Deep Learning Architiectures For Aided Melanoma Skin Disease Recognition: A Review

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***Abstract*— Melanoma, a sort of skin disease, in spite of the fact that it represents a little percentage of skin malignancies in the USA, it represents higher than seventy five percent of all skin diseases connected to all fatalities in the USA alone. This motivated researcher to seek automated techniques that facilitates early diagnosis of skin cancer. Skin lesion segmentation using machine learning became one of the best ways used for early detection and treatment of skin cancer. Recently, the researchers used a different deep network architectures, to segment and diagnose skin cancer. In this paper, we introduce a review of existing deep network architectures that have been suggested to segment skin lesions, pre-processing and post-processing methods with the available datasets that can be used for research in this area, also presented a comparison between the results of different methods used for skin lesion segmentation showing the strengths and weaknesses of each method.**

Keywords*— Deep learning, segmentation of skin lesion, lesion index network, skin cancer detection.

I. Introduction

Melanoma is a sort of skin disease that represents more than seventy five percent of all skin diseases connected to all fatalities . Indeed, melanoma is liable for more than 10,000 passing's every year in the USA alone. Nonetheless, doctors have demonstrated that the endurance paces of patients improves radically with early analysis and diagnosis. Skin lesion segmentation is a significant advance in the analysis and resulting treatment of melanoma [1]. Image segmentation using machine learning is one of the best ways for early detection and treatment of skin cancer. Researchers using a different deep network architectures with different performances. Many of the methods used by researchers provided highly accurate results in detecting skin cancer, unlike some who failed to do so. The paper is structured as follows: we present a review of existing deep network architectures that have been suggested to segment skin lesions. In addition, image pre-processing and post-processing methods are presented in Section II, we present a review of available datasets that can be used for research in this area. In addition to the evaluation metrics and results, we also presented a comparison between the results of different methods used for skin lesion segmentation showing the strengths and weaknesses of each method in Section III, summarized in Section IV.

II. Deep Learning-based Method

Deep learning based methodologies fundamentally make better segmentation results. On the other hand, these algorithms are yet dependent on the availability of great sufficient dataset so as to accomplish satisfactory outcome. In this section, we present a review of the most prominent methods recently used in segmentation the skin lesion.

A. Convolution Network-based Methods

In recent years, along with advances in the computational power of GPUs, Convolutional Neural Networks (CNNs) have feature as one of the strongest tools in image processing such as [27, 28, 29, 30]. CNN models displayed good achievement in varied areas including medical image analysis such as AlexNet [21], VGG [22]. Ahmed et al. [10], proposed a fully automated algorithm depend on CNNs to segment skin lesion in dermatoscopic images. They suggest combining decoder architectures with pyramid pooling units. This is technique doesn't need any gray scale conversion or pre-treatment. As per to the outcomes announced in[10], technique proved its strength versus in techniques and different image artifacts. They think this model can be popularize well through dependable implementation in different medical segmentation issues. In [12] Used CNN to segment image in a fully unsupervised architecture. That no training data or labels are required in advance. This unsupervised setup may be crucial when it comes to images of skin lesions that are deficient in an adequate amount of data with a specific ground truth that can be used to train CNN. An unsupervised deep learning-founded path: network begins with the prediction of group labels for stable parameters on the fore process, so that the p-dimension map of features is computed out of M convolutional components in feature extraction. Then a linear classifier (argmax classification) is exercised for get response map, which ultimately results in the naming of a cluster per pixel. Superpixel optimization step

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produce sure that cluster labels designations match the adjacent pixels. Network parameters are then train using predicted fixed-cluster labels, and the softmax loss is studied among response and the enhanced cluster labels (similar to supervised learning). The procedure is frequent T times to get the end cluster labels calculation. The unsupervised path (CNN) is allowed to detect delicate structures in skin lesions efficient. Amirreza et al. [8], suggested completely automated technique for classifying skin lesions. Specifically, shown deep learning models that pre-trained, trained to classify natural images, It can also be used to classify images with dermatoscopy. Besides, it is shown that combining deep features from different layers of a single network or from different pre-trained CNNs show to improve the performance of classification. Ashwin et al. [13] suggested method to lesions detection utilizing subregional labeling and segmentation at the end. So through, a convolutional neural network is utilized as cubic SVM classifier and feature extract. The main feature of utilize CNN it is avoid the pre-processing of the input images.

