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Article

Saliency Induced Fusion for Skin Lesion Detection

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Abstract: Skin lesion segmentation from dermoscopic images is one of the most important and fundamental step in computer-aided diagnosis (CAD). It is more challenging due to the presence of hairs, ruler marks, gels, dark corners, colour inconsistency, shape, size etc. in the images. It is highly essential by ignoring the aforementioned challenging facts to extract the accurate skin lesions. We have proposed a saliency-based approach that initially detects the different saliency maps i.e., frequency, color, location, covariance and mean. The fusion of different saliency maps is implemented in the proposed method for enhancing the lesion regions so that it will help in the segmentation process to extract the lesions precisely. One of the simplest algorithm i.e., Otsu algorithm is used for segmentation of skin lesions from dermoscopic images. The final lesion mask is obtained by further processing the segmentation output with the post processing techniques. For evaluating the proposed method, the images from ISIC datasets are considered. A large number of images having aforementioned challenging factors are considered to compute the performance metrics. The proposed method is able to extract the lesion masks and lesion regions more accurately. The method archives an average accuracy of 96.29%, 96.48% and 95.89% for ISIC 2016, ISIC 2017 and ISIC 2018 benchmarked datasets.

Keywords: skin lesion; saliency map; lesion detection; morphological operation

1. Introduction

One of the most prevalent causes of fatalities globally is skin cancer which starts when skin cells grow uncontrollably. Generally, UV radiation from sun leads to the development of skin cells and the formation of cancerous tumors. If skin cancer is detected early, fatalities can be decreased. Skin cancers are having different types i.e., melanoma and non-melanoma. Melanoma is considered as one of the deadliest forms of skin cancer as it is harmful to human life. As per Skin Cancer Foundation, there will be an expected 200,340 new cases of melanoma diagnosed in the United States in the year 2024 [1]. Visual inspection is the primary method used to diagnose skin cancer, but it is less precise. During the visual inspection, ABCDE rule is used by the experts that helps in the early detection of suspicious moles or lesions. The effectiveness of visual examination is heavily dependent on the skill and experience of the healthcare professional conducting the examination [2, 3]. Skin lesions associated with skin cancer can have diverse appearances, making it challenging to identify all potential cases through visual examination alone [4].

Computer-Aided Diagnosis (CAD) systems can play a significant role in the early detection of skin cancer by assisting dermatologists in analyzing and interpreting medical images. CAD systems can enhance the quality of dermatological images, making it easier for healthcare professionals to identify potential abnormalities or lesions. Image analysis algorithms can highlight specific features such as asymmetry, border irregularities, color variations, and size, which are important indicators of skin cancer. CAD systems use machine learning algorithms to automatically detect and highlight potential lesions or abnormalities in skin images. This automated detection can assist dermatologists by pointing out areas that may require closer inspection, reducing the chance of overlooking subtle signs of skin cancer. The number of CAD systems developed by researchers for assisting the experts for identification of melanoma and to classify it.

To assist the dermatologist for accurate skin cancer detection and classification the numerous supervised and unsupervised techniques have been developed [5, 6]. In the present era, deep learning approaches are widely used for skin cancer identification and classification as it provides better accuracy. Apart from that also the unsupervised and hybrid approaches are preferable in the recent years due to their simplicity and time-saving characteristics. This paper focuses to extract the lesion regions from dermoscopic images using a hybrid approach by combining saliency based and thresholding techniques.

The major contributions of this work is as follows:

1. Saliency feature maps from the source images are extracted using frequency, color, location, covariance and mean which provide the diverse details of the source image from different aspects.
2. The features are fused to enhance the saliency map that preserves various information with highlighted details of the lesions.
3. The feature fusion mechanism provides better lesion visualization with reduced artifacts without the usage of pre-processing strategy.
4. The proposed algorithm capable of handling different challenging datasets against recent state-of-the-art techniques.
5. The developed approach has a lesser computational complexity compared to existing techniques which may be suitable for real-time applications.

The rest of the paper is organized as follows; Section 2 describes the related work. The proposed method is discussed in Section 3.The datasets used for the experimentation is elaborated in Section 4. The performance metrices used to evaluate the proposed method results with the state-of-art approaches are given in Section 5. Results and discussion are illustrated in Section 6. Finally, the paper is concluded in Section 7.

2. Related Works

Saliency-based approaches are gaining traction in the field of skin lesion extraction due to their ability to automatically identify and prioritize regions of interest in medical images.Saliency-based approaches aim to identify the most visually ”distinct” or ”important” parts of an image. In the context of skin lesion extraction, this translates to highlighting areas potentially representing lesions based on features like color, texture, or contrast. Some of the recent saliency-based approaches used for skin lesion extraction is discussed here.

