Skinet: A Deep Learning based System for Diagnosing Skin Cancer

Rohan Gorantla, Agastya Seth, Giri Allada, Nishtha Nayar
Department of Computer Science
Shiv Nadar University, Noida, India

***Abstract*—Dermoscopy is a procedure of capturing skin images, and these images are useful for analyzing the various forms of skin diseases. Malignant melanoma is a form of skin cancer that, with its severity, often leads to death. Earlier melanoma detection prevents death, and patients can be treated by clinicians to increase the chances of survival. Quite a few machine learning algorithms were developed to use its features to detect the melanoma. This paper proposes a method for computer-aided diagnosis (CAD) which equips practical algorithms for the identification and prediction of melanoma and related skin diseases. Enhancement of the images is done using Contrast Adjustment, Histogram Equalization technique, Gaussian smoothing and median filter. MultiResUnet architecture is employed to segment the affected skin lesion from healthy skin. The extracted Region of Interest images from the segmentation step is fed into the proposed classification techniques based on CNNs. The proposed system is tested and validated with nearly 2000 images (malignant benign lesions), and it provides a high classification precision of 87.43%. The proposed CAD system can assist dermatologists in confirming the diagnosis decision and avoiding excisional biopsies.**

***Index Terms*—Melanoma, Deep Learning, Dermosocopy, UNet, Convolutional Neural Networks**

I. Introduction

Skin Cancer is the uncontrolled growth of abnormal cells in the epidermis, the outermost skin layer, caused by unrepaired DNA damage that triggers mutations. These mutations lead to the rapid proliferation of skin cells and the development of malignant tumours. Skin cancer is majorly caused by prolonged exposure to the sun's ultraviolet rays or the use of UV tanning machines. There are three major types of skin cancer: Basal Cell Carcinoma: - cancer that starts in the basal cells, Squamous Cell Carcinoma - disease caused by the out-of-control growth of the abnormal squamous cell, Melanoma -the deadliest form of skin cancer. Furthermore, there are other skin conditions that may or may not be cancerous but can be mistaken for cancer or can go undiagnosed. These include Benign Keratosis, Actinic Keratosis, Melanocytic Nevus, Dermatofibroma and Vascular Lesion.

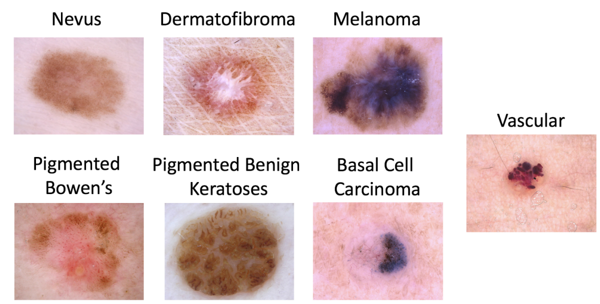

Fig. 1. Visual Representation of various skin diseases

Skin cancer is known to be the most common human malignancy. Every year in the United States, there are 5.4 million new cases of skin cancer. Statistically, Melanomas account for approximately 75% of all skin-cancer-related deaths and are responsible for over 10,000 deaths annually in the United States alone [1]. More than 13,000 new cases of Melanoma occur annually in Australia, resulting in more than 1,200 deaths. It causes more than 20,000 deaths per year in Europe. The good news is that skin cancer is treatable with high odds of being completely eliminated if diagnosed early. Early detection is critical, as the estimated 5-year survival rate for Melanoma drops from over 99% if detected in its most initial stages to about 14% if detected in its latest stages [1].