Fully convolutional residual network improved FCRN-88 in [5] attain up to date outcome to segmentation from HEp-2 sample images. Depend on FCRN-88, it builds a lesion index network (LIN) to analyze the skin lesion. Two FCRNs trained on datasets utilizing various methods of augmenting the data are included. The Lesion Index Calculation Unit (LICU) is object to improve the odds of melanoma, nevus and seborrheic keratosis. The suggested lesion feature network (LFN) obtain better average accuracy and sensitivity of dermoscopy feature extraction, demonstrating its good ability to meet the challenge.

B. Autoencoder-based Methods

U-Net is one of the most popular methods of segmenting pigmented skin lesions and has been used in several studies such as ResNet [23], SegNet [24], U-Net [25]. Venkatesh et al. [4] suggested a methodology for skin lesion segmentation the design was motivated by the residual network with UNet . The input not the model is RGBH (Red, Green, Blue and Hue planes) of the dermoscopic image, while the output is a binary segmented image with white and black pixels representing influenced skin and non-influenced ones respectively. The suggested network is composed of four parts. The first part aims at making the network scale invariant by using a multi-scale image pyramid. The second part is a U-shape convolutional network. The third adds the residual learning to maintain spatial and contextual. Lastly, a layer for a binary loss function via entropy on Jaccard index involved pixel classification index. The suggest paradigm in [4], it is successfully catches lesion locale with no post-processing procedure and the boundaries of the lesion and background regions are well separated and are subject to differentiation.

Joshua and Jagath [6] utilized an altered design of U-net. The base distinction from an authentic architecture is that the resulting output segmentation map is the similar size as the input image, not like an authentic architecture, an amount of filters is half that of an authentic architecture at every stage. An altered architecture is include a contracting way on the left and an extending way on the right. Resized each input image to 128 x 128 utilizing two-line interpolation. The grid output are sigmoid probabilities on a 128 x 128 map. After training the network, the output is modify to an image with a binary label at a threshold of 0.5 applied to the logit probabilities. This method is characterized by being simple, fast, and effective, and it can include other applications as well.

Yanjun et al. [9] suggested a methodology of UNet basically fully convolutional network (FCN) and is very successful in biomedical image segmentation. In view to U-net shape the left part captures the context and the right part gets the exact localization. The contracting path was represent left part while expanding path was represent right part. The contracting pathway follow up the standard architecture of a convolutional network and attempts to capture the propagation context. The significant part is to broaden the path that is upsampling within this part. The top resolution features of the contracting path are mix with the upsampled output so that the location of the pixels can be precisely positioned. In the upsampling pane there are a big number of distinct channels, that authorize the network to spread contextual information to the upper resolution layers. In [9], they have introduced another process for segmentation of skin lesion that depend on an adversarial network for help segmentation training. Assists improving mean accuracy from segmentation outcome contrasted to the better outcome to knowledge. Until to some difficult images it can yet to get a steady outcome and this shows that method has good durability. However, the method still have some issue to find out. For sensitivity the method did not obtain the better outcome. This means to several lesion pixels still cannot classify their properly in this method and the edge details were not good sufficient. The techniques in [16] are mostly centered around two assignments: lesion segmentation plus classification. Deep learning is a general tool for resolve a lots of issues from various fields with a high achievement rate. But, given the rarity of categorized dermatoscopic images, it is difficult to train deep convolutional neural networks to segmentation the lesions. Thus, they utilized U-Net for data augmentation plus retraction and U-Net with spatial dropout that shows good performance.

