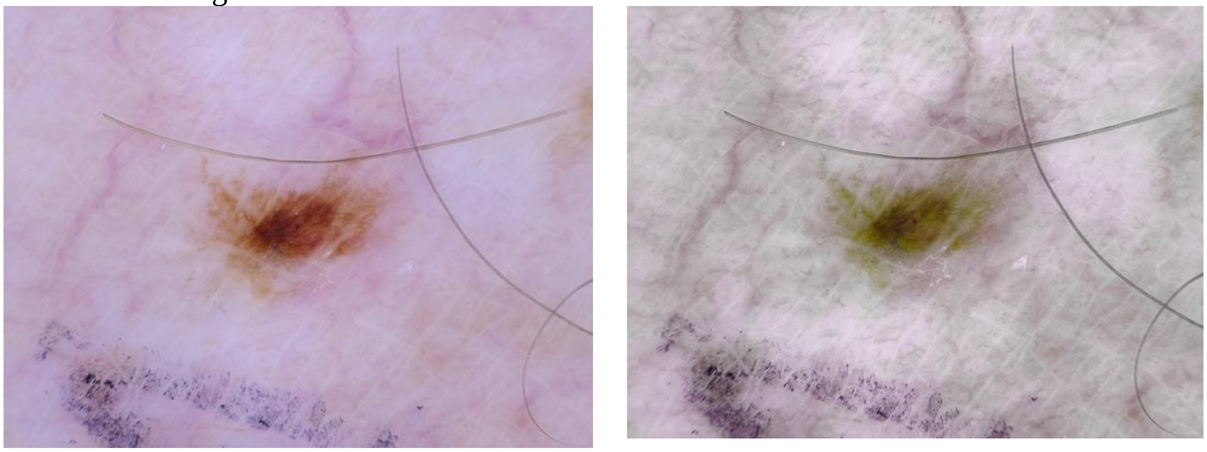
a) b)

Fig 4.6. a) Before and b) After Hair Filtering

4.2.2 Pixel-wise Transformation

To achieve a visible variation in the lesion colors, pixel-wise transformations were applied. The transformations involved are the Contrast Limited Adaptive Histogram Equalization

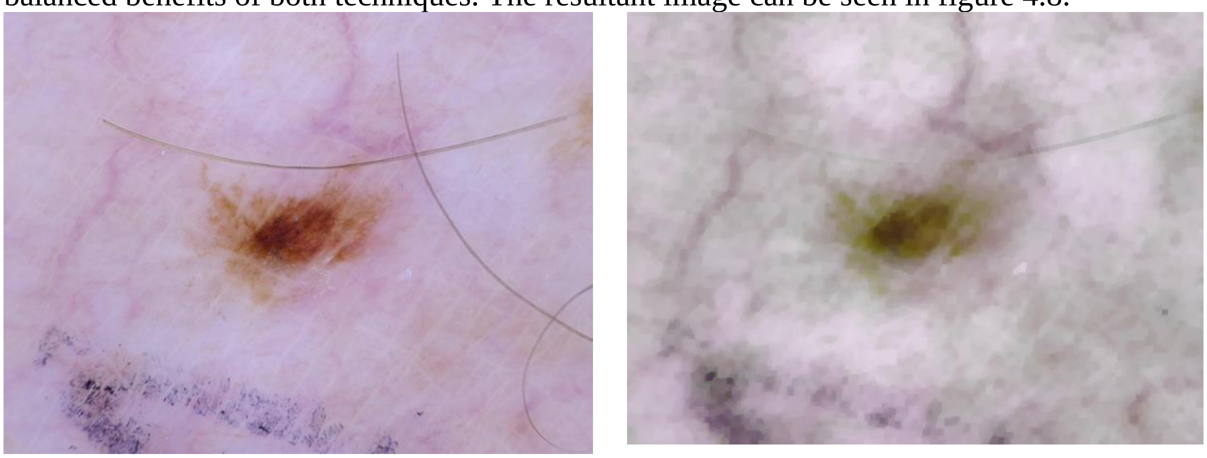
(CLAHE) transform and the Hue-Saturation-Value (HSV) transform. The visual improvement can be seen in figure 4.7.



a) b)

Fig 4.7. a) Before and b) After Pixel-wise Transformations

The overall combination of the Hair Filtering and the Pixel-wise transformations provide the balanced benefits of both techniques. The resultant image can be seen in figure 4.8.



a) b)

Fig 4.8. a) Before and b) After Hair Filtering + Pixel-wise Transformations

4.3 Proposed Model

The previous section provided details on the first stage of the proposed model. The remaining two stages are the segmentation network, and the classification network. The aim of the segmentation network is to extract the lesion affected regions of the image, excluding any skin or occluding hairs. So, the segmentation was performed with basic binary classes in this case: background and foreground. After extraction, the segmented images are input to the classification network. This network aims to precisely classification all seven classes of skin lesions.

4.3.1 Stage 1 – Segmentation Network

The implemented segmentation network was inspired and constructed to combine the basis of residual networks and dilated convolutions. The proposed model is made up of 22 blocks, with over 15 million parameters.