For multiclass lesion segmentation and classification, Khan et al. [7] developed an automated approach. Initially, the local-control histogram intensity values are implemented for contrast stretching. Morphological operations are used for lesion extraction. Zortea et al. [8] developed an unsupervised method that uses one of the simplest method called as Otsu thresholding for skin lesion extraction. Initially the pre-processing technique is implemented to reduce the shadow attenuation from images. Eltayef et al. [9] introduced an automated detection of lesion borders by integrating Particle Swarm Optimization and Markov Random Field Methods and was tested on a dataset of 200 dermoscopic images. Thapar et al. [10] introduced a reliable approach to the diagnosis of skin cancer. Here the Swarm Intelligence (SI) algorithm was implemented for skin segmentation. Thus, Speeded-up robust features (SURF) were used for feature extraction of ROI by using the Grasshopper Optimization algorithm. The skin lesion is classified into two groups using a convolution neural network and tested with three datasets such as ISIC 2017, ISIC 2018, and PH2 dataset. Garg et al. [11] introduced a segmentation technique by combining K-mean and an optimized Firefly Algorithm and the proposed method is evaluated using ISIC and PH2 dataset images. The dermoscopic images are having irregular border and to detect the accurate border region is also a challenging task. So, for accurate border detection Meskini et al. [12] developed an algorithm that combines particle swarm optimization (PSO) and Chan and Vese active contour. PSO algorithm is employed for obtaining the gray level image with maximum coefficients and which is applied as an input to multi Ostu method to get the initial border contour. The final border is detected using Chan and Vese active contour method. Fan et al. [13] demontrated an algorithm by combing saliency and Otsu thresholding for skin lesion segmentation. The methodology involves the development of an automatic segmentation algorithm for dermoscopy images, including an enhancement stage with prior information extraction and saliency map construction, and a segmentation stage with an optimized Otsu threshold method. The method is able to segment the images with better accuracy. However, the approach heavily rely on a single threshold which is heavily dependent on the pixel intensities of the input dermoscopic images. Alhamadi et al. [14] proposed a MSAU-Net mechanism for segmenting skin lesions. To simulate the hierarchical representation, authors have enhanced the standard U-net by incorporating an attention mechanism at the network's bottleneck.

Erdem et al. [15] presented novel bottom-up saliency model. The methodology involves extracting basic visual features, decomposing the image into non-overlapping regions, estimating their covariances, comparing each rectangular image region against its immediate context, and using region covariances to capture local structure information and nonlinearly integrate different features. Zhou et al. [4] proposed slaiency-color contextual extractor module for lesion saliency detection. The method used an adaptive threshold strategy for lesion extraction. However, it is sensitive to perceptually uniform color differences within the lesion regions and inapplicable to images interrupted with hairs.

In order to segment skin lesions, Tahir et al. [16] offered a weighted visual saliency-based approach as well as an enhanced HDCT based saliency estimation. Image fusion and classification were then performed using the Inception-ResNet-V2 pre-trained model with transfer learning.

Jahanifar et al. [17] introduced discriminative regional feature integration with saliency approach tailored for detecting lesions in dermoscopic images. The framework uses the detected saliency map to construct an initial mask of the lesion through thresholding and postprocessing operations. The methodology includes the introduction of a new pseudo-background region to identify the lesion and background. Although the approach using a superior deep neural network provides better result compared to other state-of-art-approaches it may not work for all types of dermoscopic images. However, the approach uses mid-level features and handcrafted features which may suffer the generality.

Ramella [18] demonstrated the combined use of saliency and color information for improved skin lesion segmentation. The approach initially reduces the size/color of the input image, removes hairs followed by saliency map construction. Later, in segemntation process it uses the saliency map obtained from the former step to construct the binary map followed by lesion detection. In the post-processing step, the approach uses foreground expansion for effective lesion extraction. When pre-processing is not done enough to thoroughly clean the image, the approach fails to determine the skin lesion precisely. With the highest saliency values in the background and the lowest saliency value within the skin lesion, saliency-based segmentation may not always be sufficient to extract the appropriate foreground.

Ahn et al. [19] present a new approach using saliency detection and a Bayesian framework to accurately segment skin lesions and further discussed about the potential extension of their framework as a saliency optimization algorithm for lesion segmentation.The methodology involves saliency detection using reconstruction errors from a sparse representation model combined with background, a Bayesian framework for delineating the shape and boundaries of the lesion, and evaluation of the approach on two public datasets with comparison to other methods.The limitations of the study include degradation of segmentation performance due to visual artifacts such as skin hair occluding parts of the lesion, and the potential for mistakenly detecting small, visually indistinct lesions located at the image boundary as part of normal background regions. The paper also suggests that further research and improvements may be needed to address these limitations.

A supervised saliency detection method developed by Jahanifar et al. [20] for lesion segmentation. The methodology involves proposing a supervised saliency detection method based on the discriminative regional feature integration. New features have been added to the regression property descriptors and a new pseudobackground region have been included in the enhanced saliency detection method, or mDRFI. Through thresholding and post-processing processes, the detected saliency map is used by the overall lesion segmentation framework to create an initial mask of the lesion. This mask is then evolved in a level set framework to better fit on the lesion's boundaries.

Khan et al. [21] developed an approach for segmentation and classification of lesions using discriminant deep fea- tures. For segmentation performance, PH2 and ISIC datasets are used. HAM10000 dataset is used for evaluating the classification performance. But the usage of meta-heuristics in conjunction with pre-trained deep networks may increase the overall time complexity of the network.