In [12] a comparison of supervised deep learning with an unsupervised deep learning for segmentation of skin lesions in dermatoscopic images. The foundations of supervised deep learning have U-Net segmentation as a supervised deep learning network architecture. U-Net is a semantic segmentation end-to-end decoder network that was primarily utilized in medical image segmentation. U-Net appears to give much preferable accuracy in expression of dice coefficient and Jaccard index.

Zahra et al. [11] use PyTorch system to actualize the deep reweighting network. they embrace the architecture from fully convolutional U-Net lends it a Gaussian random distribution. Utilize a gradient random-proportions algorithm to learn network parameters from scratch as well as spatial weight maps on a range of small sizes. This method can significantly decrease the requirements for accurate labeling of images without losing segmentation accuracy. An end-to-end weight re-weighing fractionation network is trained, can be integrated with any segmentation network structure, and do not need additional tuning for hyperparameters.

For skin cancer discovery task in [16], they suggest feature extraction based on DCNN technique for SVM classifier that classification of skin lesions from dermoscopic images that display good performance.

Chaitanya et al. [3] suggest the FocusNet architecture, that utilizes two parallel branches for data stream with only one branch being allocated to attention. The attention branch uses a decoder architecture with skip links of encoder to decoder to ease best gradient flow. The architecture used gives robust bias for the two networks to specialize and learn various performance. The network planning used attention to provide best predictions of each pixel, resulting in best segmentation.

Researchers in [7] used fully automatic deep learning method to segmenting skin lesions. Specifically, they utilize deep convolutional decoder architecture to strong semantic marking of pixels. The architecture selection is depending on SegNet segmentation mechanism including from a coding network and identical decoding network go after by pixel-wise categorization layer. They display a solution for segmenting dermoscopy images utilize the pixel-wise deep convolution approach. The suggest approach was utilized to segment the overtly available data, gaining a segmentation accuracy of over 90%.

C. Generative *Adverserial-based Methods*

GAN manners depend on training the generator network to generate images that have pattern alike to that followed by the training data [26]. Kumar and Ghassan [1] used Mask2Lesion, a GAN-based modal model for creating skin lesion images from binary masks and constrained by them, and these recently created images were utilized along with their corresponding masks to increase the training data set to improve the accuracy of segmentation of the skin lesion images. In especially, they utilized segmentation masks of original data set as input into the generative algorithm to shun manual annotations on images of recently combined skin lesions. The results appeared progress in segmentation accuracy while the training data set to segmentation network was increased with these created images.

In [2] using data generation network for decouple DC-GANs, they suggest a technique for generating data using decouple DCGANs and they employ two different deep convolutional generation adversarial networks (DCGANs). They displayed a solution to problem large training data sets are required through depend on fine data cleaning that removes common blockages from dermatoscopy images and magnification that utilize modern technology to generate data based on deep learning to improve data balance. The system demonstrated efficiency in the lesion classification task.