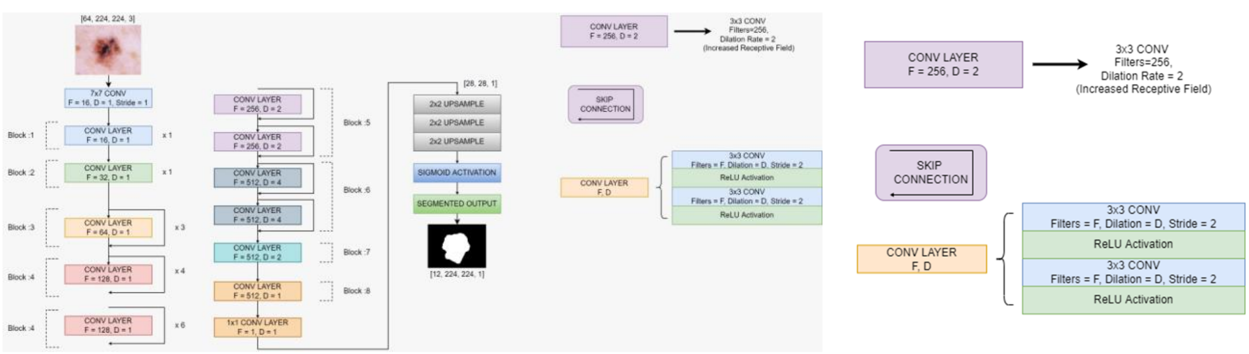
In a residual network, each layer feeds into the next layer and directly into the layers further away using skip connections. We are able to bypass the vanishing gradient problem and accuracy saturation problem by using residual blocks while training.

Dilated convolutions increase the overall receptive field of the filters. This allows for more information to be extracted without losing out on resolution. A global context is maintained and retains any significant information extracted.

In segmentation tasks, the extracted features are generally upsampled after downsampling due to convolutions. The features are upsampled to the original size of the image to report the final segmented mask. However, if the downsampled image is of low resolution, the segmentation of the object will not be of good quality.

In the original, ResNet architecture the final feature maps are of low dimensionality. There is some amount of loss in valuable information and thus, the segmentation will look rough. This is not noticeable in classification tasks. Thus, dilated convolutions are a replacement for subsampling and maintain the size of the receptive field, without losing the context.

However, the advantages of residual skip connections are maintained. They provide a way to retain the spatial resolutions through the end. The overall architecture of the proposed model can be seen in Figure 4.9 a and 4.9 b



a) b)

Fig 4.9 a) Architecture diagram of the proposed segmentation network b) Sub-block architecture

4.3.2 Stage 2 – Classification Network

The proposed classification network is similar to the employed segmentation network in terms of its basic architecture. However, the number of blocks and dilation rates vary as per the classification requirements. The proposed classification network is made up of 38-blocks and over 41 million parameters. A deeper model was chosen for the benefit of precise feature extraction. The proposed model was characteristically beneficial in spatial feature extraction, and hence was the preferred choice for the classification network as well (in comparison to default convolution networks).

Furthermore, the classification was modified in terms of additional convolutional and dense layers to suit the task at hand. Batch normalization and dropout layers were included to promote regularization as seen in Figure 4.10.

The dataset employed for the classification network were resultant of the segmentation network. The segmented images are categorized, pre-processed and balanced. A visualization of the segmented images can be seen in Figure 4.11.

In addition to this, the classification network is structured as a classification tree. As seen in Figure 4.10., the input image is first classified by the model in the root position, termed as “root model”. The root model categorizes the input images into samples of the Melanocytic Nevus (NV) class and those that do not belong to this class. This was proposed to boost the overall inter-class performance. The Melanocytic Nevus (NV) class is characteristically complex attributed to its small size and low color discrimination.

Further, the images classified by the root model as not Melanocytic Nevus (NV) are then classified into one of the 6 other classes by the model termed as “node model”. This combination resulted in the best inter-class performance as represented in the ablation studies of section 5.3.

The node model was trained for 45 epochs within which the first 40 epochs were trained with a learning rate of 0.0001, whereas the final five epochs were trained with a learning rate of 0.00001.