Khan et al. [22] presented an efficient model for accurate border detection and classification of skin lesions, including contrast enhancement, fusion of multiple features, and classification using SVM. The methodology involves conducting experiments on three datasets, improving segmentation accuracy through contrast enhancement, utilizing optimized features for SVM classification, and comparing the system's performance with recent methods. The method uses a PSO based heuristic technique for segmentation which increases the time complexity of the model. But the accuracies obtained for this approach varies between 93 to 99 percentage for various datasets which indicates the huge variations in the model outcome.

From the above discussion, it may be deduced that saliency based approach which is based on human visual attention mechanism has a huge potential in discriminating the lesions from challenging dermoscopic images. However, it is observed that the recent approaches developed so far either uses a supervised based deep neural network approach or some meta heuristics for effective segregation of lesions from dermoscopic images. The limitations of these approaches are as follows: Although they have used saliency-driven mechanism in deep neural networks, their complexity would increase which makes them inefficient for real-time implementation with reduced complexities. Here, efforts are made to extract saliency based on different features of the dermoscopic images and fused together for better lesion extraction.

3. Proposed Method

The proposed method comprises of two stages i.e., saliency map detection and lesion extraction using thresholding algorithm. The architecture of the proposed method is illstrated in Figure 1. The more details about the proposed method is explained below. The proposed method includes the following steps to extract the lesion regions from dermoscopic images such as input image, saliency maps extraction, fusion of saliency maps to enhance the lesion region, thresholding algorithm to extract the lesion region and post processing techniques.

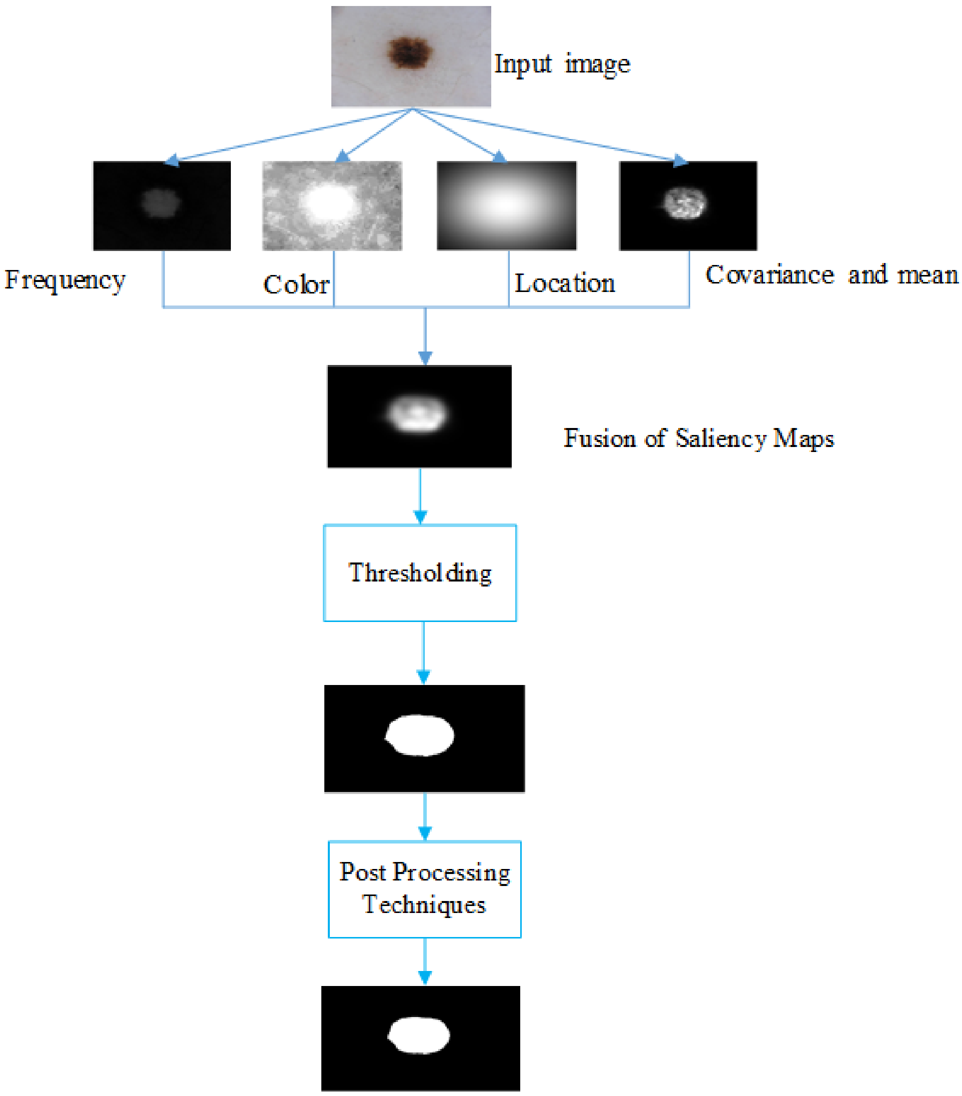

Figure 1. Architecture of the Proposed Method.

