Extraction of Abnormal Skin Lesion from Dermoscopy Image using VGG-SegNet

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***Abstract*— Skin is one of the vital and well-known sensory organs in human physiology and due to various reasons, the abnormality in skin arises. Skin Melanoma (SM) is one of the medical crisis in humans and the untreated SM will cause various abnormalities, such as skin irritation, spreading the cancerous cells through the blood stream, etc. Efficient assessment of the SM is essential to identify the severity of the disease and hence the proposed work implemented a Convolutional-Neural-Network (CNN) based approach to support the automated SM examination. This work employed the VGG-SegNet scheme to extract the SM section from the Digital-Dermoscpy-Image (DDI). After the extraction, a relative assessment between the segmented SM and the Ground-Truth (GT) is executed and the essential performance indices are then computed. The proposed scheme is tested and validated using the benchmark ISIC2016 database and the average result attained with the proposed study helped to achieve a better values of Jaccard-Index, Dice, and Accuracy for the DDI with and without the artifacts. These results confirm that, proposed technique is significant in evaluating the clinical grader DDI.**

Keywords—Skin-Melanoma, Digital dermoscopy, VGG-SegNet, Segmentation, Evaluation.

I. INTRODUCTION

The skin is one of the vital sensory organ and also responsible to protect the inner organs from the outer environment. The disease in skin will cause various difficulty in humans and hence a considerable precautionary measures are needed to prevent the skin from the diseases [1-3].

In humans, skin cancer is one of the medical emergency and timely recognition and handling is essential to cure the disease [4,5]. The skin cancer is categorized as non-melanoma and melanoma and the report of World-Health-Organisation (WHO) confirms that, globally 3 million active non-melanoma and 132,000 melanoma cases are existing and every year the infection rate is rising in alarming rate [6,7]. The WHO also confirms that the risk factor in Caucasian populations is more than dark-skinned populations. To reduce the skin cancer occurrence rates, the WHO recommended various guidelines and also insisted to conduct the awareness programs to save the human community from skin cancer.

From the earlier study, the main cause for the Skin Melanoma (SM) is predicted to be the intermittent and high exposure of the skin to ultraviolet (UV) radiation. The early study also reported that the untreated sun burn will lead to the skin melanoma. When the SM is not treated in its early phase, the cancerous cells will spread through the blood stream; which cannot be cured completely. Hence, to support the early detection and treatment of SM, a number of scheduled health examinations is recommended by the doctors to patients.

The various stages involved in the detection of SM includes; (i) Self examination by the patient to identify the doubtful skin sections, (ii) Detailed examinination of suspicious skin section by a dermatologist, (iii) Dermoscopy based assessment with prescribed clinical protocol, (iv) Recommending the needle biopsy test to confirm the cancer stage, and (v) Minor/major surgery to completely remove the cancerous skin section.

The clinical level assessment of the SM is commonly performed using the ABCD/ABCDE rule, in which the shape and the structural features of the abnormal skin section and examined by the dermatologist and based on the finding treatment related decision will be taken by the dermatologist. When the number of patients to be examined is more, then the skin clinics will recommend the Digital-Dermoscopy-Image (DDI) based examination procedures in order to support the accurate estimation of the SM. If the recorded DDI is very clear, then evaluation of SM is uncomplicated and the skin infection level can be accurately examined. If the abnormal section in DDI is associated with artefacts, such as, hair, medical gel, markings, etc, then the assessment of the SM seems to be complex and needs a special tool for efficient diagnosis.

Development of an automated scheme for the accurate diagnosis of SM for clinical grade DDI is very essential and hence, the proposed work employed the Convolutional-Neural-Network (CNN) based system. The extraction of the SM section from DDI is one of the common practice and this work implements the VGG-SegNet scheme to extract the SM section from the DDI with and without the artefact. In this work, a pre-trained VGG-SegNet is employed to examine the SM fragment of the benchmark DDI images of International-Skin-Imaging-Collaboration (ISIC2016) database [8-11]. This database consist 1250 DDI images (900 training+350 testing) along with the related Ground-Truth (GT). The employed VGG-SegNet helps to get the binary form of the SM fragment. After the extraction, a relative appraisal of SM and the GT is implemented and based on the computed values of Jaccard-Index, Dice, Accuracy (ACC), Precision (PRE), Sensitivity (SEN), Specificity (SPE) and Negative-Predictive-

Value (NPV) the merit of the proposed segmentation scheme is confirmed.