For the precise and early detection of Melanoma, highly trained expert clinicians with dermoscopic instruments are currently needed, but their number has not kept up with demand. To diagnose skin cancer, a physician generally examines the affected area and based on his experience, diagnoses the condition. If needed, a biopsy is performed. Hence, diagnosis is based mainly on the physician's personal experience. Without computer-based assistance, the clinical diagnosis accuracy for melanoma detection is reported to be between 65 and 80% [2]. Use of dermoscopic images improves this significantly. Currently, highly trained expert clinicians with dermoscopic devices are needed for accurate and early detection of melanoma, but the number of experts has not kept up with demand. Dermoscopy is a specialized method of high-resolution imaging of the skin that reduces skin surface reflectance, allowing clinicians to visualize deeper underlying structures. Using this device, specially trained clinicians have demonstrated a diagnostic accuracy as high as 75 to 84%. However, recognition performance decreases significantly when the clinicians are not adequately trained. While in the United States there are more than 10,000 dermatologists, in other areas of the world, the supply of expertise is limited. For example, in Australia, the number of registered dermatologists in 2004 was approximately 340, and in New Zealand, there were 16. Restricted access to expert consultation leads to additional challenges in providing adequate levels of care to the populations that are at risk. To address the limited supply of experts, there has been an effort in the research community to develop automated image analysis systems to detect a disease from dermoscopy images. Such technology could be used as a diagnostic tool by primary care physicians and staff for regular screening, or by clinicians who are otherwise not trained to interpret dermoscopy images.

The primary motivation behind the project is to create an end to end deep learning approach for early detection and classification of skin cancer which can benefit a large number of people. In this paper, we propose a novel methodology called SkiNet, which enhances the dermoscopic input images using our Image Enhancement algorithm. For this, we extract the Region of Interest (RoI) using MultiResUNet and use a two-stage classification algorithm : The first stage involves detecting whether the condition in the image is cancerous followed by the second stage which identifies the type of cancer if found carcinogenic, or predicts the associated skin disease.

II. Related Work

Skin cancer is one of the most common cancers worldwide, however, it can be treated if detected early on. There has been an extensive amount of research done in the field of skin cancer detection especially Melanoma detection which is the deadliest form of skin cancer.

Computer vision for Skin cancer detection can be traced back to the late 1980s where researchers have processed images using techniques like border detection, semi-translucency detection, Telangiectasia detection and ulcer and crust detection [3]. In this work, the researchers approach the problem of image analysis using a cognitive model of features important to the dermatologist. They work on automatic detection of several features of basal cell epitheliomas, along with using image processing methods like frequency analysis of the Fourier transform of skin images and the Sun-Wee texture analysis algorithm. Throughout various research studies, it's noticed that the two main tasks which researchers perform for skin cancer detection are segmentation and classification.

Early works of Skin cancer segmentation can be traced back to the 1990s. Ercal [4] detects the boundaries of the skin tumor from colored skin images and uses an adaptive color metric from RGB planes that contain information to discriminate the tumour from the background. This tumour is then segmented from the rest of the image using a coordinate transformation. This technique is based on a segmentation algorithm that uses an adaptive transformation function followed by thresholding.

In Xu *et al.* [5] segmentation is done using intensity thresholding. The method followed in the paper first reduces a colored image into an intensity image and then carries out the thresholding. It further refines the process using image edges, if a lesion boundary exists, double thresholding is used to focus on it. An elastic curve is fitted to the initial boundary, and is locally expanded or shrunk to approximate edges in its vicinity. The use K-means clustering for image segmentation could be observed in Azad *et al.* [6], the segmented image could then be used for feature extraction.Recent advancements in deep learning has led to the usage of CNNs for the process of image segmentation. This could be observed in Yuan *et al.* [7], Jafari *et al.* [8] etc.

One of the early uses of image processing for skin cancer classification could be observed in Stolz [9] where they had used scanned and digitized melanocytic lesions from which features where extracted and statistical algorithms were used for the classification. These features along with histologic diagnosis are then used as the input in a statistical classification program which gives about 92 percent accuracy. In Romero-Lopez [10] we observe the usage of VGGNet convolutional neural network architecture for the purpose of classification along with the transfer learning paradigm. Deep learning-based approaches to skin cancer classification can also be observed in Esteva [11], Kawahara [12] etc. Elgamal [13] has used a three stage approach with extraction, dimensionality reduction and classification for skin cancer detection. Work by Hoshyar *et al.* [14] shows the importance of the pre-processing step in skin cancer detection. Different types of neural net and pre-