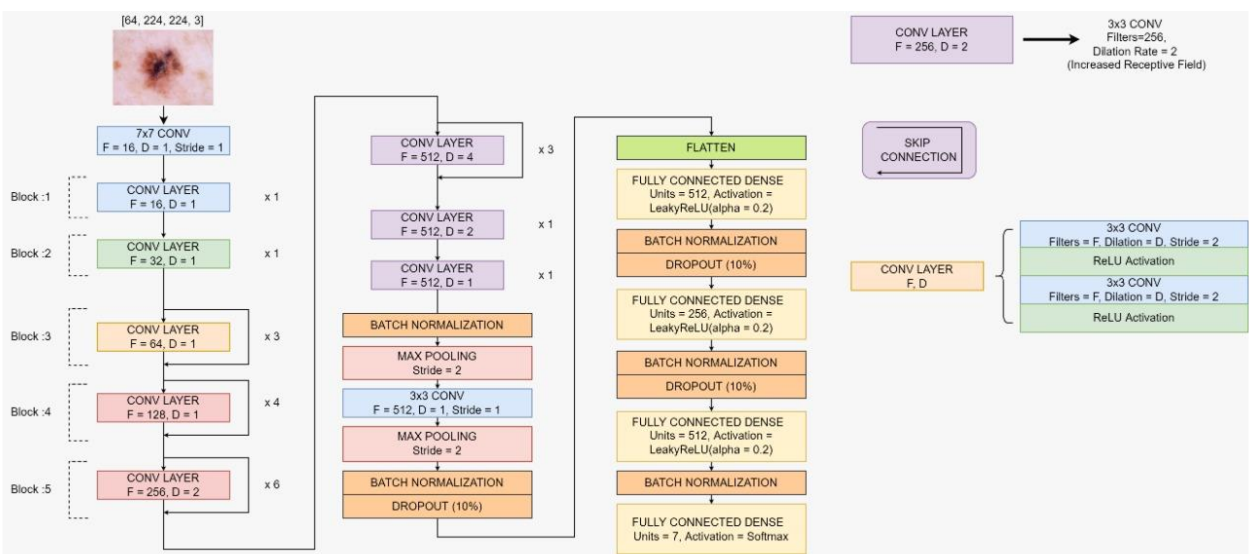


Fig 4.10. Architecture diagram of the proposed classification network

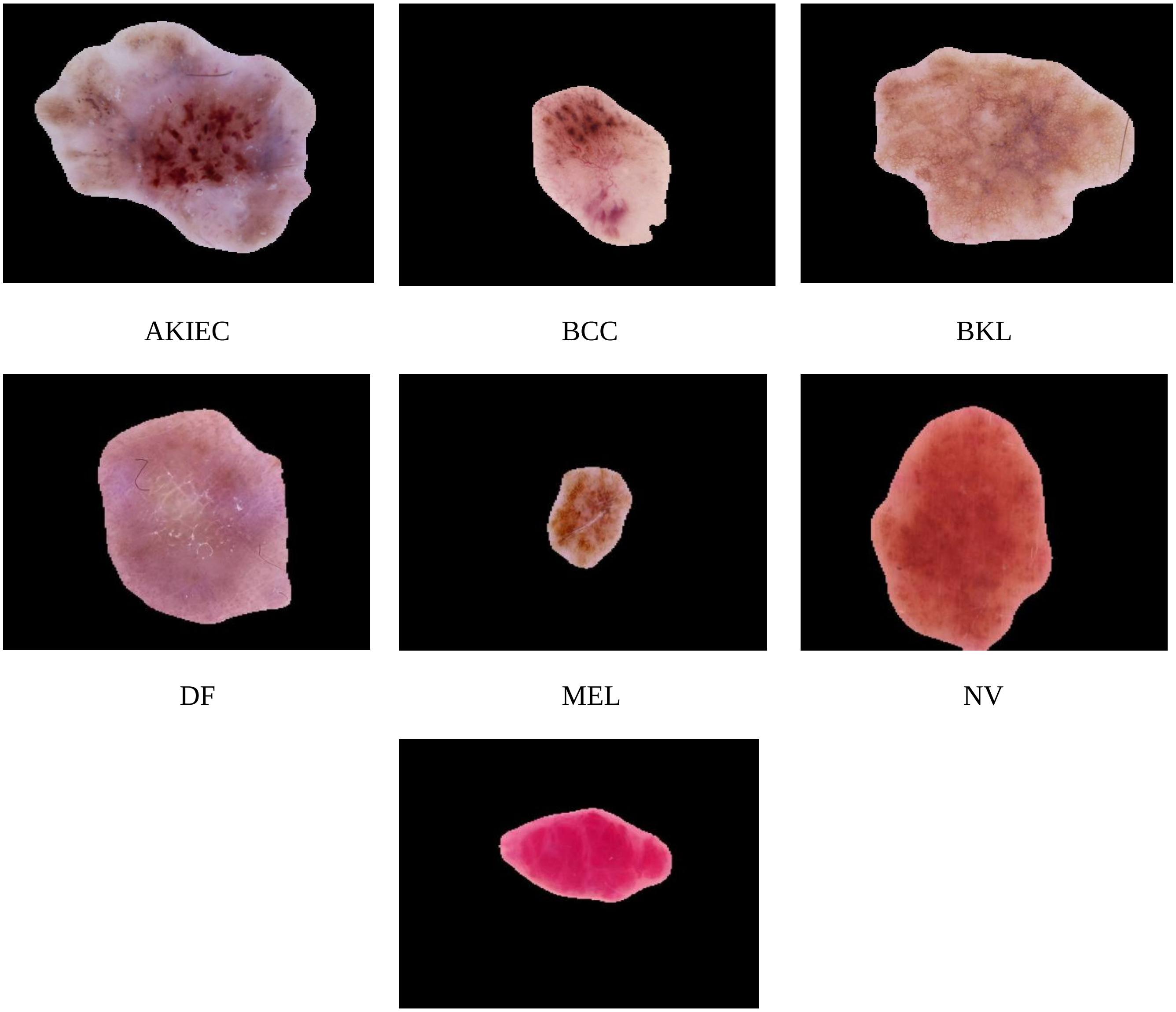


Fig 4.11. Examples of the segmented samples belonging to each class of the HAM10000 dataset

CHAPTER 5
RESULTS AND DISCUSSIONS

5.1 Experimental Setup

The experiments conducted in this study were performed in a Python 3 environment on the Keras and Tensorflow frameworks. The model employed an ADAM optimizer and a learning rate of 0.001 with binary cross entropy loss. A Tesla K80 GPU was used to train the model and a GTX 1660-Ti, 6GB RAM graphics card and a 16GB RAM system was used for the pre-processing steps. The dataset was split into an 80% training set and 20% testing set split.

