

Hybrid channel and spatial attention-UNet for skin lesion segmentation

Soumya Gadag¹, Pradeepa Palraj²

¹Department of Electronics and Communication, S. G. Balekundri Institute of Technology,
Research Scholar at Jain Deemed to be University, Bangalore, India

²Department Electrical and Electronics Engineering, Faculty of Engineering and Technology,
Research Supervisor Jain Deemed to be University, Kanakapura Campus Bangalore, India

Article Info

Article history:

Received May 12, 2023

Revised Oct 20, 2023

Accepted Nov 7, 2023

Keywords:

Computer vision

Deep learning

Image processing

Melanoma

Segmentation

ABSTRACT

Melanoma is a type of skin cancer which has affected many lives globally. The American Cancer Society research has suggested that it is a serious type of skin cancer and lead to mortality but it is almost 100% curable if it is detected and treated in its early stages. Currently automated computer vision-based schemes are widely adopted but these systems suffer from poor segmentation accuracy. To overcome these issue, deep learning (DL) has become the promising solution which performs extensive training for pattern learning and provide better classification accuracy. However, skin lesion segmentation is affected due to skin hair, unclear boundaries, pigmentation, and mole. To overcome this issue, we adopt UNet based deep learning scheme and incorporated attention mechanism which considers low level statistics and high-level statistics combined with feedback and skip connection module. This helps to obtain the robust features without neglecting the channel information. Further, we use channel attention, spatial attention modulation to achieve the final segmentation. The proposed DL based scheme is instigated on publically available dataset and experimental investigation shows that the proposed Hybrid Attention UNet approach achieves average performance as 0.9715, 0.9962, 0.9710.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Soumya Gadag

Department of Electronics and Communication Engineering, S. G. Balekundri Institute of Technology

Jain Deemed to be University

Bangalore, Karnataka, India

Email: soumya.gadag5@gmail.com

1. INTRODUCTION

Cancer is considered as the most challenging issue for the modern medical science. Cancer is a process under which body cells start growing unusually and becomes of control. This abnormal growth of cells affects other stronger cells and deteriorates the body's immune system [1]. These cancer cells may spread to other areas of the body from existing body part. The liver, lung, bone, breast, prostate, bladder, and skin are just a few of the bodily areas that can be impacted by cancer [1]. In this work, we emphasis on studying the skin cancer and current advancements in this field to detect the skin cancer. Skin cancer is one of the most dangerous cancers which may lead to death if not diagnosed early. It is an invasive disease instigated due to the unconventional progression of melanocyte cells in the human body. Later, this abnormal growth tends to reproduce and inflate through the lymph nodes resulting in destroying the surrounding tissues [2]. These damaged cells lead to escalate a mole on the peripheral layer of skin, which is categorized as benign, malignant. Generally, Melanoma (mel), Basal-cell carcinoma (BCC), non-melanoma skin cancer

(NMSC), and squamous-cell carcinoma (SCC) are the most widely known form of the skin cancer [3]. Melanoma is characterized by the malignancy of melanocytes which are known as the melanin (pigment) producing cells in the basal layer of the epidermis. Below given Figure 1 illustrates the different categories of skin cancer.

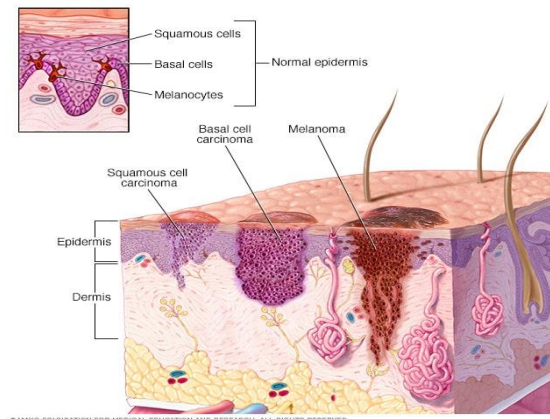


Figure 1 Skin cancer

According to a study presented by Majumder and Ullah [4] reported that around 287,723 melanoma cases were identified globally and around 60,172 deaths were also reported. This study predicted total number of expected melanoma cases 96,480 and 7230 deaths (including 2490 female and 4740 male) [5]. Similarly, International Agency for Research on Cancer (IARC) presented a study in [6] which reported the 19.3 million new cases and 10 million deaths globally by year of 2020. Moreover, 100,350 new cases were identified in US and 6850 deaths also were reported in 2020. The American Cancer Society [7] projected that in 2021 there would be 106,110 new instances of melanoma identified which includes around 62,260 and 43,850 men and women, and 7180 melanoma patients would die. Rahib *et al.* [8] predicted that by 2040 the melanoma would overtake the lung cancer as second most common type of cancer. These studies have reported the prevalence and severity of skin cancer. Therefore, early detection is considered as one of the most beneficial solutions. Moreover, the early detection helps to increase survival rate up to 95% [9].