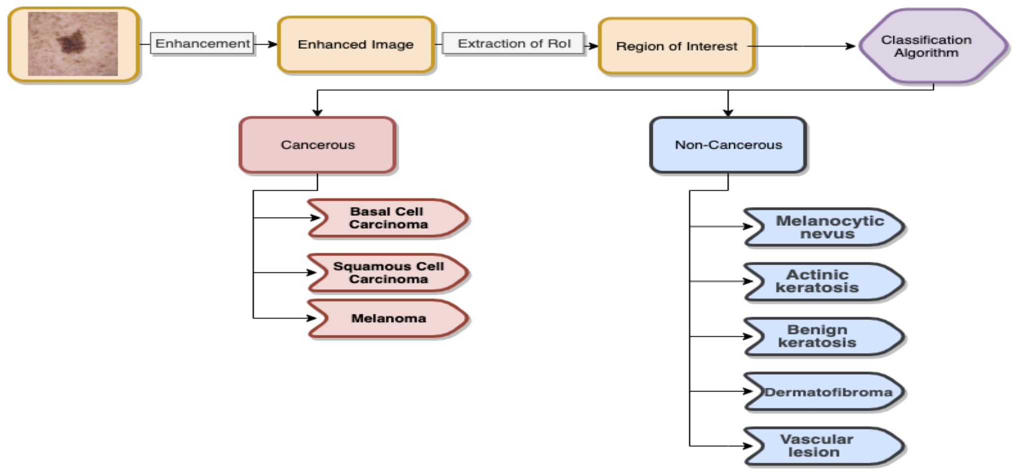

Fig. 2. Workflow of Proposed Methodology

processing steps are also studied by works of Lau and Al-Jumaily [15] and Samavi *et al.* [16]. Other novel deep learning methods like Support Vector Machine are implemented for detection and classification of skin cancer by Alquran *et al.* [17] and Premaladha *et al.* [18].

Recent works like Codella [19], Alom [20] etc. have combined the combined the power of both segmentation and classification. Segmentation first is used as pre-processing step and then that processed image has been used for classification. Maglogiannis *et al.* [21] have worked on intelligent approaches for the same.

III. Proposed Methodology - SkiNet

Our proposed SkiNet methodology automatically enhances the input image by performing contrast adjustment, intensity adjustment and also helps in reducing background noise using the gaussian smoothing and median filter. RoI is then extracted from the enhanced image by performing segmentation using MultiResUnet algorithm. We then perform classification of skin lesions using standard CNNs.

A. Image Enhancement and Augmentation

Different factors influence the image quality that may affect a clear understanding of the forms of dermoscopic images. Some of these factors are low contrast between the lesions and skin, hairs covering the affected skin area, specular reflections, and the background noise. Due to the above factors, there is a compelling need to enhance the quality of images to enable adequate accuracy in both segmentation as well as classification. We employed contrast adjustment and histogram equalization techniques to remove specular reflections and adjust the illumination, resulting in a more consistent set of images. The median filter along with gaussian smoothing helped in curtailing the background noise and thereby improving the overall quality of the image. Our proposed enhancement technique is explained in Algorithm 1.

Algorithm 1: *Our Proposed Image Enhancement Algorithm on Dermoscopic Images*

Input : Raw Skin Lesion Images, L_i(x,y)
 ▷ 'x' : width and 'y' : height
Initializations: Set σ, φ, ψ, α and β
for $i = 1, 2, .., N$ **do**
  Compute σ empirically
  $I_1 \leftarrow$ C(x,y;σ) $*$ L_i(x,y)
   ▷ where C is a contrast adjustment technique
  Compute α and β empirically
  $I_2 \leftarrow I_1$ * G(x,y;[$\alpha\,\beta$])
   ▷ where G is image intensity adjustment technique
  Compute φ and ψ empirically
  $I_3 \leftarrow I_2$ * M(x,y;φ; ψ)
   ▷ where M is a Median filter
  Compute η empirically
  $I_O \leftarrow I_3$ * $\lambda(x, y; \eta)$
   ▷ where λ is a histogram equalization operation
Output: Enhanced Skin Lesion Images