3.1 Input Image

ISIC 2016, ISIC 2017 and ISIC 2018 images are taken as input images in the proposed method. The datasets contain RGB images as well as their corresponding ground truths. The RGB images available in the datasets are having large variation with respect to color, texture, border etc. Performance metrics are computed by comparing the extracted lesions and ground truths available in the datasets.

3.2 Saliency Maps Extraction

The images available in the datasets are having large variation with respect to intensity, color, shape, size, border etc. It is quite challenging for segregating the lesions from healthy skins for low illumination images. Hence, a saliency detection method is employed in the proposed method for identifying the salient regions more prominently from the background regions and also reduces the complexity of the images for further processing. The proposed method focuses to detect the different saliency maps such as frequency, location, color [23] and covariance of an image. The more details about the saliency detection are explained below;

1. For frequency map detection different filters i.e. band-pass filter, Difference of Gaussian (DoG) filter and log-Gabor filter are used the researchers. The proposed method employed the log-Gabor filter to detect the salient region from an image. At first, the input image i.e. I_x is converted into CIE $L\star a\star b\star$ space and as it is an opponent color space. The three resulting channels are represented as $I_L(x)$, $I_a(x)$, $I_b(x)$. Now, the frequency saliency map $S_F(x)$ is expressed as

$$\begin{aligned} S_F(x) = ((I_L(x)\star g(x))^2 + (I_a(x)\star g(x))^2 \\ +(I_b(x)\star g(x))^2)^{\frac{1}{2}} \end{aligned} \tag{1}$$

   where $\star$ represents the convolution operator and $g(x)$ is the transfer function of a log-Gabor filter.

2. As initially the input RGB image i.e. I_x is converted into CIE $L\star a\star b\star$ space and the resulting channels are reprtesented as $I_L(x)$, $I_a(x)$,and $I_b(x)$. The color saliency is detected based on the following equation for a given pixel if the pixel has a higher $a\star$ or $b\star$ value.

$$S_c(x) = 1 - exp(-\frac{I_{an}^2(x) + I_{bn}^2(x)}{\sigma_c^2}) \tag{2}$$

   where $I_{an}(x) = \frac{I_a(x)-mina}{maxa-mina}$, $I_{bn}(x) = \frac{I_b(x)-minb}{maxb-minb}$, and σ_c is a parameter.

3. Generally, the images present at the centre are more appealing to the viewers. So, the areas closer to the image's centre will probably be more salient than areas farther out. So, the location saliency for an image $I(x)$ can be stated as a Gaussian map

$$S_L(x) = exp(-\frac{\parallel x - c \parallel^2}{\sigma_L^2}) \tag{3}$$

   where c is the centre of the image and σ_L is a parameter.

4. Tuzel et al. first suggested covariance of features as a compact region descriptor. Since then, it has proven useful in a number of challenging computer vision issues. In the proposed method, we have considered initially the covariance and mean features [24] for saliency detection in dermoscopic images where the second-order statistical connections among features are utilised by covariance matrices to convey the information about local structure (lesion) and the first-order statistics i.e. mean helps for capturing the saliency of a dermoscopic image region in relation to its surrounds (background). Both the features i.e. covariance and mean helps to detect the saliency for the images having different illumination in the dermoscopic images.

The saliency maps i.e., frequency, color, location, covariance and mean features detected from the images are shown in the Figure 2.

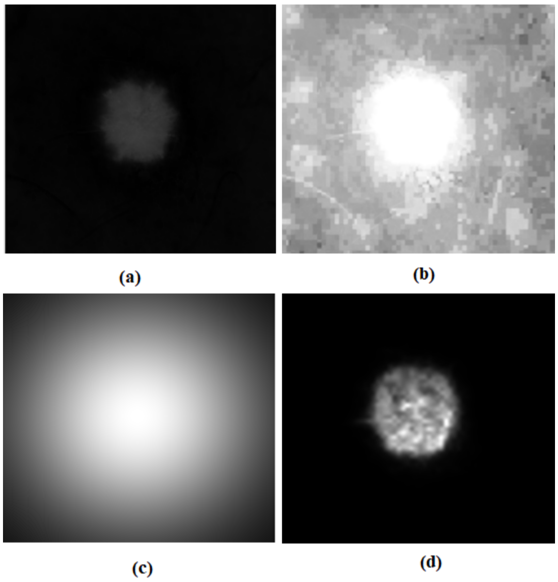

Figure 2. Saliency-Map obtained from (**a**) Frequency, (**b**) Color, (**c**) Location and (**d**) covariance and mean saliency maps detected from the input image.

3.3 Fusion of Saliency Maps to Enhance the Lesion Region

The different saliency maps detect from the images are fused to achieve the final saliency map. The fusion method helps to enhance the lesion region as well as to acquire the accurate lesion regions after the segmentation technique.