5.2 Evaluation Metrics

Classification Accuracy (ACC), Precision (PRE), Recall (REC), and F1 score are the measures ut ilised to assess the performance of our proposed classification models. From Equations 3 through 6, the equations for the aforementioned evaluation metrics are provided below.

$$ACC = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad \textbf{(Eq 3)}$$

$$PRE = \frac{T_P}{T_P + F_P} \quad \textbf{(Eq 4)}$$

$$REC = \frac{T_P}{T_P + F_N} \quad \textbf{(Eq 5)}$$

$$F1\ score = 2 \times PRE \times \frac{REC}{REC + PRE} \quad \textbf{(Eq 6)}$$

where T_P stands for true positive, T_N stands for true negative, F_P stands for false positive and F_N stands for false negative. True positive results are those in which the model correctly predicts the positive class, whereas true negative results are those in which the model correctly predicts the negative class. False positives arise when the model predicts the positive class incorrectly, whereas false negatives occur when the model predicts the negative class incorrectly.

Additionally, we used Intersection Over Union (IOU) and Dice Scores (DSC) to evaluate the results of our segmentation models.

DSC measures the overlapping volume between two segmentations, as seen in Eq. (7).

$$DSC = \frac{2|A \cap B|}{|A| \pm |B|} \quad \textbf{(Eq 7)}$$

where A and B denote the voxel sets for segmentation and ground truth respectively.

Intersection Over Union (IOU) or Jaccard Index is determined as the area of overlap between the prediction and actual ground truth, divided by the area of union between the prediction and ground truth. Eq. (8) illustrates this.

$$JI = \frac{I_G \cap I_R}{I_G \cup I_R} \quad \textbf{(Eq 8)}$$

where I_G= Ground Truth Image, and I_R= Predicted Segmentation map.

5.3 Ablation Studies

5.3.1 Effect of Pre-processing and Augmentation

In the first section of the ablation studies, the performance of the pre-processing and the augmentation techniques proposed was analyzed. Each technique was included sequentially on an existing segmentation architecture. The U Net architecture was used for the ablation experiments. These results can be seen in table 1.

Table 1. Observations of ablation results for proposed pre-processing and augmentation results

S.No	**Pre-processing Technique and Model**	**Dice Score (%)**	**IoU Score (%)**
1.	Patched – Original Dataset	49.32	41.81
2.	Patched – Hair Filtered Dataset	55.35	47.68
3.	Patched – Augmented Dataset	39.30	33.12
4.	Patched- Hair Filtered + Augmented Dataset	55.24	49.76

5.3.2 Effect of proposed Segmentation network

The proposed segmentation networks aimed to the leverage the advantages of dilated residual networks to report precise segmentation performance.

Table 2. Observations of ablation results for proposed segmentation network

S.No	Model Used	Dice Score (%)	IoU Score (%)
1.	Proposed Network- Without Dilation and Residual layers	87.63	80.23
2.	Proposed Network- Without Dilation	88.44	80.91
3.	Proposed Network- Without Residual layers	89.16	81.86
4.	Proposed Network- With Dilation and Residual layers	89.69	82.11

5.3.3 Effect of proposed Classification network

Table 3. Observations of result for proposed classification network

S.No	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1.	Proposed Model	88	88.28	88.29	88.29