The DL models are data-intensive. In the medical domain, one of the common problems is the availability of good amount of data to train the DL models for various segmentation and classification tasks. Although there is a good amount of data, there may be an imbalance

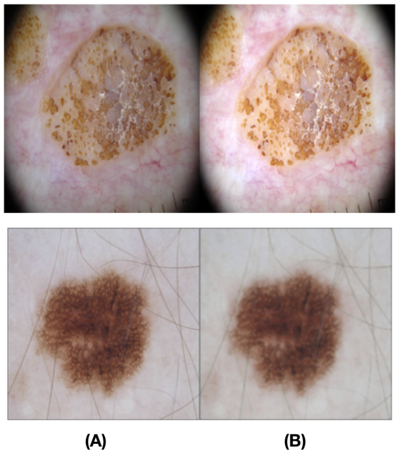

Fig. 3. Visual Representation of our proposed image enhancement algorithm (A)Shows the input image (B)Shows the Enhanced image

between classes. To fix the class imbalance and also to mitigate the problems of overfitting when training the DL models, we implement augmentation strategies that can effectively augment the dataset by maintaining a balance between classes. The augmentation strategies employed by us include random rotations between 20 to 70 degrees and flips both horizontal and vertical.

B. *RoI Extraction*

In medical image analysis, each pixel of the image contains vital information which plays a crucial role in deciding the treatment. It is essential to pass only the RoI onto the classification stage as it would help us obtain precise results from a well-trained model. Moreover, this would also reduce computation time due to the optimal utilization of the available computational resources. The skin lesion is detected in the dermoscopic image with segmentation and is differentiated from the healthy skin in the background.

Deep Learning has made a breakthrough in the segmentation of biomedical images in recent years. U-Net has been the most successful architecture in the field of medical imaging in this regard. Despite excellent overall performance in segmenting multimodal medical images, the work done by Nabil et al. [22] proposed an advanced segmentation technique known as MultiResUnet which demonstrated that the classical U-Net architecture appears to be lacking in certain aspects through extensive experimentation. Using Keras and Tensorflow backend, a MultiResUnet was implemented for lesion segmentation. It is similar to U-Net architecture. In general, the method is a modeling system that learns from an input image to an output image a functional mapping. The original image is the input image, and a segmentation mask is the output image. The network structure involves a series of operations of convolution and pooling, followed by a single fully connected layer, followed by a series of operations of unpooling and deconvolution. Skip connections are used to connect convolutional data with deconvolution operations before pooling. It helps the network to model functional residuals as well as provide the output layers with higher resolution information in order to boost network performance compared to networks without skip connections.

Nabil et al. work noted some inconsistencies between the features transferred from the network of encoders and the features propagating through the network of decoders. Res paths have been proposed to merge these two conflicting sets of features, adding some extra processing to make the two feature maps more homogeneous. In addition, MultiRes blocks were proposed to increase U-Net with the ability of multi-resolution analysis. Inspired by Inception blocks and formulated a compact analogous structure that is relatively lightweight and requires less memory. Compared to traditional UNet, MultiResUNet works effectively by integrating these changes.

C. *Classification*

It is essential to classify the RoI into one of corresponding skin disease to provide the appropriate treatment. Considering that the smaller data sets are an inherent problem in the field of biomedical imaging, a robust classification technique is needed that can take into account the overfitting problem and can work effectively in such scenarios. CNNs are a deep learning technique that implicitly perform feature extraction on image data with deeper networks generally learning more sophisticated representations of the image data. Training CNNs to perform this kind of automated feature extraction typically comes with the onus of requiring large volumes of labelled training data. When such training corpora are available, CNNs are capable of achieving state-of-the-art performance in general object recognition, as evidenced by their dominance of the ImageNET benchmark. A variety of CNN architectures have been introduced and continue to be improved. Individual architectures have different capabilities in their ability to characterise or represent image data, which is often linked to the depth of the CNN. CNNs are the state-of-the-art deep learning method for image classification as demonstrated by their dominance of the ImageNet benchmark. A variety of different architectures have been introduced for the classification of the 1000 categories in the ImageNet dataset. CNNs generally require large training datasets