3.4 Thresholding Algorithm to Extract the Lesion Region

The final saliency map obtained after the fusion method are further processed to extract the lesion regions from dermoscopic images. One of the simplest segmentation technique called as Otsu thresholding is implemented for extracting the lesion regions. Based on the integration of the histogram, the optimal thresholded value is chosen automatically. The thresholded value is used to divide the image into two classes, such as background (healthy skin) and foreground (lesion). The output of the thresholding operation is a binary image that depends on the following algorithm;

$$I_{th} = \begin{cases} 1 & if\&I_{GF}(x,y) > Th \\ 0 & if\&I_{GF}(x,y) \leq Th \end{cases} \tag{4}$$

where the I_{th} is the threshold image obtained after Otsu algorithm and $I_{GF}(x,y)$ is the input image. The saliency map is shown in Figure 3.

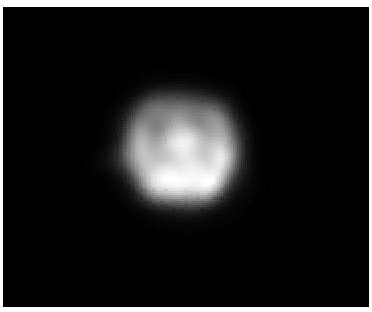

Figure 3. Fusion of saliency maps to enhance the lesion region .

3.5 Post Processing Techniques

In the segmentation of skin lesions, the post processing techniques are also very important. Better segmentation results are obtained by removing the unwanted small pixel regions from the lesion regions. The following sub-steps are implemented in the proposed method as post processing techniques for final lesion extraction. The more details about the post-processing techniques are explained below;

3.5.1 Morphological Operations

A thresholded image with two regions i.e., lesion regions and healthy skin regions are the result of the preceding phase. The background regions are the healthy skins and the lesion regions are the foreground parts. The thresholded image undergoes morphological operation to eliminate unwanted regions, such as spikes, dispersed pixel regions, etc. For the purpose of morphological erosion and region filling, a disk-type structuring element with a size of 15 is used in the proposed method.

3.5.2 Biggest Blob Extraction

The previous stage provides a binary image by neglecting the undesired pixel regions present in the lesion regions. The binary image is further processed using the biggest blob extraction algorithm to obtain the final lesions. The lesion regions have the largest connected component of white pixels, whereas the undesirable locations have smaller connected pixel areas. So, this algorithm helps to obtain the largest linked component of the binary image by neglecting all of the smaller parts. Finally, a binary is obtained where the lesion regions are represented in white and healthy regions are in black. The corresponding results after thresholding and after post-processing is demonstrated in Figure 4.

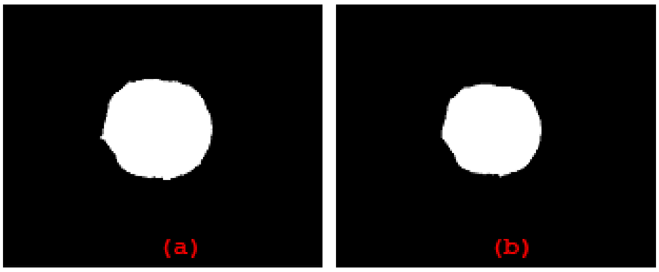

Figure 4. (**a**) Output after thresholding and (**b**) output after post processing techniques.

4. Datasets Used

For evaluation, ISIC 2016, ISIC 2017 and ISIC 2018 datasets are used in the proposed method. The datasets contain the images having large variation with respect to shape, size, illumination, boundaries, color etc. The images having number of artifacts such as hairs, gels, ruler marks etc. are also found in the datasets. Apart from this, images with large variation in illumination are also available in the datasets that becomes more challenging for extracting the accurate lesions. The images having black frames are also available. The sample of images having different challenging factors are shown in the Figure 5. It can be observed that, the images present in the datasets have hairs, ruler marks and black frames while acquisition process.

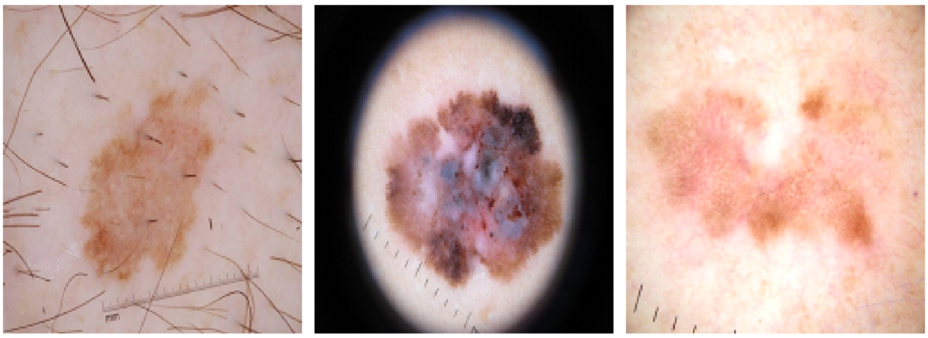

Figure 5. Samples of images from the datasets having different artifacts.