Currently, the advancement in digital image processing system has gained huge attention in various real-time medical applications. Biomedical image analysis provides several critical information. Thus, recent biomedical systems are widely dependent on the image analysis systems. In this field of skin cancer detection, the dermatoscopy is considered as a promising solution because it provides magnified (typically by x10) skin image. The manual analysis of these images requires more time and effort and accuracy also varies according to the expert skills of the dermatologists. Therefore, researchers have focused on development of automated process of biomedical image analysis for skin cancer detection. Several methods have been presented to accomplish this task where ABCDE measurement method has been considered as a reliable solution. This method considers several parameters such as asymmetry, border, colour, diameter over 6 mm, and development. However, accuracy and reliability of this system depends on the skills of dermatologists. Moreover, Dermatologists' ability to accurately detect skin lesions is reported to be less than 80% accurate [10].

In order to detect the skin cancer, skin lesion segmentation is a crucial process where affected region is extracted and used for further analysis for classification. Several segmentation methods have been presented such as Hu *et al.* [11] presented adaptive thresholding approach by considering saliency maps in wavelet domain, fuzzy logic [12], clustering [13], and region growing [14]. However, these methods suffer from the poor accuracy issues moreover the complex nature of skin lesion images due to inaccurate boundaries, colour variations affect the outcome of these segmentation methods. Currently, deep learning-based methods have been adopted widely in bio medical image analysis. Ronneberger *et al.* [15] presented a Convolutional Neural Network based architecture called as UNet which is based on the encoder and decoder modules. This architecture uses down sampling, up sampling and skip connection modules to enhance the segmentation outcome. Based on this architecture, several deep learning models have been presented for skin lesion segmentation such as DSNet, separable-UNet and attention UNet. to improve the skin lesion segmentation performance. Literature review presents a brief discussion about these methods.

As discussed before, the main aim of skin lesion segmentation is to identify the lesion boundaries from dermoscopic images and separating the lesion area from surrounding healthy skin or background. Generally, skin lesion segmentation faces several challenges such as variability in Lesion appearance, image quality, overlapped lesion, variations in anatomical location of body, and expertise of dermatologist. Several methods have been developed such based on traditional approaches of image pre-processing methods however, these methods face challenges due to variability and complexity of skin lesions. Similarly, machine and deep learning-based methods also adopted for segmentation and classification using convolutional neural networks (CNNs), Fully Convolutional Networks (FCNs), U-Net, and Mask R-CNN for semantic and instance segmentation tasks. Though, computational complexity and classification accuracy remains challenging issues in this domain. Therefore, development of efficient segmentation and classification method is highly recommended to obtain the reliable classification performance. Rest of the article is organized in following segments: section II presents literature review about various deep learning-based segmentation methods, section III presents proposed deep learning based UNet architecture, section IV presents outcome of proposed model and comparative analysis, finally, section V presents concluding remarks about the research.

In this work, we focus on developing a new deep learning architecture for skin lesion segmentation by using UNet as base architecture of work. The main contributions of this work are as:

- a) To present a novel pre-processing method for hair removal to improve the image quality.
- b) In next stage, we present a UNet based model along with the low and high order statistics for feature extraction with attention mechanism.
- c) The attention-based feature extraction mechanism also uses a feedback module to retain the rich feature information.
- d) Finally, we present channel and spatial attention module to obtain the final segmentation.

2. LITERATURE SURVEY

Previous section has described the importance of deep learning-based systems for skin cancer segmentation and classification. This section presents the brief overview of existing schemes of skin lesion and tumor segmentation. Conventional skin lesion segmentation procedures rely on thresholding, edge-detection, active contours including level sets, clustering, expectation maximization and region-based techniques such as region growing and region merging. However, the thresholding-based methods fail to overcome the skin lesion complexities and artifacts. Similarly, the region and boundary-based methods provide only a coarse segmentation. The threshold-based methods require a predefined threshold which may not provide stable results due to noise and intensity variations of skin images. Clustering based approaches require high-resolution images and requires addition pre-processing steps. Moreover, the performance of these methods is influenced by the parameter tuning and finding the universal parameter is a challenging task. Therefore, advanced research has focused on development of artificial intelligence-based approaches [16].

Baig *et al.* [17] presented a detailed review about melanoma segmentation and classification. Authors have reported that the skin lesion image analysis suffer from various issues such as poor contrast, fuzzy borders, irregular boundaries, hairs, bubbles and various other kind of distortions. However, the current advancement in deep learning schemes has led to increase the segmentation accuracy. Several studies have reported that the semantic segmentation by using CNN led to providing the robust solution for segmentation tasks by using pixel-wise classification.