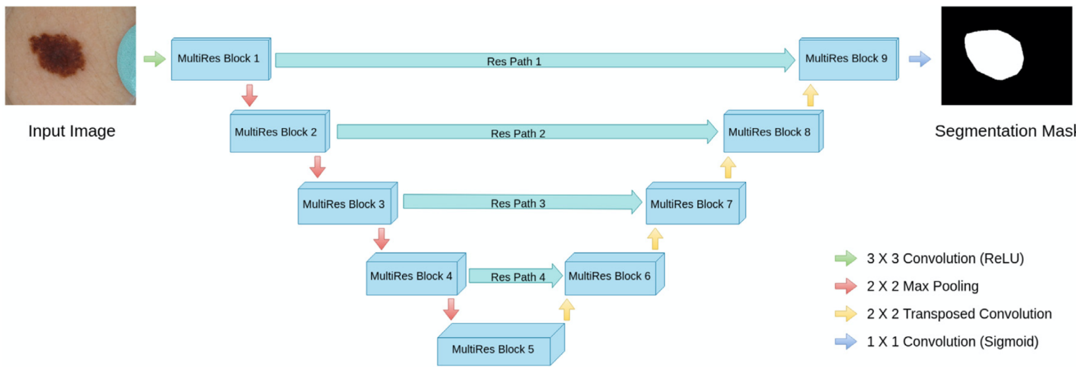

Fig. 4. Architecture of MultiResUnet

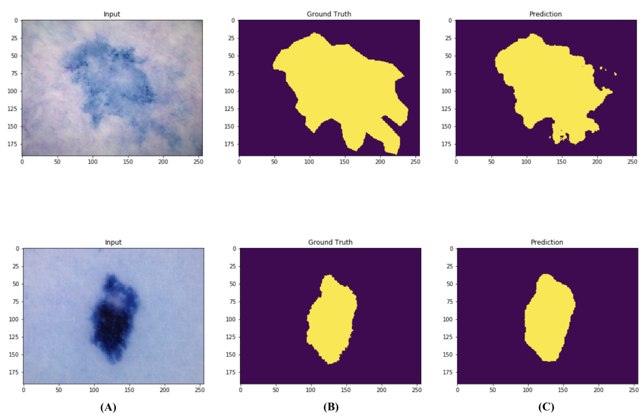

Fig. 5. Visual Representation of results obtained using our RoI extraction step (A)Denotes the input image (B)Denotes the ground truth corresponding to input image (C) Denotes the predicted RoI by MultiResUnet

and as such their direct application to medical imaging is difficult due to the time and labour cost involved in creating expertly labelled training datasets. Anthimopoulos et al. showed that CNN architectures have higher accuracy than other methods when significant effort has been expended to acquire labels for the training data. However, when only small training datasets are available, which is the norm, CNN-based methods may overfit and struggle to learn the best image features. We perform classification using ResNet 50, DenseNet and Inception architectures.

IV. Experiments and Results

A. Dataset

For experimentation we have mainly used an ISIC 2018 dataset. For Lesion Boundary Segmentation we used a dataset that consists of about 2594 Images for training, 100 images for validation and 1000 images for testing. For Lesion Diagnosis i.e. Classification we used a dataset that consists of about 10015 Images for training, 193 images for validation and 1512 images for testing.