5. Performance Metrics

Various metrics, including Accuracy (Acc), Dice Coefficient (DC), Sensitivity (SN), Specificity (SP), and Jaccard Index (JI) are employed in the proposed method for performance analysis. To compute the various metrics, the ground truths are compared with the lesions extracted from the proposed method. The formulas used to calculate the performance metrics are given below;

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

$$DC = \frac{2 \times TP}{(TP + FP) + (TP + FN)} \quad (6)$$

$$SN = \frac{TP}{TP + FN} \quad (7)$$

$$SP = \frac{TN}{TN + FP} \quad (8)$$

$$JI = \frac{TP}{(TP + FP + FN)} \quad (9)$$

where TP—True Positive, TN—True negative, FP—False Positive and FN—False Negative rates.

6. Results and Discussion

For experimentation, MATLAB R2018b is used in a PC with core i3 processor and 8GB of RAM. A variety of images from the three datasets are considered for evaluating the proposed method with respect to different performance measures such as Acc, SN, SP, DC and JI.

Initially, the images from ISIC 2016 dataset are considered for evaluating the proposed method. The performance metrics obtained using ISIC 2016 dataset is compared with the existing methods for validating its performance. Table 1 demonstrates the comparison with respect to performance metrics of proposed method and existing methods. The bold values of a particular measure indicate best performance against all other approaches.

Table 1. Comparison of proposed method with existing methods on ISIC 2016 dataset.

Algorithms	**Acc**	**DC**	**SN**	**SP**	**JI**
Fan et al. [13]	91.8	81.8	74.7	—-	—-
Zamani et al. [25]	93.5	89.5	83.2	98.7	80.2
Yuan et al. [26]	95.5	91.2	91.8	96.6	87.4
Jahanifar et al. [20]	94.2	91.7	88.7	98.4	85.5
Arroyo et al. [27]	93.4	86.9	87.0	97.8	79.1
Bozorgtabar et al. [28]	91.0	80.0	—	86.0	67.0
Khan et al. [29]	83.2	—-	75.5	93.0	—-
Bi et al. [30]	85.68	75.88	78.30	91.31	66.19
Ahn et al. [19]	84.67	69.97	70.04	97.31	57.20
Celebi et al. [31]	91.0	80.0	—-	86.0	67.0
Moradi et al. [32]	93.0	91.2	93.1	91.5	83.6
Yu et al. [33]	94.9	89.7	91.1	95.7	82.9
Bozorgtabar et al. [34]	92.3	89.2	—	—	80.6
Xie et al. [35]	93.8	91.8	87.0	96.4	85.8
Nida et al. [36]	94.2	94.0	**95.0**	94.0	**93.0**
Proposed Method	**96.29**	**94.41**	94.39	**99.32**	90.62

From the Table 1, it is identified that the proposed method provides the overall accuracy of 96.29% on ISIC 2016 dataset which is the highest value in comparison with the other methods. The lesions extracted from the images are illustrated in Figure 6 for effective visual analysis. The input images and their corresponding ground thruths are shown in Figure 6a,b. The saliency maps extracted from the input images are given in Figure 6c–f. The fusion of saliency maps are in Figure 6g. The extracted lesion masks and lesions are illustrated in Figure 6h,i.

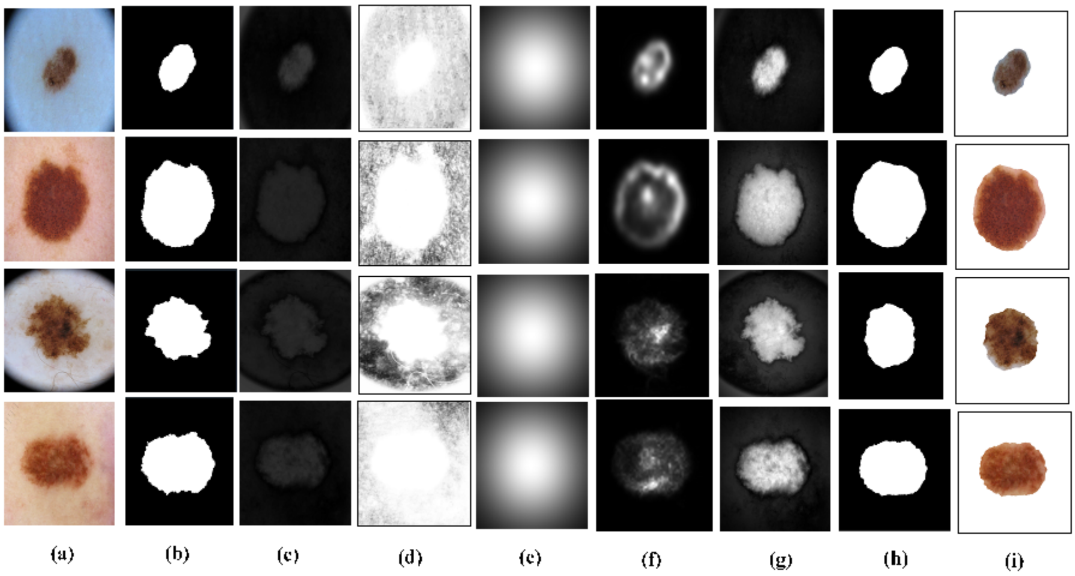

Figure 6. (**a**) Original images from ISIC 2016 dataset, (**b**) Ground truth, (**c**) Frequency, (**d**) Color, (**e**) Location, (**f**) covariance and mean features, (**g**) fusion of saliency maps, (**h**) lesion mask and (**i**) extracted lesion.