Based on this concept of deep learning, Hasan *et al.* [18] presented an automated segmented approach called as DSNet. Generally, the Deep Learning based methods require a greater number of training parameters which increases the computational complexity and training duration. Therefore, authors presented a lightweight approach which uses depth-wise separable convolutions to the replace the standard convolution. The depth-wise convolution helps to discriminate the features on pixel space at different states of encoder. UNet, an encoder –decoder based deep learning architecture has become popular in biomedical image segmentation due to its property to use the global and local information at the same time [19]. Therefore, several UNet based architectures are developed to increase the segmentation accuracy such as improved UNet [20], separable-UNet [21], and U-Net++ [22]. According to the study presented in [20] the existing UNet architecture is improved by incorporating the batch normalization and dilated convolution layers. The dilated convolution layer helps to expand the receptive field and batch normalization helps to mitigate the overfitting problem without affecting the image resolution.

Tang *et al.* [21] presented separable-UNet which uses separable convolution blocks along with UNet architectures. The separable convolutions use stochastic weight averaging that is useful in context feature correlation and high-semantic feature information extraction. On the other hand, the stochastic weight averaging method is used to handle the over-fitting issue. Zhao *et al.* [22] discussed the importance of fully

connected network and UNet. However, these networks are prone to gradient vanishing issue which increases due to increase in depth. Thus, the reduced gradient result in the Jaccard index.

Generally, these deep learning models require huge computation resources to meet the computational requirement of all activations. Recently, attention-based mechanisms are widely adopted in this context which helps to highlight the most relevant activations during training process. Arora *et al.* [23] adopted this mechanism and presented attention based deep learning mechanism by modifying the UNet model which introduces Group Normalization in the encoder and decoder layers. This model also uses attention gate in skip connection and further it is incorporated with Tversky Loss (TL). The group normalization replaces Batch Normalization with GroupNorm to extract the feature maps. Moreover, the attention module helps to identify the high-dimensional information from background region. Moreover, it uses atrous convolutions to improve the feature reuse. Tong *et al.* [24] presented a modified UNet model by incorporating the triple attention mechanism. The attention gate is used to compute the attention coefficients which are used for selecting the regions. In next stage, a dual attention module is incorporated which has spatial and channel attention blocks to estimate the spatial correlation among features. Dong *et al.* [25] developed a feedback attention model which consist of feedback fusion block and attention block. The amalgamation of these two blocks helps to achieve the rich feature mapping without employing data enhancement.

Aghdam *et al.* [26] reported that the performance of traditional UNet is limited due to several restrictions of convolution operations and capturing the long-term dependencies in UNet. To overcome this issue, authors presented transformer based UNet architecture Attention Swin u-net where CNN blocks are replaced with the Swin transformer blocks. This arrangement helps to capture the local and global representation. The skip connection layer is useful in feature reusability and suggested to include the attention mechanism to improve the performance of traditional skip connection. Jiang *et al.* [27] considered UNet as baseline model and incorporated an attention mechanism to consider the position and context information. Along with this, a global context information complementary module is also developed to achieve the long-term dependencies. Similarly, the multi-scale grouped dilated convolution feature extraction module (MSEM) is also presented to extract the multi-scale feature details.

This section has discussed about recent skin lesion segmentation methods where most of the recent methods are based on the deep learning-based approaches. However, these methods face several challenges such as unavailability of skin lesion dataset as limited datasets are available which leads to cause data imbalance problem. Moreover, the current deep learning methods are trained on specific datasets which doesn't cover the diverse demographics skin types. Similarly, the supervised classification models require precise annotations which becomes time consuming process. Some skin lesions, such as non-melanoma skin cancers or lesions on anatomically complex regions, can be challenging to segment accurately. Research that focuses on improving the segmentation of these challenging cases would be valuable.

3. PROPOSED MODEL

This section describes the proposed deep learning-based solution for skin lesion segmentation along with pre-processing approach for hair removal. The hair removal process is based on the adaptive gradient mechanism which helps to improve the boundary detection. Further, Dull Razor model is adopted for hair removal [28]. Later, we present UNet Based deep learning architecture for segmentation. The proposed architecture uses spatial and channel attention models to increase feature quality. Moreover, this model uses small and large order statistics to extracts the features from different channels. Later, a feedback model is used to obtain the information from decoder blocks.