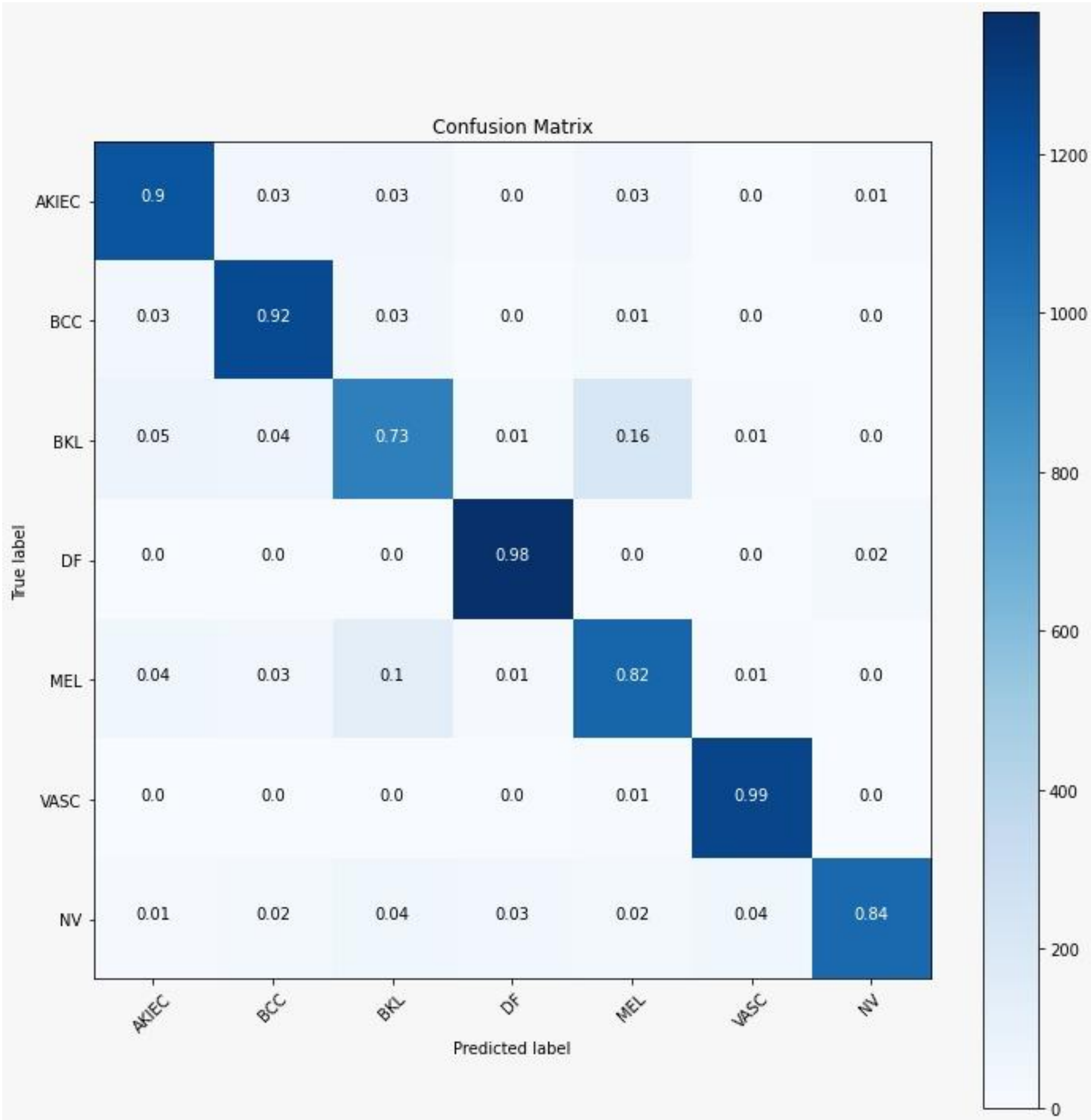


Fig 5.1. Confusion Matrix of Classification

5.4 Performance Comparison

5.4.1 Comparison of proposed Segmentation network to state-of-the-art models

The implemented network was compared with popular segmentation architectures on the same dataset. This provides a comparison of our performance to the state-of-the-art benchmark.

Table 4. Performance comparison of proposed segmentation model and state-of-the-art models

S.No	Model Used	Dice Score (%)	IoU Score (%)
1.	U Net	49.32	41.81
2.	PSPNet	40.73	30.36
3.	LinkNet	55.51	47.23
4.	Proposed Model	89.69	82.11

5.4.2 Comparison of proposed Classification network to state-of-the-art models

Table 5. Performance comparison of proposed classification model and state-of-the-art models

S.No	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1.	Mobilenet V2	44.5	24.87	56.86	16.86
2.	Proposed Model	88	88.28	88.29	88.29

5.5 User Interface – Web App

- Our deployed model is connect to our website using Flask API.
- All the GET and POST routes of API have been tested using the Postman tool.
- The front end part of the UI development has been done using React JS
- For authentication purposes we have used Email/password log-in details and further the user details are being stored in a NoSQL Firestore Database.
- The images would be stored in a storage bucket within the Firebase backend.
- The patient will be able to upload the images, which in turn will get segmented and classified by our model.
- The original image, segmented image and the classification results can be viewed by the doctor.