The other sections are organised as below; Section 2 discuss the Related works, Section 3 demonstrates the methodology, Section 4 and 5 give the experimental outcome and discussions and Section 6 concludes the proposed work.

II. RELATED WORKS

Due to its significance, a number of DDI assessment methods are proposed and implemented for efficient detection of SM. Most of the earlier research suggests segmentation or a classification approach to detect the SM from the DDI. The employment of semi-automated/automated segmentation and machine/deep learning classification can be found in earlier works [1-3, 12,13].

In the SM segmentation approach, the main aim is to develop a methodology which supports the mining of the SM section from the considered DDI. The implementation of thresholding and segmentation is widely found in the literature and the aim of this technique is to mine the SM with better accuracy. Normally, the segmentation methods helps to get the binary version of the SM fragment, which is then evaluated using the standard techniques. The earlier work implemented a method to evaluate the skin melanoma harshness based on the ABCD/ABCDE rule [1,13]. In this approach, essential information such as area, boundary, and diameter are measured using the binary version of the SM section.

Classification of the DDI into normal/melanoma class is also one of the promising works, in which a suitable machine/deep-learning scheme is implemented to categorize the considered DDI using suitable two/multi class classifiers [12].

The ultimate aim of the SM examination procedure is to develop an appropriate methodology to confirm the melanoma and its harshness in the DDI using the implemented method. To support the efficient diagnosis of the SM, this work implemented an automated CNN scheme to support the efficient SM fragment mining. In this work, a pre-trained VGG-SegNet is implemented to evaluate the DDI with and without artefact and the attained result with ISIC2016 confirms that, proposed work is appropriate to examine the clinical grade DDI.

III. METHODOLOGY

This section presents the methodology employed in this research work for DDI assessment. After gathering the necessary trial picture from the ISIC2016 database, every image is resized to the dimension of 224x224x3 pixels. Initially, this work considered the pre-trained Vgg-SegNet scheme to extort the SM part from the adopted trial images. The total numbers of trial images considered are 1250 numbers. Further, the image augmentation (horizontal & vertical flip, $\pm 45^{0}$ rotation) is also employed during the pre-training process of the VGG-SegNet for the considered DDI.

Figure 1 presents the implemented scheme to extract the SM. Initially, the essential images of dimension 2048x1536x3 pixels is collected from the database and all the trial images and GT are then resized to a dimension of 224x224x3 pixels (recommended size for VGG scheme). The resized images are then considered to train the SegNet scheme and after the essential training, SM part of every image is segmented and compared against the GT. This comparison will help to get the essential values of the Image-Performance-Measures (IPM) and based on the average of IPMs of all 1250 images, the segmentation performance of the VGG-SegNet is validated.