3.1. Pre-processing for hair removal

This sub-section presents a brief discussion on proposed model for skin hair removal where a skin lesion image is presented as $u(\mathbf{x})$, $\mathbf{x} = (x_1, x_2) \in \mathbf{R}^2$. This image is presented as local surface where (i, j) denotes the pixels position. The local shape of input image can be presented as shown in (1):

$$\mathbb{H}(\mathbf{x}, \sigma) = \begin{pmatrix} \frac{\partial^2 w}{\partial x_1^2}(\mathbf{x}) & \frac{\partial^2 w}{\partial x_1 \partial x_2}(\mathbf{x}) \\ \frac{\partial^2 w}{\partial x_1 \partial x_2}(\mathbf{x}) & \frac{\partial^2 w}{\partial x_2^2}(\mathbf{x}) \end{pmatrix} \quad (1)$$

where σ denotes the standard deviation parameter and it is used for Gaussian Kernel representation for low-pass filters, given as shown in (2):

$$G_{\sigma}(y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{y_1^2 + y_2^2}{2\sigma^2}\right) \quad (2)$$

where $\mathbf{y} = (y_1, y_2)$ and $w = G_{\sigma}(y) * u$ where $*$ denotes the 2D convolution operation. In this work, we use symmetric Gaussian kernel. We compute the maximum and minimum Eigen values of \mathbb{H} to obtain the principal curvatures as λ_{ij}^+ and λ_{ij}^- , respectively. The obtained maximum curvature helps to identify the black lines on images with bright background and the minimum curvature helps to obtain the light lines on dark background. This method helps to overcome the issues of traditional gradient magnitude-based methods because the existing methods detect only hair borders whereas the proposed model helps to produce the solid structure. Further, we used Dull Razor model for hair removal process [29].

3.2. Hybrid spatial and channel attention UNet architecture

Traditional deep learning-based architectures are mainly focused on the developing the deep and wider architecture for learning. However, these techniques ignore exploring the correlations among different channels which is helpful in extracting the rich feature information. To address this issue, we introduce a novel deep learning architecture which is based on the working of UNet segmentation model. In order to increase the performance of segmentation, we incorporated a hybrid attention mechanism which considers channel and spatial attention models to generate the rich feature information as shown in Figure 2 .

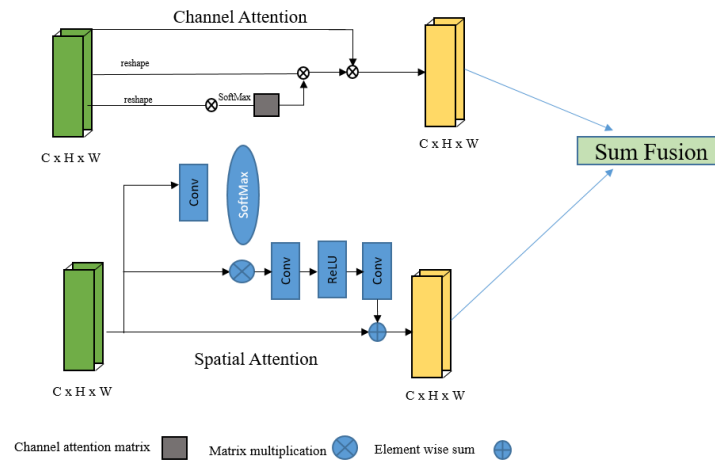


Figure 2. Channel and spatial attention modules

3.2.1. Hybrid model and its components

In traditional segmentation methods, the receptive field is minimized to local region. This restricts the performance to obtain the broad and rich contextual information. Therefore, we introduce channel and spatial attention mechanism. Below given figure depicts the architecture of channel attention module. This map can be computed directed as $X \in R^{C \times C}$ from actual features $A \in R^{C \times H \times W}$. Specifically, the original features are reshaped as from A to $R^{C \times N}$ and then perform product operation between A and A' (transpose of A). Finally, we use SoftMax layer to achieve the channel attention map $X \in R^{C \times C}$ as (3):

$$x_{ij} = \frac{\exp(A_i A_j)}{\sum_{i=1}^C \exp(A_i A_j)} \quad (3)$$

where x_{ij} represents the impact of i^{th} channel on j^{th} channel. Next, we perform multiplication between X' and A . The obtained outcome is reshaped to $R^{C \times H \times W}$. The obtained outcome is multiplied with scale parameter β and element-wise sum with A to obtain the final outcome as (4):

$$E_j = \beta \sum_{i=1}^C (x_{ji} A_i) + A_j \quad (4)$$

where β denotes the weight learning

Similarly, below given figure denotes the architecture of spatial attention mechanism. It consists of lightweight squeeze and excitation block. Moreover, it uses a layer normalization before ReLU. This layer

normalization block increases the object detection and segmentation performance. This module can be expressed as (5):

$$Z_l = A_i + Wv_2 ReLU \left(LN \left(Wv_1 \sum_{j=1}^{N_p} \frac{e^{W_k A_j}}{\sum_{m=1}^{N_p} e^{W_k A_m}} A_j \right) \right) \quad (5)$$

where A is the feature map (also input), N_p denotes the number of position in feature map, and A & Z denotes the input and output, respectively, $\frac{e^{W_k A_j}}{\sum_{m=1}^{N_p} e^{W_k A_m}}$ denotes the weight of global attention and $\delta(.) = Wv_2 ReLU(LN(Wv_1(.)))$ represents the bottleneck transformation. Finally, element-wise sum is performed to obtain the final feature map.