The images from ISIC 2017 and ISIC 2018 are also considered to measure the effectiveness of the proposed method. A number of images having variation in illumination, color, shape and size are considered for this purpose. The performance metrics obtained from the ISIC 2017 and ISIC 2018 datasets are given in Tables 2 and 3. The results are compared with different methods for validating the performance of proposed method. From the Tables 2 and 3, it is noticed that the overall accuracy of 96.48% and 95.89% are acquired from ISIC 2017 and ISIC 2018 datasets respectively.

Table 2. Comparison of proposed method with existing methods on ISIC 2017 dataset.

Algorithms	**Acc**	**DC**	**SN**	**SP**	**JI**
Zhang et al. [37]	92.7	81.7	83.7	96.4	72.9
Lei et al. [38]	93.5	85.9	83.5	97.6	77.1
Pour et al. [39]	94.5	87.1	88.3	98.1	78.2
Bi et al. [30]	94.08	77.73	86.20	96.71	**85.66**
Barın et al. [40]	93.47	87.35	79.25	97.8	77.54
Ren et al. [41]	93.43	85.23	85.43	96.83	76.92
Öztürk et al. [42]	91.76	82.09	80.05	95.37	69.63
Tong et al. [43]	92.6	—	82.5	96.5	74.2
FocusNet [44]	92.14	83.15	76.73	98.96	75.62
Liu et al. [45]	93.00	84.00	82.9	98.8	75.20
Mirikharaji et al. [46]	93.8	85.7	85.5	98.5	77.3
Li et al. [47]	93.55	85.60	85.40	97.59	77.23
Venkatesh et al. [48]	93.6	85.6	83	98.5	76.5
Tang et al. [49]	94.31	86.93	89.53	96.32	79.26
Ünver et al. [50]	93.3	84.2	**90.8**	92.6	74.8
Soudani et al. [51]	94.9	88.1	85.8	95.6	78.9
Proposed Method	**96.48**	**89.23**	90.06	**99.51**	81.92

Table 3. Comparison of proposed method with existing methods on ISIC 2018 dataset.

Algorithms	Acc	DC	SN	SP	JI
Lei et al. [38]	92.9	88.5	95.3	91.1	82.4
Ali et al. [52]	93.6	88.7	—	—	81.5
Arora et al. [53]	95.0	91.0	94.0	95.0	83.0
Venkatesh et al. [48]	—	89.5	91.1	96.7	82.6
Shahin et al. [54]	—	90.3	90.2	97.4	83.7
Nazi et al. [55]	—	87 .0	—	—	80.0
Azad et al. [56]	93.7	—	78.5	98.2	—
Jin et al. [57]	93.4	87.7	**96.7**	90.4	79.4
Salih et al. [58]	89.47	80.67	79.45	95.09	72.45
Proposed Method	**95.89**	**92.37**	95.8	**98.62**	**87.94**

The segmentation results obtained from ISIC 2017 and 2018 datasets are given in Figures 7 and 8. After analysing the results, it is found that the proposed method is able to extract the lesions more precisely for both the datasets. The fusion of different saliency maps enhances the lesion regions that helps for accurate identification of lesion masks in the segmentation process.