B. Performance measure

We have employed widely used metrics like - Dice coefficient(DI), Jaccard index (JI) and Pixel Accuracy(AC) are used to quantify the performance of image segmentation. Dice coefficient and Jaccard Index essentially measure the similarity between the ground truth and the predicted segmented image in terms of the extent of overlap between the two images while pixel accuracy reports the percent of pixels in the image which were correctly predicted. The Jaccard index is given by:

$$d_J(M,C) = 1 - J(M,C) = 1 - \frac{|M \cap C|}{|M| + |C| - |M \cap C|} \tag{1}$$

where M represents the ground truth of segmentation, which is normally a manually-identified tumor region, and C represent a mask.

$$\begin{aligned} AC &= (TP+TN)/(TP+FP+TN+FN) \\ SE &= TP/(TP+FN) \\ SP &= TN/(TN+FP) \\ DI &= 2 \cdot TP/(2 \cdot TP+FN+FP) \\ JA &= TP/(TP+FN+FP) \end{aligned} \tag{2}$$

To evaluate the effectiveness of our proposed classification solution, a confusion matrix is employed which is a widely used evaluation measure in classification tasks. Based on the confusion matrix, the values of accuracy, precision, sensitivity(SE), specificity(SP) and F1-score are used for performance evaluation at the patient level.

C. Results

We have inspected the validity of our proposed image enhancement technique, evaluated state of the art image segmentation techniques and compared our proposed SkiNet methodology to already existing solutions as well as with widely used CNN based models.

1) Segmentation: Evaluating the results obtained from the segmentation techniques shown in table I, our proposed image enhancement methodology has provided significant improvements in the segmentation task on both the architectures. As observed in Table I, MultiResUNet with enhancement does slightly better than the usual MultiResUNet and with a Dice Coefficient of 0.8963, Jaccard Index of 0.592 and Pixel accuracy of 0.9357, it performed significantly better than U-Net and U-Net along with enchancement.

TABLE I
COMPARITIVE STUDY OF VARIOUS SEGMENTATION MODELS ON THE ISIC DATASET

Model	Dice Coefficient	Jaccard Index	Pixel Accuracy
U-Net	0.8496	0.549	0.8702
U-Net+Enhancement	0.8632	0.566	0.8863
MultiResUNet	0.8841	0.581	0.9233
MultiResUNet+Enhancement	0.8963	0.592	0.9357

TABLE II
COMPARITIVE STUDY OF VARIOUS CLASSIFICATION MODELS ON THE ISIC DATASET

Model	Precsion	Specifity	Sensitivity	F1 Score
SqueezeNet	76.2%	84.63%	65.21%	0.80
ResNet	81.8%	89.53%	71.87%	0.86
VGGNet	79.3	87.63%	68.44%	0.83
Inception V3	83.4%	90.89%	72.41%	0.87
DenseNet	86.67	92.81%	74.73%	0.91

TABLE III
COMPARITIVE STUDY OF VARIOUS CLASSIFICATION MODELS AFTER SEGMENTATION ON THE ISIC DATASET

Model	Precsion	Specifity	Sensitivity	F1 Score
SqueezeNet	77.6%	85.42%	66.21%	0.81
ResNet	82.9%	90.49%	69.98%	0.86
VGGNet	78.67	86.54%	68.44%	0.84
Inception V3	84.1%	92.36%	73.86%	0.89
DenseNet	87.43	94.21%	75.69%	0.92

2) Classification: In order to evaluate the performance of the Skinet in the classifcation task, we use the performance metrics discussed in Section IV part B. From Table II we observe that the DenseNet architecture does better compared to other state of the art networks thus we employ it our SkiNet pipeline and Fig. 4 show