The proposed Hybrid Spatial Channel Attention (HSCA) model uses smallest statistics and larger order statistics to compute the correlation among attributes to obtain the power representation of attributes. It contains two modules as small order statistic (SOSCA) and largest order statistic (LOSCA). The SOSCA model uses global average pooling method to extract the small order features. Later, these features are processed through a small customized Fully connected. The obtained outcome is further rescaled to achieve the intermediate features. On the other hand, the LOSCA attention mechanism uses bilinear pooling to obtain the intermediate features of different channels. Further, these features are used as input to Full connected network. The final outcome of this hybrid model is obtained by performing the element-wise addition of LOSCA and SOSCA. This helps to explore the correlation among features.

a. Small order channel attention block (SOCA)

In this stage, we use global average pooling to contract the gating attributes with the help of its spatial dimensions. Let, \mathcal{X} is the attribute set denoted as: $\mathcal{X} = [X_1, \dots, X_c, \dots, X_c] \in \mathbb{R}^{H \times W \times C}$ and its corresponding gating features are given as $\mathcal{Y} = [Y_1, \dots, Y_c, \dots, Y_c] \in \mathbb{R}^{H \times W \times C}$. During the max pooling operation, it extracts the maximum value of each channel but it doesn't utilize the global information. Therefore, we incorporate global average pooling operation which is expressed as expressed in Figure 3.

$$y_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W Y_c(i, j) \quad (6)$$

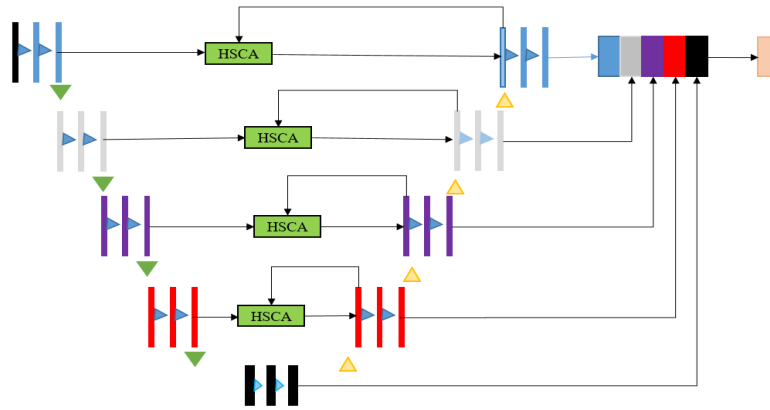


Figure 3. Proposed hybrid attention Unet

Later, these features are fed to the FC layers. Here, $\theta_1(W_1, b_1)$ is the FC_1 and $\theta_2(W_2, b_2)$ denotes the FC_2 . The obtained channel attention weights denoted as $f = [f_1, \dots, f_c, \dots, f_c] \in \mathbb{R}^C$ which can be derived as (7):

$$f = \sigma(W_2^T (\delta(W_1^T y + b_1)) + b_2) \quad (7)$$

where δ characterise the rectified linear unit (ReLU) activation function and σ represents the sigmoid activation function. The ReLU activation function helps to improve the non-linearity of the network whereas

the Sigmoid function helps to scale the input as (0,1) to obtain the weights. This design helps to institute the correlation among different channels to learn the intermediary features. With the help of attention weights, the final features can be represented as (8):

$$\hat{X}_c = f_c \cdot X_c \quad (8)$$

b. Largest order channel attention block (LOSCA)

The aforementioned attention module computes mean of the gating attributes. These gating attributes are used in rescaling the input attributes. However, it fails to establish the correlation among channel intermediate attributes. Therefore, we incorporate large order statistic computation. In this module also, we consider the input as $\mathcal{X} = [X_1, \dots, X_c, \dots, X_c] \in \mathbb{R}^{H \times W \times C}$ and its corresponding gating features are given as $\mathcal{Y} = [Y_1, \dots, Y_c, \dots, Y_c] \in \mathbb{R}^{H \times W \times C}$. According to this process, the bilinear pooling is applied on the gating feature where B represents the pooling matrix. this can be expressed as (9):

$$B = \begin{bmatrix} \text{vec}(Y_1) \\ \vdots \\ \text{vec}(Y_c) \\ \vdots \\ \text{vec}(Y_c) \end{bmatrix} \begin{bmatrix} \text{vec}(Y_1)^T \\ \vdots \\ \text{vec}(Y_c)^T \\ \vdots \\ \text{vec}(Y_c)^T \end{bmatrix} \in \mathbb{R}^{C \times C} \quad (9)$$