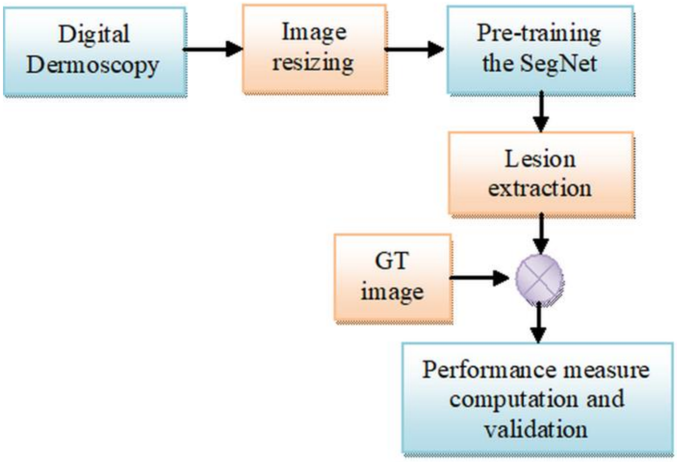


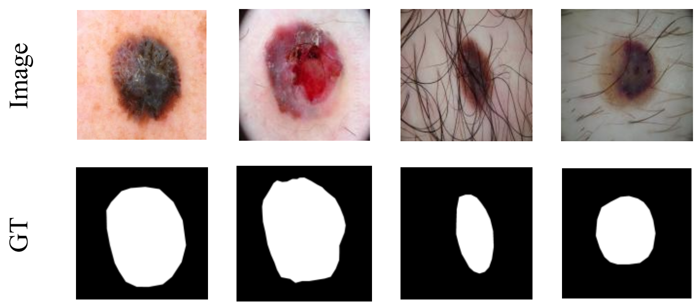
Fig.1. Proposed SM segmentation scheme

A. Image database

Due to its significance, a number of SM evaluation systems are proposed to examine the cancerous fragment from the DDI. In this work, the proposed CNN scheme is tested and validated using the benchmark ISIC2016 database. It is a commonly adopted DDI dataset consist 1250 numbers of RGB scaled pictures with a dimension of 2048x1536x3 pixels and every image is associated with its related GT.

The recommended image dimension for VGG-SegNet is 224x224x3 pixels; hence every image and GT of ISIC2016 is resized before the assessment. This dataset consist images with various categories, such as clear, with hair section, with medical-gel, with scale markings, etc. Segmentation of SM fragment from clear image is quite uncomplicated compared with the DDI with artefact. Hence, the considered scheme is appropriately trained with the original as well as the augmented test images.

Figure 2 depicts the sample trial pictures collected from ISIC2016 and Fig 2(a) and (b) depicts the image without and with artefact, respectively.



(a) Clear image (b) Image with artefact

Fig. 2. Sample test images of ISIC2016

B. VGG-SegNet

This work employs the pre-trained VGG-SegNet scheme to extract the SM fragment from the DDI and the architecture of this scheme is depicted in Figure 3. This method consists of two divisions namely the encoder and decoder parts as depicted in Figure 3. The Encoder consist a down convolution, which converts the given images into possible learned features and the decoder consist the up-convolution, which converts the images from the learned features [14-17]. The final segment of the decoder division consists of the SoftMax layer, which wills support a binary classification to separate the SM from background. The proposed scheme helps to get a binary SM fragment, which is then compared against the GT for validation. Other essential information regarding the VGG-SegNet can be found in earlier works [18-22].

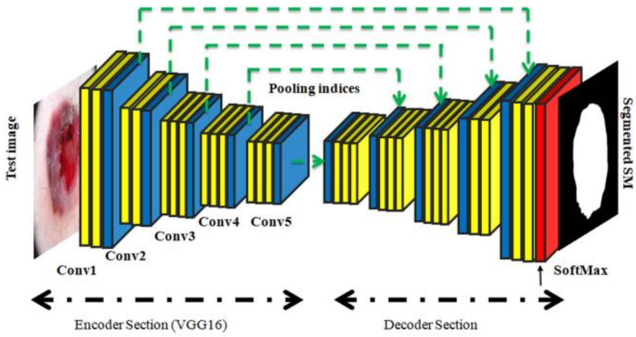


Fig. 3. Scheme of prêt-rained VGG-SegNet

Considered VGG-SegNet scheme is initially trained using the considered DDI and later every image (1250 numbers) are tested with the trained system and the extracted binary SM is then considered for further evaluation.

C. Validaion

In medical image assessment, there is a proved practice to validate the constructed disease recognition scheme using the prescribed protocol to confirm its clinical significance.

This protocol suggests the validation of the proposed scheme by computing the important Image-Performance-Measures (IPM) during the assessment between the SM fragment and GT. In this work, the IPMs, such as True-Positive (TP), False-Positive (FP), False-Negative (FN), and True-Negative (TN) are computed. From these measures, other values, such as Jaccard, Dice, Accuracy (ACC), Precision (PRE), Sensitivity (SEN), Specificity (SPE), and Negative-Predictive-Value (NPV) are also accomplished, and based on the computed IPMs; the significance of VGG-SegNet is validated [21-25].

IV. Experimental Result

This division of the research disclose the experimental results attained with the implemented scheme. This work is performed using the workstation; Intel i5 2.5GHz processor with 16GB RAM and 2GB VRAM set with MATLAB®.