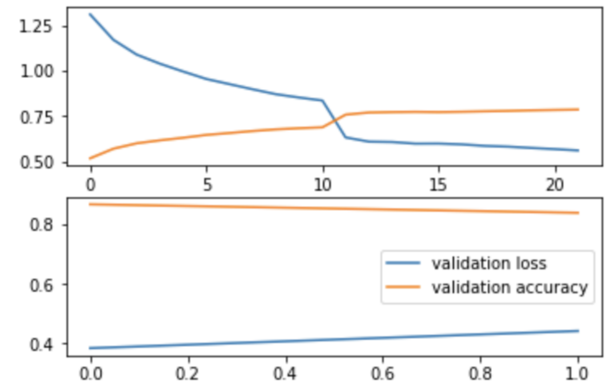

Fig. 6. Validation Results of SkiNet

the confusion matrices. Table III specify the performance of our methodology with MultiResUNet based segmentation. These results highlight the fact the existing models perform poorly as compared to our proposed methodology. Classification preceded by segmentation yielded a better performance validating the inclusion of segmentation into our pipeline. We can observe that our pipeline MultiResUNet segmentation + DenseNet classification outperforms all the existing results. We have achieved an overall precision of 87.43%, an average sensitivity of 96.82%, an average specificity of 75.69%, an average precision of 94.21% and an average F1-Score of 0.92. The confusion matrix can be observed in Fig.7 .The superiority of the SkiNet model can be attributed to the pipelined architecture of our model where we take the best of both worlds i.e segmentation and classifcation models thus making it even better when compared to other state of the art models.

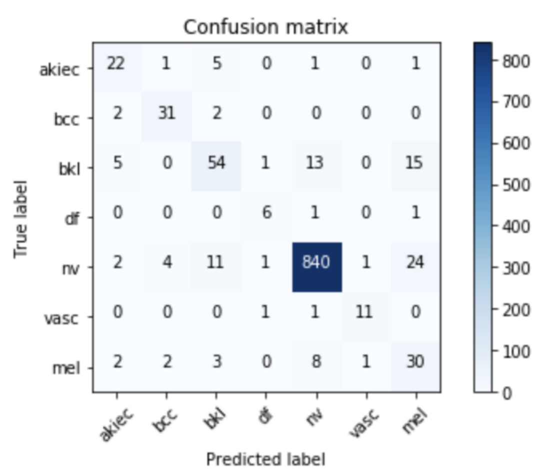

Fig. 7. Confusion Matrix of SkiNet

V. Conclusion

SkiNet is a novel pipelined architecture that segments the tumor as a form of preprocessing and then classifies the tumor accordingly. This model might be skewed due to the limited amount of data we have in our current ISIC dataset. We could thus improve the performance of this model with the availability of more data which could be generated with the use of General Adversarial Networks(GANs).

References

[1] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, p. 115, 2017.

[2] A. R. Lopez, X. Giro-i-Nieto, J. Burdick, and O. Marques, "Skin lesion classification from dermoscopic images using deep learning techniques," in *2017 13th IASTED International Conference on Biomedical Engineering (BioMed)*, IEEE, 2017, pp. 49–54.

[3] R. H. Moss, W. V. Stoecker, S.-J. Lin, S. Muruganandhan, K.-F. Chu, K. M. Poneleit, and C. D. Mitchell, "Skin cancer recognition by computer vision," *Computerized Medical Imaging and Graphics*, vol. 13, no. 1, pp. 31–36, 1989, ISSN: 0895-6111. DOI: https://doi.org/10.1016/0895-6111(89)90076-1.

[4] F. Ercal, M. Moganti, W. V. Stoecker, and R. H. Moss, "Detection of skin tumor boundaries in color images," *IEEE Transactions on Medical Imaging*, vol. 12, no. 3, pp. 624–626, Sep. 1993, ISSN: 1558-254X. DOI: 10.1109/42.241892.

[5] L. Xu, M. Jackowski, A. Goshtasby, D. Roseman, S. Bines, C. Yu, A. Dhawan, and A. Huntley, "Segmentation of skin cancer images," *Image and Vision Computing*, vol. 17, no. 1, pp. 65–74, 1999, ISSN: 0262-8856. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0262885698000912.

[6] M. K. Uddin, I. Azad, and A. Bhuiyan, "Image processing for skin cancer features extraction," *International Journal of Scientific Engineering Research*, vol. 4, Feb. 2013.

[7] Y. Yuan, M. Chao, and Y. Lo, "Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance," *IEEE Transactions on Medical Imaging*, vol. 36, no. 9, pp. 1876–1886, Sep. 2017, ISSN: 1558-254X. DOI: 10.1109/TMI.2017.2695227.

[8] M. H. Jafari, N. Karimi, E. Nasr-Esfahani, S. Samavi, S. M. R. Soroushmehr, K. Ward, and K. Najarian, "Skin lesion segmentation in clinical images using deep learning," in *2016 23rd International Conference on Pattern Recognition (ICPR)*, Dec. 2016, pp. 337–342. DOI: 10.1109/ICPR.2016.7899656.