D. Pre-Processing & Post-processing Techniques

Raw images have noise in them, thus the premier step in the detection procedure is pre-processing to improving the image quality for further use through removing undesirable image information this is indicated to as image noise. Various classification errors may happen if this problem is not properly handled. Beside to the imprecision, the requirement to perform this pre-processing is due to the low contrast between the skin lesions and the normal skin around it, abnormal borders and skin deformities, namely hair, shadow, skin lines, air bubbles, reflection and black frames. Several filters can be used to elimination Gaussian noise inclusive the medium filter, the adaptive medium filter, the Gaussian filter [17] and the adaptive Wiener filter. For instance, an image that has hair in it with a lesion may lead to misclassification. Image noise is assumed to be elimination or fine-tuned through performing pre-processing tasks like adjusting contrast, removing vignetting, color correcting, smoothing the image, removing hair, normalizing, and localizing. Correct combination gives pre-processing tasks more precision, Kumar and Ghassan [1] used to augment the training data set to improve the accuracy of segmentation of skin lesion images. Devansh et al. [2] presented a solution to occlusions problem that relies on fine-tuning of data that removes common occlusions from dermatoscopy images and augmentation that utilized modern technology to generate data based on deep learning to improve data balance. There are efficient methods that depend on data augmentation by rotating the image and applying horizontal flipping [5,8,10,12,7], resized [8,7,11], illumination correction [13,6], hair removal [13], contrast enhancement [7], just as preprocessing procedure it has been suggested to get better segmentation accuracy. For pre-processing of both micrographs and dermatoscopy, input for network is RGBH (red, green, blue and tone levels respectively) for the dermatoscopy image and output is a binary segment image for black and white pixels perform influenced skin and non-influenced area respectively [4,6,8]. Lokesh et al. [15] suggested that SVM be used to classify skin lesion by utilizing dermoscopy images. Looking at the input color image, a pre-processing is step to remove the noise. In the next stage, the adaptive segmentation manner is utilized to segment skin lesions for dermoscopy images. The suggested segmentation manner yields more effective segmentation results.

After going through the pre-processing and image segmentation stages, there wait for post-processing where the task is to elicit the features. To achieve this, most commonly post-processing methods are open-and-close operations [6], expansion of boundaries, merging of region, removal of islands, and smoothing [13]. Some of the techniques utilized for feature extraction are: principle component analysis (PCA), available texture information, Gaussian derivative kernels , resolution boundary features and region of interest (ROI) [18]. Lokesh et al. [15] the ABCD (asymmetry, border, color, diameter) base is used to post-segmentation dermoscopy images to extract several features.

III. Data Set, Evaluation Metrics and Results Summary

Dataset is one of the most important challenges when applying deep learning. In the absence of enough dataset, this will lead to a big problems because each learning algorithm needs a large amount of training to measure performance [31]. Nevertheless, there is a great effort to establish archives to collect the largest amount of medical images while preserving confidential information for patients. Researchers are resort to utilizing images of data from cancer research institutions and hospitals to implement their algorithms. Typically, researchers utilize a small data set which may affect the results, to deal with problem of limited dataset sometimes resort to pre-processing. a lot of researchers are utilizing data augmentation, which contain methods like resized, rotation, flipping, and illumination correction to raise the number of data that can be obtained as previously described. ISIC and PH2 of the most commonly used dataset available for online access. The International Skin Imaging Collaboration (ISIC) the skin cancer project is an academic and industry co-partnership destined to support application of digital skin imaging to assist reduce skin cancer deaths. Additionally, ISIC has developed and expanded an open source archive of public access to skin images to test and validate proposed standards. This archive serves as a general resource for images for teaching, development and testing of automated diagnostic systems. PH^2 is a database of dermoscopic images obtained from the Dermatology Service of Hospital Pedro Hispano, Matosinhos, Portugal. The PH^2 dataset has been developed for research and standardization purposes, in order to facilitate comparative studies on both segmentation and classification algorithms of dermoscopic images. This image database contains a total of 200 skin images of melanocyte lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. In Table I we will explain the data set used and the number of image for each challenge.

It is mentioned that, citing the 2016 and 2017 data sets: a challenge at the International Symposium on Biomedical Imaging (ISBI) 2016 and 2017, hosted by the International Skin Imaging Collaboration (ISIC).

In the this section, we show evaluate network performance in different researches used the following metrics, Accuracy (AC), Dice coefficient (DI), Specificity (SP) and Sensitivity (SE). Looking at βtp, βtn , βfp and βfn which are positive integers, false-positive, and false-negative integers respectively. All of the above metrics are calculated using equations (1)–(5):

$$\text{Accuracy(AC)} = \frac{\beta tp + \beta tn}{\beta tp + \beta tn + \beta fp + \beta fn} \quad (1)$$

$$\text{Sensitivity(SE)} = \frac{\beta tp}{\beta tp + \beta fn} \quad (2)$$

$$\text{Dice coefficient(DI)} = \frac{2 * \beta tp}{2 * \beta tp + \beta fp + \beta fn} \quad (3)$$

$$\text{Specificity(SP)} = \frac{\beta tn}{\beta tp + \beta fn} \quad (4)$$

$$\text{Jaccard Index(JA)} = \frac{\beta tp}{\beta tp + \beta fp + \beta fn} \quad (5)$$