Initially, the VGG-SegNet is trained using the resized trial images of dimension 224x224x3 pixels and during this task the ooriginal and augmented images are considered. When the scheme is properly trained, then every test image of the ISLC2016 is separately tested and the attained results are tabulated for further assessment. The attained result of this work confirms that, proposed scheme helps to get better result on the clear as well as the DDI with artefact.

Figure 4 depicts the result attained for a clear DDI. Fig 4(a) depicts the chosen trial picture and Fig. 4(b)-(e) depicts the results obtained from various sections of VGG-SegNet. Finally, the segmented binary SM is depicted in Fig 4(f).

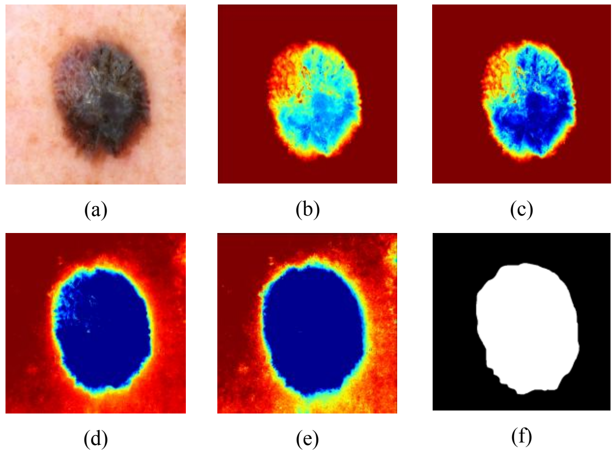


Fig. 4. Segmentation result attained with sample DDI

Test picture, (b),(c) sample result from encoder, (d), (e) Sample result of decoder, (f) Extracted SM

Similarly, Figure 5 depicts the outcome of the DDI with hair section. Extraction of the SM when the DDI is associated with the hair is very complex and from the results of Fig. 5, it is observed that the VGG-SegNet helped to extract SM with better accuracy. The sample image is depicted in Fig 5(a), Fig (b)-(e) depicts the intermediate results of this scheme and the final outcome is depicted in Fig 5(f).

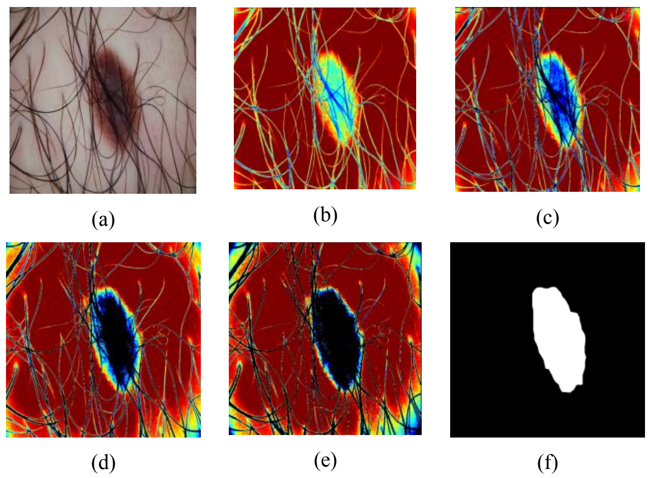


Fig. 5. Segmentation result attained with DDI with hair

(a) Test picture with artefact, (b),(c) sample outcome from encoder, (d), (e) Sample outcome of decoder, (f) Extracted SM

From the results of figure 4 and 5, it can be noted that the proposed scheme is efficient in localizing and segmenting the SM section from the considered DDI. Similar procedure is executed on all the test images and the extracted SM fragments are recorded.

After extracting all the SM sections of the database, an assessment is implemented with the GT and the necessary values of the IPMs are computed.

V. Discussion

This research work aims to implement the CNN segmentation to extract the SM fragment from the DDI with superior accuracy. The implemented method is tested and evaluated on ISIC2016 database and the results attained for sample DDI (DDI1 and DDI2) are depicted in figure 4 and 5 respectively.

After extracting the essential SM, an assessment is implemented with the GT and the essential IPMs are computed. The IPMs attained for DDI1 and DDI2 is depicted in Table I and II and these values confirm that the proposed VGG-SegNet scheme works well on the clear and the DDI with artefact. The IPM attained with the clear image is better compared to the image with the hair section. Similar procedure is employed to evaluate all the 1250 test images and the average of the computed IPMs are considered to validate the implemented scheme.