Here, vec denotes the vectorization operation, the obtained pooling matrix is semi-symmetric positive definite in nature which contains inner-product of two different feature channels. This inner-product is helpful in incorporating the high-order feature. Further, we apply, matrix logarithmic normalization model to normalize the SPD matrix data. This matrix can be represented in the Eigen form as (10):

$$B = U \Sigma U^T \quad (10)$$

where U denotes the Eigen-vector, $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_c, \dots, \sigma_c)$ denotes the diagonal matrix. the matrix normalization can be represented as (11):

$$\hat{B} = B^\alpha = U \Sigma^\alpha U^T \in \mathbb{R}^{C \times C} \quad (11)$$

where α represents the positive real number and $\Sigma^\alpha = \text{diag}(\sigma_1^\alpha, \dots, \sigma_c^\alpha, \dots, \sigma_c^\alpha)$. With the help of this normalized matrix $\hat{B} = [b_1, \dots, b_c, \dots, b_c]$ we obtain the channel wise attributes as $d \in \mathbb{R}^C$ which is computed as:

$$d = \frac{1}{C} \sum_i^C b_c \in \mathbb{R}^C \quad (12)$$

the obtained d is processed through the fully connected networks given as $\theta_3(W_3, b_3)$ and $\theta_4(W_4, b_4)$. It generates the attention weights $s \in \mathbb{R}^C$ which is learned as (13).

$$s = \theta_4(\theta_3(d)) = \sigma(W_4^T \delta(W_3^T d + b_3)) + b_4 \quad (13)$$

The outcome of SOCA is rescaled to generate the final output of SOCA $\tilde{X}_s, \dots, \tilde{X}_c, \dots, \tilde{X}_c$. Therefore, the final outcome of this hybrid model is given as (14):

$$\tilde{X}_c = s_c \cdot X_c \quad (14)$$

3.2.2. Loss function

In this article, we use Binary Cross Entropy as the main objective function of training. Let us consider that Pre_i denotes the predicted output of i^{th} model, ground truth of i^{th} image is GT_i , the pixel values at i and j position in ground truth is $GT_{i,j}$ similarly, $Pre_{i,j}$ denotes the pixel values at i and j positions in predicted image. The binary cross entropy for these images can be expressed as (15):

$$\begin{aligned} L_{BCE} &= BCE_{Loss}(Pre_i, GT_i) \\ &= - \sum_{i=1}^W \sum_{j=1}^H [(GT_{i,j} \times \log Pre_{i,j}) + (1 - GT_{i,j}) \times \log(1 - Pre_{i,j})] \end{aligned} \quad (15)$$

where W and H denotes the width and height of the image, respectively.

4. RESULTS AND DISCUSSIONS

This section presents the detailed discussion on the outcome of proposed model. The proposed model is implemented by using Python 3.8 running on windows platform where Keras and Tensor flow model are used in backend. The performance of proposed approach is compared with several schemes in terms of Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Sensitivity, and specificity for the considered three different datasets.

4.1. Dataset details

In this work, we explore the diverse array of datasets critical to our analysis. We have measured the performance of proposed approach for different datasets and compared the outcome with existing schemes. PH2, International Skin Image Collaboration (ISIC) 2017, ISIC 2018 and Human Against Machine (HAM)10000 dermoscopic images are considered for analysis and evaluation of the proposed model. This dataset played a pivotal role in our segmentation tasks, allowing us to assess the accuracy of our models with precision.

4.1.1. ISIC 2017 DATASET

The ISIC 2017 dataset is also known as International Skin Imaging Collaboration (ISIC)2017 Challenge dataset, is a comprehensive collection of dermoscopic images used in ISIC 2017 Skin lesion analysis to Melanoma Detection challenge. This dataset contains total 2000 dermoscopic images which are acquired with the of eliminating the surface reflection technique. The dataset includes images of various skin lesion classes such as melanoma, seborrheic keratosis, and benign nevi(moles). The images in the ISIC 2017 dataset are of high quality, captured using dermoscopy, a non-invasive imaging technique. The ISIC 2017 dataset is publicly available and can be accessed through the official ISIC Archive.

4.1.2. ISIC 2018 DATASET

ISIC 2018 dataset plays a vital role in advancing research related to dermatology and computer-aided diagnosis of skin lesions, particularly melanoma. There are 2594 images in this dataset, and each one has a grand truth mask. This dataset is used for three different tasks such as lesion segmentation, lesion feature analysis, and classification. The dataset has been divided into three sub-sections: test data, which contains 520 images, evaluation data, which contains 259 images, and train data, which contains 1815 images. Additionally, we downsized the input photos from 2016×3024 pixels to 256×256 pixels in order to lower the computational and network training costs.