TABLE I. THE DATA SET USED AND THE NUMBER OF IMAGES FOR EACH CHALLENGE

Data Set	Training Data	Test Data	Ref. No.
ISIC 2016	900 lesion images in JPEG format	379 lesion images in JPEG format	[5,8,9,14]
ISIC 2017	2000 lesion images in JPEG format	150 lesion images in JPEG format	[1,2,3,4,5,7,8,11]
ISIC 2018	2594 lesion images in JPEG format	1000 lesion images in JPEG format	[2,6,10,12,16,17,19,20]
ISIC 2019	25,331 lesion images in JPEG format	8,238 lesion images in JPEG format	Not used
ISIC 2020	33,126 lesion images in JPEG format	10,982 lesion images in JPEG format	Not used
PH2	200 images	-	[2,7,9,14,15,16,18,20]

Due to the multiplicity of methods used to segmentation the skin lesion, we will present the research results according to the evaluation metrics and the data set used. In addition, we will present the strengths and weaknesses of each method in a Table II.

IV. Discussion & Conclusions

Early identification of melanoma skin disease assumes a significant part to diminish its death rate definitely. Image segmentation using machine learning is one of the best ways for early detection and treatment of skin cancer. This paper has examined all the periods of computer aided melanoma skin disease recognition strategy in detail. Several criteria were used to measure the accuracy of image segmentation, such as sensitivity, specificity, accuracy, fmeasure, jaccard index, dic coefficient. Many of the methods showed good results compared to other methods that were not up to the required standard like gain an segmentation accuracy of over 90% in [7], the adversarial networks in [9] is collectively superior to the other methods except for sensitivity, U-Net appears to give a lot best accuracy from where Dice coefficient and index Jaccard in [12], the CNN method which gave good results in the jaccard index in [13] and for some lesion pixels in [9] the U-Net method still was not able to classify them properly and the edge detailing isn't good enough. ISIC and PH2 are two of the most common datasets available for online access. Usually, one or both of them are used to segmentation in dermoscopy images.

From the review presented, one can conclude that dermatoscopy images should be utilized more commonly in computational diagnosis of skin lesions, since these images present fewer artefacts and more detailed features, which may lead to more appropriate segmentation and analysis of lesions. However, artifact removal or reduction techniques are commonly requisite to gain robust segmentation results.

Image segmentation is a significant advance to the successful diagnostic calculation to images skin lesion pigment. Diagnosis of skin lesions is region of growing enthusiasm, due to the significance of protection and soon determination cancer of skin. Though image segmentation was treated for skin lesions has been dealt with in many research and effective implementation there is possibility for developing new methodologies and beneficent the presentation of existing approaches. In this paper, we introduce a review of existing deep network architectures that have been suggested to segment skin lesions. Image pre-processing and post-processing methods used in this context has been also explained along with the available datasets that can be used for research in this area. We also presented a comparison between the results of different methods used for skin lesion segmentation showing the strengths and weaknesses of each method.

In conclusion, future trends concerning image segmentation of skin lesions are to investigation for superior accuracy with regard to detecting lesion edges, as well as taking into account other problems in developing computational solutions, like level of automation, performance of computation, image noise and image enhancement.

TABLE II. COMPARISON THE RESULTS, ADVANTAGES AND DISADVANTAGES OF SKIN LESION SEGMENTATION.