TABLE I. Vital image performance mesure calculated using comparision of SM and GT

Image	TP	FP	TN	FN	Jaccard	Dice
DDI1	16647	1854	31607	68	89.65	94.54
DDI2	5213	1523	43405	35	76.99	86.99

TABLEII. Image performance measures for chosen test picturesof sample test images

Image	ACC	PRE	SEN	SPE	NPV
DDI1	96.17	89.98	99.59	94.46	99.78
DDI2	96.89	77.39	99.33	96.61	99.92

The main advantage of the proposed scheme is, it is an automated technique and does not need any hair removal approaches as discussed in the earlier research work. Table III compares the performance of the proposed technique with other existing method in the literature. The results presented in this table confirms that, proposed approach help to get better values of ACC, PRE and SEN compared to the other existing methods. The SPE attained in earlier works are better compared to VGG-SegNet.

TABLE III Assessment of implemented scheme with existing results

Method	ACC (%)	PRE (%)	SEN (%0	SPE (%)
EXB [26]	95.30	-	91.00	96.50
CUMED [26]	94.90	-	91.10	95.70
Mahnudar [26]	95.20	-	88.0	96.9
ALL-FCNs [12]	95.20	89.90	92.40	96.00
OSO-FCNs [12]	95.80	91.30	92.50	96.40
Rajinikanth et al. [2]	92.16	89.18	93.16	92.18
Dey et al. [3]	92.84	90.06	94.18	92.31
Rajinikanth et al. [13]	92.29	89.74	92.88	92.25
VGG-SegNet	97.16	92.81	95.04	94.75

The Glyph-plot depicted in figure 6 confirms that the overall performance attained with VGG-SegNet is superior compared to other techniques.

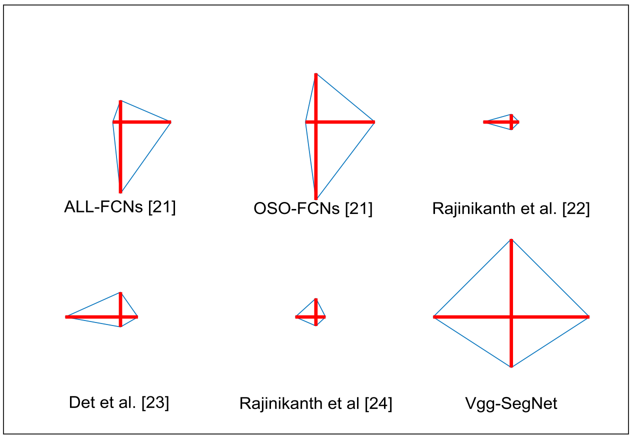


Fig. 6. Glyph-Plot to confirm the merit of VGG-SegNet

In the proposed research, only the segmentation is performed with the considered VGG-SegNet scheme. This scheme consist the combination of Encoder and Decoder section and the encoder section is the traditional VGG16 architecture without the Fully-Connected-Layer (FCL). When this section is associated with the FCL and the SoftMax classifier, then it is possible for us to classify the existing DDI into melanoma/non-melanoma class. The implementation of VGG16 based classification of the ISIC2016 is one of the recommended future scopes of this research. Further, in future, the extracted SM section can also be considered to get the essential texture and the shape features to implement the ABCD/ABCDE rule supported examination.

VI. Conclusion

Examination of the skin cancer using the computerized tool will considerably reduce the diagnostic burden during the mass screening. Hence a number of methods are proposed and implemented to detect the skin abnormalities using the DDI. This work employed a pre-trained VGG-SegNet scheme to extract and evaluate the SM fragment from the DDI with dimension 224x224x3 pixels. The proposed section consist encoder-decoder section and at the end it has a SoftMax classifier to execute a binary classification. The classifier unit separates the SM from the background and the binary form of SM is then compared ageist the GT to find the IPMs. The average values of IPMs of all the 1250 images are then computed and validated against the existing methods in the literature. The result of this work confirms that, proposed work offers better result with the ISIC2016 database.

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