[9] T. Schindewolf, W. Stolz, R. Albert, W. Abmayr, and H. Harms, "Classification of melanocytic lesions with color and texture analysis using digital image processing.," *Analytical and quantitative cytology and histology*, vol. 15 1, pp. 1–11, 1993.

[10] A. Romero Lopez, X. Giro-i-Nieto, J. Burdick, and O. Marques, "Skin lesion classification from dermoscopic images using deep learning techniques," in *2017 13th IASTED International Conference on Biomedical Engineering (BioMed)*, Feb. 2017, pp. 49–54. DOI: 10.2316/P.2017.852-053.

[11] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017, ISSN: 1476-4687. DOI: 10.1038/nature21056. [Online]. Available: https://doi.org/10.1038/nature21056.

[12] J. Kawahara, A. BenTaieb, and G. Hamarneh, "Deep features to classify skin lesions," in *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, Apr. 2016, pp. 1397–1400. DOI: 10.1109/ISBI.2016.7493528.

[13] M. Elgamal, "Automatic skin cancer images classification," *International Journal of Advanced Computer Science and Applications*, vol. 4, Apr. 2013. DOI: 10.14569/IJACSA.2013.040342.

[14] A. Hoshyar, A. Al-Jumaily, and A. Hoshyar, "The beneficial techniques in preprocessing step of skin cancer detection system comparing," *Procedia Computer Science*, vol. 42, pp. 25–31, Dec. 2014. DOI: 10.1016/j.procs.2014.11.029.

[15] H. T. Lau and A. Al-Jumaily, "Automatically early detection of skin cancer: Study based on nueral netwok classification," in *2009 International Conference of Soft Computing and Pattern Recognition*, Dec. 2009, pp. 375–380. DOI: 10.1109/SoCPaR.2009.80.

[16] E. Nasr-Esfahani, S. Samavi, N. Karimi, S. M. R. Soroushmehr, M. H. Jafari, K. Ward, and K. Najarian, "Melanoma detection by analysis of clinical images using convolutional neural network," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2016, pp. 1373–1376. DOI: 10.1109/EMBC.2016.7590963.

[17] H. Alquran, I. A. Qasmieh, A. M. Alqudah, S. Alhammouri, E. Alawneh, A. Abughazaleh, and F. Hasayen, "The melanoma skin cancer detection and classification using support vector machine," in *2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*, Oct. 2017, pp. 1–5. DOI: 10.1109/AEECT.2017.8257738.

[18] P. Jayaraman and K. S. Ravichandran, "Novel approaches for diagnosing melanoma skin lesions through supervised and deep learning algorithms," *Journal of Medical Systems*, vol. 40, Apr. 2016. DOI: 10.1007/s10916-016-0460-2.

[19] N. Codella, Q.-B. Nguyen, S. Pankanti, D. Gutman, B. Helba, A. Halpern, and J. Smith, "Deep learning ensembles for melanoma recognition in dermoscopy images," *Ibm Journal of Research and Development*, vol. 61, Jun. 2017. DOI: 10.1147/JRD.2017.2708299.

[20] M. Z. Alom, T. Aspiras, T. M. Taha, and V. K. Asari, *Skin cancer segmentation and classification with nabla-n and inception recurrent residual convolutional networks*, 2019. arXiv: 1904.11126 [cs.CV].

[21] I. Maglogiannis, E. Zafiropoulos, and C. Kyranoudis, "Intelligent segmentation and classification of pigmented skin lesions in dermatological images," in *Advances in Artificial Intelligence*, G. Antoniou, G. Potamias, C. Spyropoulos, and D. Plexousakis, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 214–223, ISBN: 978-3-540-34118-5.

[22] N. Ibtehaz and M. S. Rahman, "Multiresunet: Rethinking the u-net architecture for multimodal biomedical image segmentation," *Neural Networks*, vol. 121, pp. 74–87, 2020.