4.1.3. PH2

The dataset includes images of different skin lesion classes, such as melanocytic lesions, nevi, and seborrheic keratosis. These classes are important for training machine learning models to differentiate between different types of skin lesions, including malignant and benign ones. This dataset contains 200 dermoscopic images of skin lesion. In this work, we have divided 100 images for training purpose and 100 images for evaluation purpose. PH2 contains high quality images of pigmented skin lesions frequently used for evaluation and developing computer aided diagnostic systems for skin lesions classification and diagnosis of diseases.

4.1.4. HAM 10000

HAM10000 is a public dataset of skin lesion images, which is designed to facilitate research on automated skin lesion classification using machine learning and computer vision techniques. The dataset consists of 10,015 dermatoscopic images of skin lesions, which are categorized into seven different classes based on their clinical diagnosis. The dataset was released in 2018 by the International Skin Imaging Collaboration (ISIC), which is a global network of experts in the field of skin imaging. The seven different classes in the HAM10000 dataset are: Melanoma, Melanocytic nevus, Basal cell carcinoma, Actinic keratosis, Benign keratosis-like lesions, Dermatofibroma, Vascular lesions

4.2. Evaluation metrics

In order to quantitatively assess the performance of proposed model, we used five different metrics considered and popularly used to evaluate the segmentation performance. These metrics provide a standardized way to measure the outcomes against the ground truth. These metrics are described as follows in Table 1.

The skin lesion images capture the skin hair along with the affected region. This type of images affects the diagnosis performance. Therefore, we apply image pre-processing technique for hair removal. Below given

Figure 4, shows some sample outcome of hair removal process. The obtained images are used for further analysis where we measure the performance and compare with existing schemes. Table 2 shows the comparative performance analysis for ISIC 2017 dataset.

Table 1. Evaluation metrics

Matrix	Formula	Description
Dice similarity coefficient	$DSC(S, G) = \frac{2 \times S \cap G }{ S + G }$	It is used to compute the spatial overall between predicted and groundtruth image.
Intersection over Union	$IoU(S, G) = \frac{ S \cap G }{ S \cup G }$	It is used to evaluate the segmentation accuracy. It is measured by evaluating the ratio of object and corresponding union which are projected in the same plane
F-Measure	$FMeasure = \frac{2 \times P \times R}{P + R}$	It denotes the weighted harmonic mean of precision and recall
Sensitivity	$Sen(S, G) = \frac{ S \cap G }{ G }$	It measures the percentage of correctly classified pixels
Specificity	$Spe(S, G) = \frac{ (1 - S) \cap (1 - G) }{ 1 - G }$	It measures the correct classification percentage of pixels of background class

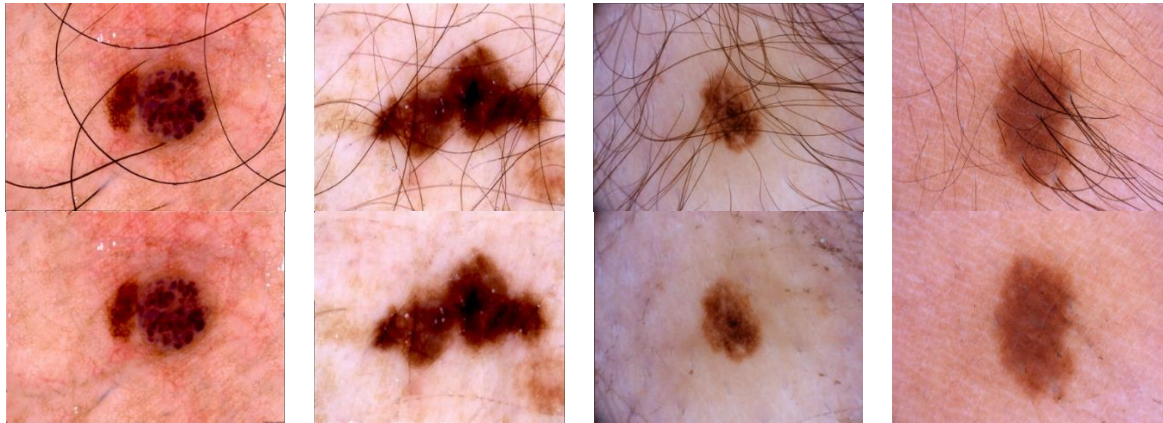


Figure 4. Outcome of hair removal process

Table 2. Comparative analysis for ISIC 2017 dataset

Technique	Accuracy	Sensitivity	Specificity	F1-score	Jaccard Similarity
Full resolution CNN [30]	0.934	0.825	0.975	0.884	0.9365
R2UNet [30]	0.9424	0.9414	0.9425	0.8920	0.9421
MCGUNet [31]	0.9570	0.8502	0.9855	0.8927	0.9570
Baseline [32]	0.9314	0.9479	0.9263	0.8682	0.9314
Multiscale UNet [32]	0.9576	0.8870	0.9714	0.9032	0.9576
Proposed Model	0.9762	0.9516	0.9899	0.9215	0.9718

The proposed approach achieves the average performance as 0.9762, 0.9516, 0.9899, 0.9215, and 0.9718 in terms of Accuracy, Sensitivity, Specificity, F1-score, and Jaccard Similarity for ISIC 2017 dataset. The proposed approach outperforms the recent attention and UNet based segmentation models. Similarly, we measure the performance for ISIC 2018 dataset. Table 3 shows the comparative analysis for ISIC 2018 dataset.