Ref.	Method	Data set	AC	DI	JA	SE	SP	Advantages & Disadvantages
Jose-Agustin et al. (2020) [17]	CNN	ISIC 2018	92.40%	-	-	86.41%	90%	Improved implementation compared to the latest techniques in terms from accuracy, sensitivity and specificity got in the training and testing phases.
Ahmed et al. (2019) [10]	CNN	ISIC 2018	-	90.3	83.7	90.2	97.4	The procedure has appeared its strength versus various procedure and different image artifact. The problem of separating the lesion from the skin areas, due to the extreme contrast through the two categories.
Abder-Rahman et al. (2019) [12]	CNN	ISIC 2018	-	40%	30.4%	-	-	The unsupervised process is fit to discover accurate structures in lesions area best than some test samples in U-Net, but display lower quality result than U-Net results.
Zabir and Tasnim (2020) [16]	U-Net	ISIC 2018	-	0.87±0.31	0.80±0.36	-	-	U-Net with spatial dropout executed good which showed promising performance.
		PH2	-	0.93±0.13	0.87±0.19	-	-	
Abder-Rahman et al. (2019) [12]	U-Net	ISIC 2018	-	52.3%	41.8%	-	-	The process can highly diminish the matter for accurate labeling of images without relinquishing segmentation accuracy.
Venkatesh et al. (2018) [4]	U-Net	ISIC 2017	0.936	0.856	0.764	0.83	0.976	The suggested model successfully catches the lesion area without any steps of post-processing.
Joshua and Jagath (2018) [6]	U-net	ISIC 2018	-	-	0.756	-	-	The structure is fast, straightforward, and effective and can be reached out to different applications as well.
Zahra et al. (2019) [11]	U-net	ISBI 2017	-	73.55%	-	-	-	The process can highly diminish the matter for accurate labeling of images without relinquishing segmentation accuracy.
Kumar and Ghassan (2019) [1]	GAN-AUG	ISIC 2017	-	0.7830 ± 0.0197	-	-	-	The results showed the change for the better in segmentation resolution.
Devansh et al. (2019) [2]	DCGAN	ISIC 2017	-	-	-	0.648	0.697	It requires large sets of training data, and thus its applicability to dermatology is compromised by the volume of dermatological data sets available to all, Which are often small and contain blockages.
Lokesh et al. (2020) [15]	SVM	PH2	92.5%	-	-	100%	87.5%	The suggest segmentation approach supply additional effective segmentation result in compare to approach utilized in literature.
Maria and Cataldo (2020) [18]	DFCN	PH2	95.37%	95.32%	91.05%	93.60%	98.77%	The technique accomplished great in general execution, and in subtleties the best specificity.
Chaitanya et al. (2019) [3]	FocusNet	ISIC 2017	0.9214	0.8315	0.7562	0.7673	0.9896	The network provide the best predictions of each pixel, resulting in the best segmentation. The disadvantages of the network is that it is less responsive to measure of data sensitivity.
Yuexiang et al. (2018) [5]	LIN	ISIC 2017	0.950	0.839	0.753	0.855	0.974	The proposed LFN achieves the best average accuracy and sensitivity of dermatoscopy feature obtaining, demonstrating its excellent ability to meet the challenge.
Ali et al. (2018) [7]	pixel-wise	PH2	0.36	-	-	0.87	0.12	The process achieved even in the presence of hair and air / oil bubbles the segmentation very accurate and obtained a segmentation accuracy of more than 90%.
Yanjun et al. (2018) [9]	adversarial networks	ISBI 2016	0.97	0.94	0.88	0.90	0.99	Helps to better mean accuracy of segmentation. The stable output. As for sensitivity, did not obtain the better outcome. The edge precision is not good adequate.
Teck et al. (2020) [19]	HLPSO	ISIC 2018	0.9137	-	0.7315	-	-	HLPSO based feature chosen has accomplished extraordinary predominance more than the other present lesion classification.
Omran and Serestina (2020) [20]	MRF and stochastic region-merging	PH2	91.51	89.65	78.35	84.07	95.55	It gave an extra accurate segmentation, that will help dermatologists to automatically determine the area of the skin lesion for further diagnosis.

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