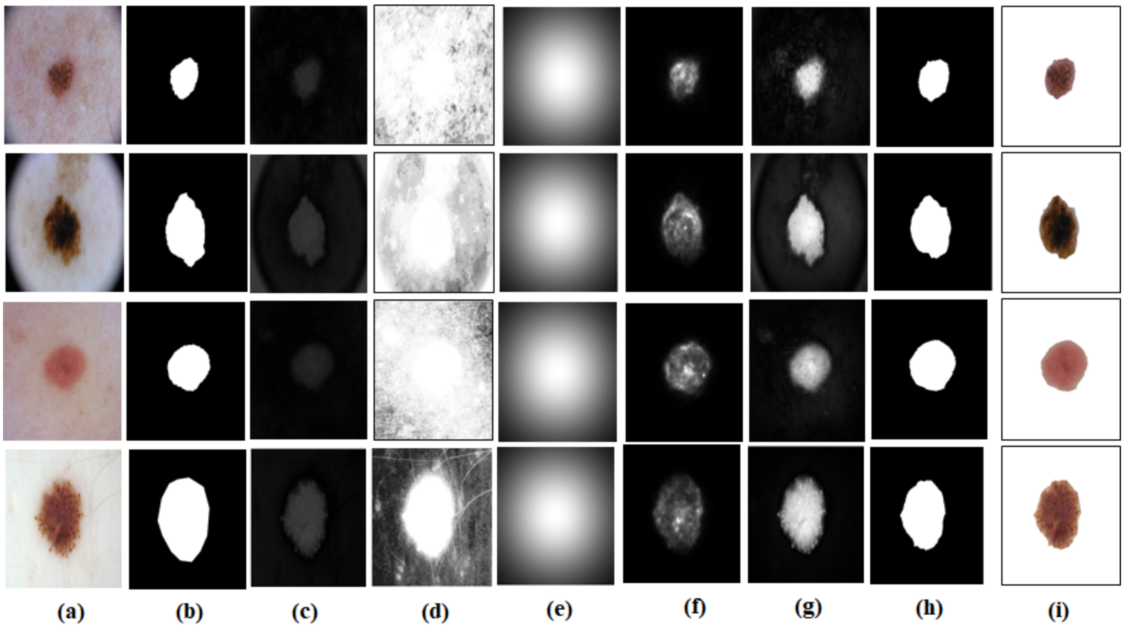

Figure 7. (**a**) Original images from ISIC 2017 dataset, (**b**) Ground truth, (**c**) Frequency, (**d**) Color, (**e**) Location, (**f**) covariance and mean features, (**g**) fusion of saliency maps, (**h**) lesion mask and (**i**) extracted lesion.

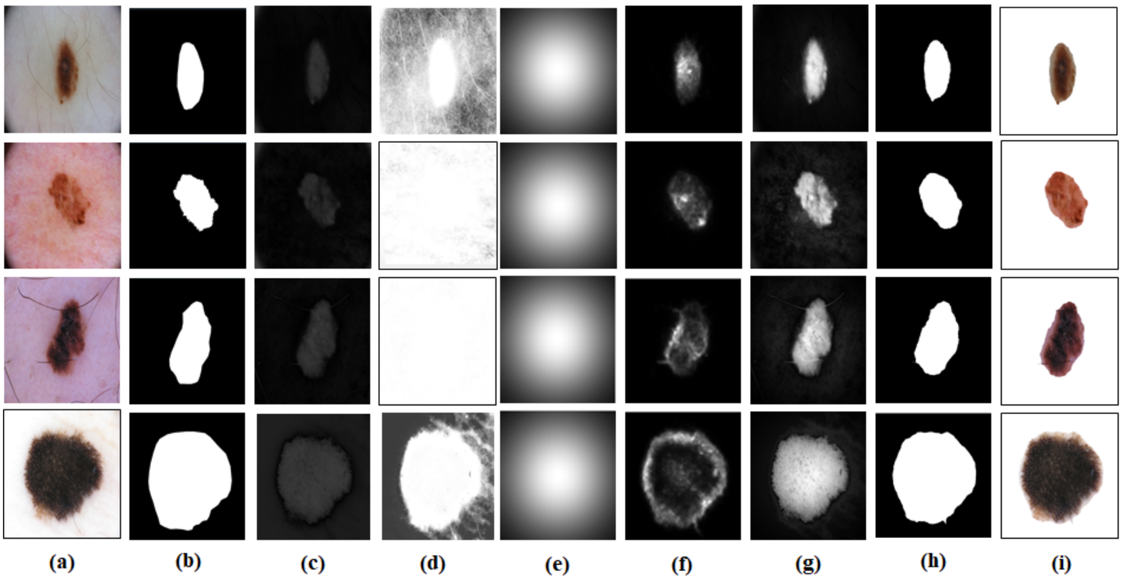

Figure 8. (**a**) Original images from ISIC 2018 dataset, (**b**) Ground truth, (**c**) Frequency, (**d**) Color, (**e**) Location, (**f**) covariance and mean features, (**g**) fusion of saliency maps, (**h**) lesion mask and (**i**) extracted lesion.

The extracted lesions represent the effectiveness of the proposed method on ISIC datasets as compared to the existing methods.

7. Conclusions

One of a challenging task in skin lesion segmentation is to extract the lesion regions more accurately from the dermoscopic images due to the presence of artifacts and large variation in color, size, shape and illumination etc. In this study, we proposed a saliency-based method that detects the different saliency maps i.e. frequency, color, location, covariance and mean. To enhance the lesion regions more accurately for better segmentation, fusion of different saliency maps are done in the proposed method. Otsu thresholding algorithm is implemented to obtain the lesion masks from dermoscopic images. The images from ISIC datasets are used to measure the performance of the proposed method and results are compared with the existing supervised and unsupervised methods.

Author Contributions

Conceptualization, R.R., P.P., S.S.R. and M.K.P.; methodology, R.R.; software, P.P.; validation, R.R., P.P. and M.K.P.; formal analysis, R.R.; investigation, R.R.; resources, R.R.; data curation, R.R.; writing—original draft preparation, R.R.; writing—review and editing, R.R., P.P., S.S.R. and M.K.P.; visualization, R.R.; supervision, P.P. and M.K.P.; project administration, R.R.; funding acquisition, S.S.R. All authors have read and agreed to the published version of the manuscript.

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Author declares no conflict of interest.

Data Availability Statement

Data will be made available on request.

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