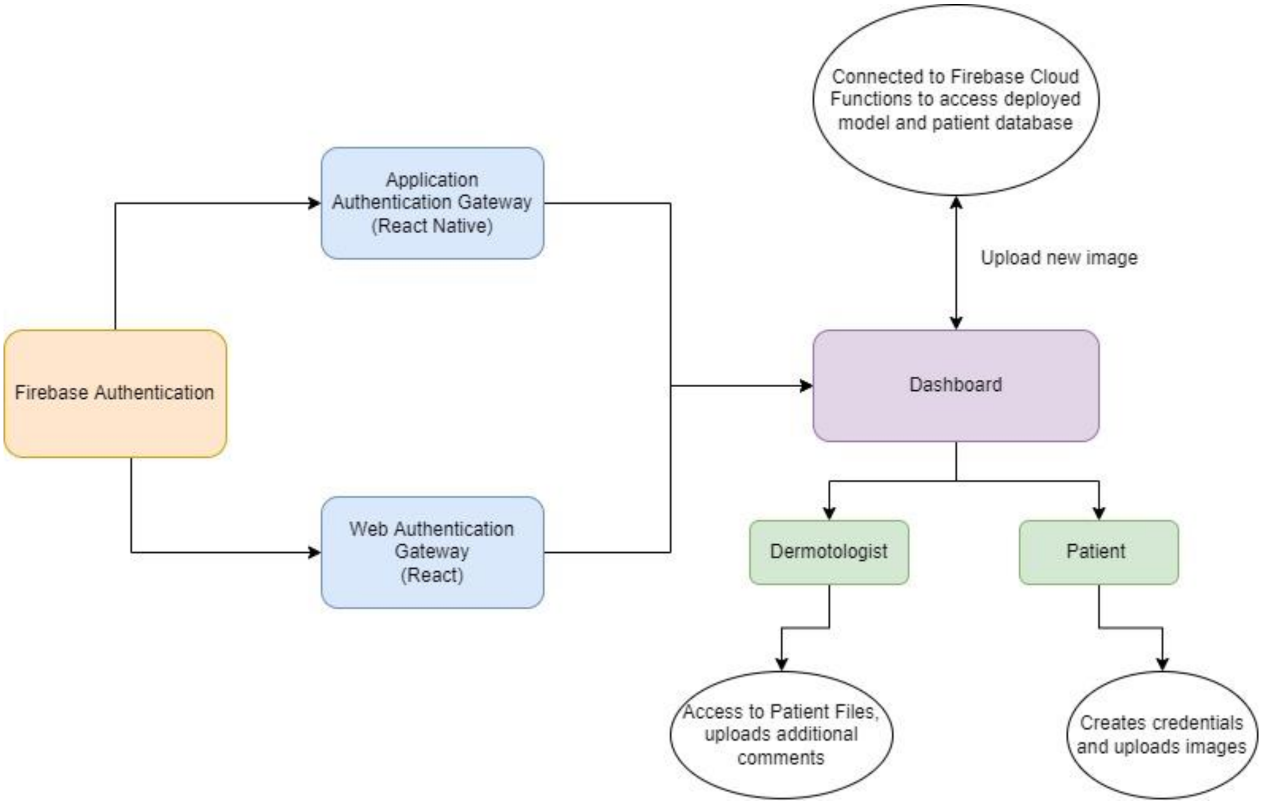


Fig 5.2. Overall architecture of the User Interface

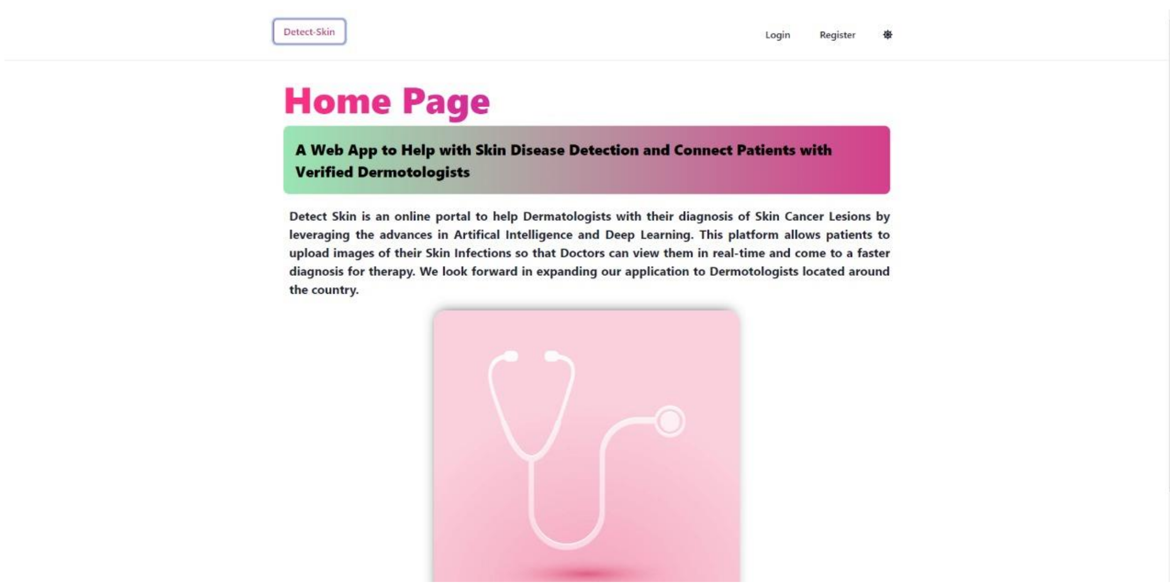


Fig 5.3. Home Page of the User Interface

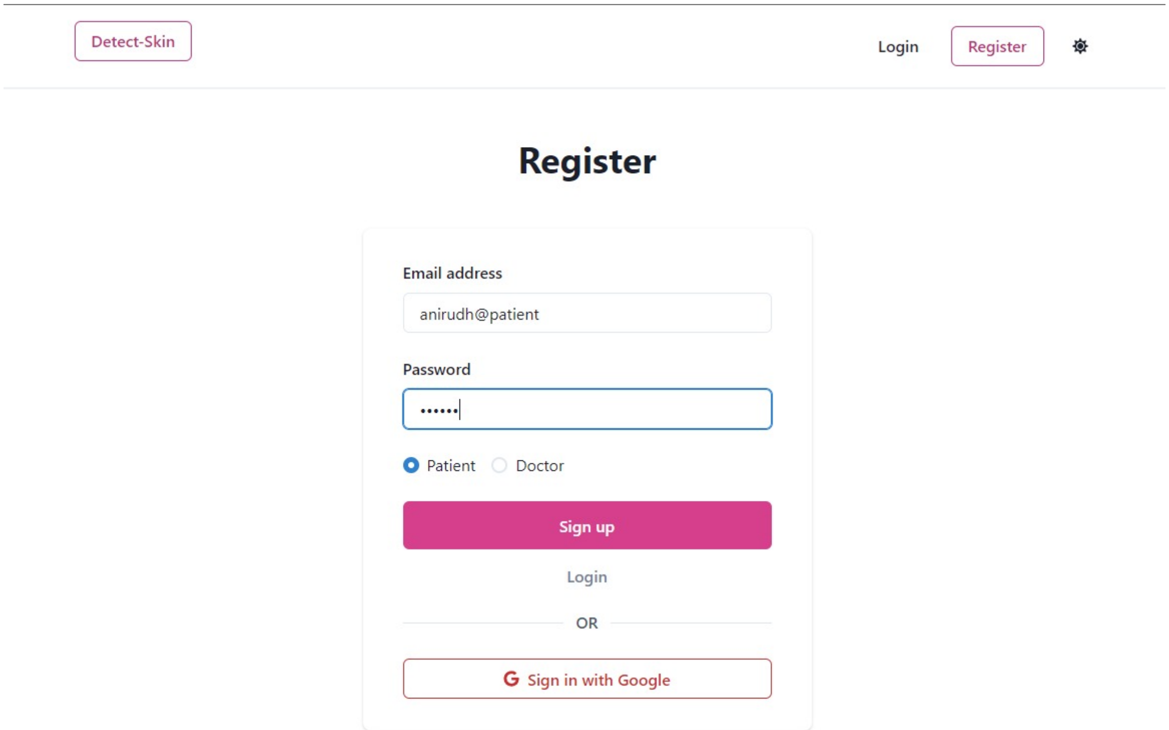


Fig 5.4. Patients and Doctors registration page

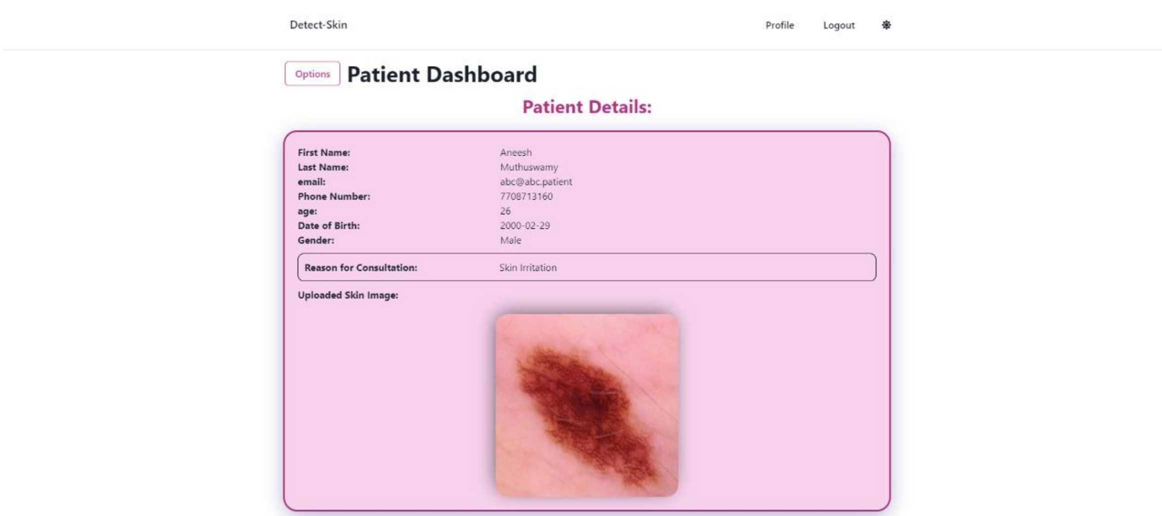


Fig 5.5. Patient details and image upload

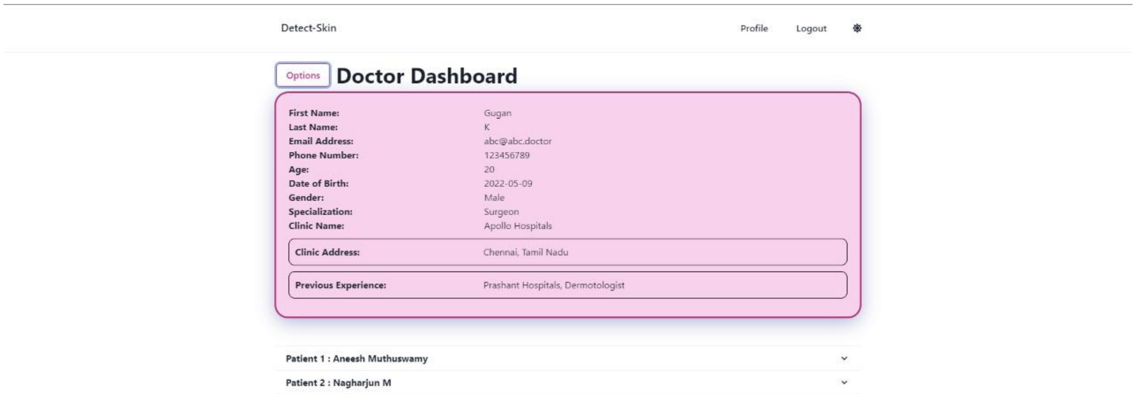


Fig 5.6. Doctor details and patient details

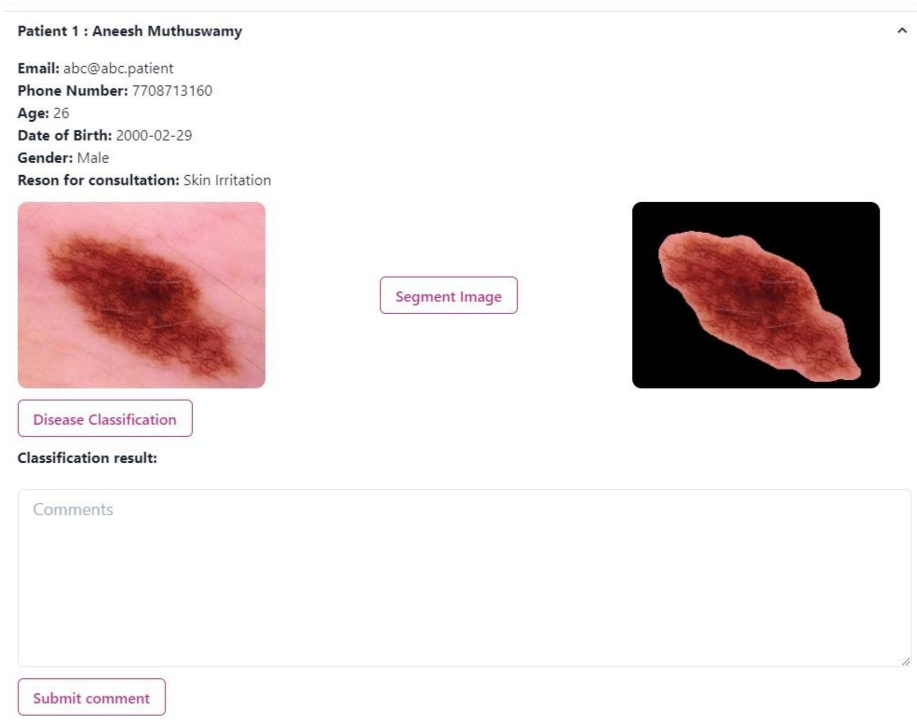


Fig 5.7. Segmentation Result

Fig 5.8. Classification Result

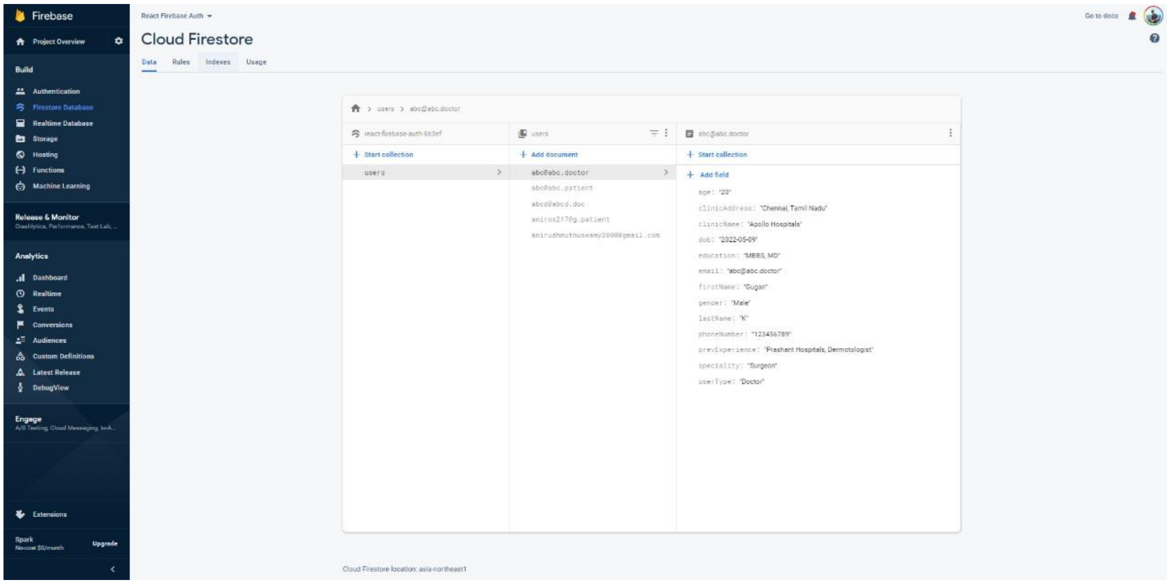


Fig 5.8. Firebase Cloud Database

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusion

Skin lesions can increase the risk of developing skin cancer. Owing to its perception as a low-risk disease, lesions are often overlooked. This attributes to a delay in diagnosis where the undiagnosed skin lesions have the possibility of manifesting as skin cancer. The more the delay, the higher the risk to the patient's life. Hence, early detection of skin lesions and the identification of its severity is essential to starting timely treatment. In the proposed work, we have leveraged deep learning algorithms to segment lesion affected regions, and classify them into multiple categories of cancerous and non-cancerous lesions. While an abundance of recent works that employ deep learning for skin lesion classification, there are research gaps to be addressed. These include improving discrimination, augmentation, and precise segmenting of lesion features. The proposed model presents three stages, dedicated to address the gaps. The combination of pre-processing, a novel dilated residual segmentation network, and noise-robust classification network, aim to report balanced classification with competing inter-class accuracy.

6.2 Future Works

- Improvements can be done in terms of improving the performance of the segmentation and classification models which can yield high accuracy of the segmentation of skin lesions and prediction of skin cancer.

- The number of patches can be increased further to get a more accurate segmented image.

- More number of images can be added to the dataset for training and testing.

- Major improvements in the User Interface can be done by addition of new features and deploying it for the use of doctors and patients.

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