The proposed approach obtained highest performance as 0.968, 0.99, 0.999, 0.912, and 0.977 in terms of Accuracy, Sensitivity, Specificity, F1-score, and Jaccard Similarity, respectively. The studies presented in [30] and [33] reported the importance of Attention mechanism thereby we have adopted the attention process and improved its performance. Further, we evaluate the performance of proposed approach for PH² dataset. The obtained performance is presented in Table 4. Further, the performance of proposed

approach is compared with several schemes in terms of DSC, IoU, Sensitivity, and specificity for the considered three different datasets. Table 5 shows the comparative analysis with state-of-art algorithms.

Table 3. Comparative analysis for ISIC 2018 dataset

Technique	Accuracy	Sensitivity	Specificity	F1-score	Jaccard similarity
R2UNet [30]	0.880	0.792	0.928	0.679	0.581
Attention R2UNet [30]	0.904	0.726	0.971	0.691	0.592
MCGUNet [31]		0.848	0.986	0.895	0.955
Baseline [32]	0.890	0.708	0.964	0.647	0.549
Multiscale UNet [32]	0.949	0.841	0.979	0.896	0.956
Attention UNet[33]	0.897	0.717	0.967	0.665	0.566
Proposed Model	0.968	0.99	0.999	0.912	0.977

Table 4. Comparative analysis for PH² dataset

Technique	Accuracy	Sensitivity	Specificity	DICE	Jaccard Similarity
Full Convolution Network [23]	0.9282	0.903	0.9402	0.8903	0.8022
FrCN [30]	0.9508	0.9372	0.9565	0.9177	0.8479
MCGUNet [31]	0.9537	0.8322	0.9714	0.9263	0.9537
Baseline [32]	0.9255	0.8163	0.9776	0.8761	0.7795
Multiscale UNet [32]	0.9617	0.943	0.9698	0.9377	0.9617
SegNet[34]	0.9336	0.8653	0.966	0.8936	0.8077
Proposed Model	0.9715	0.9962	0.9710	0.9997	0.9815

Table 5. Comparative analysis for different dataset

Dataset	Techniques	mDSC	mIoU	mSen	mSpe
PH2	UNet [16]	0.876	0.780	0.816	0.978
	Al <i>et al.</i> [29]	0.919	0.849	0.935	0.956
	SegNet [34]	0.894	0.808	0.865	0.966
	Double UNet [34]	0.907	0.899	0.945	0.966
	Goyal <i>et al.</i> [35]	0.910	0.838	0.933	0.930
	Hasan <i>et al.</i> [18]	-	0.870	0.929	0.968
	Ozturk <i>et al.</i> [36]	0.931	0.872	0.968	0.954
	Xie <i>et al.</i> [37]	0.920	0.858	0.964	0.945
	Unver <i>et al.</i> [38]	0.882	0.798	0.837	0.941
	Bi <i>et al.</i> [39]	0.907	0.840	0.948	0.942
	Bi <i>et al.</i> [40]	0.921	0.859	0.965	0.946
	MFSNet [41]	0.954	0.914	0.995	0.997
	Proposed	0.9610	0.935	0.996	0.997
	UNet [17]	0.778	0.683	0.812	0.805
	SegNet [34]	0.821	0.696	0.801	0.954
ISIC 2017	Double UNet [35]	0.913	0.918	0.963	0.974
	Ozturk <i>et al.</i> [36]	0.793	0.872	0.898	0.951
	Xie <i>et al.</i> [37]	-	0.776	0.879	0.956
	Bi <i>et al.</i> [40]	0.844	0.749	0.910	0.925
	MFSNet [41]	0.988	0.975	0.99	0.999
	Al <i>et al.</i> [29]	0.855	0.773	0.825	0.980
	Proposed	0.991	0.981	0.991	0.999
	UNet [16]	0.781	0.774	0.799	0.802
	Double UNet [34]	0.843	0.812	0.961	0.845
	SegNet [34]	0.816	0.821	0.867	0.854
HAM10000	MFSNet [34]	0.906	0.902	0.999	0.99
	Saha <i>et al.</i> [42]	0.891	0.819	0.824	0.981
	Abraham <i>et al.</i> [44]	0.856	-	-	-
	Shahin <i>et al.</i> [45]	0.903	0.837	0.902	0.974
	Bissoto <i>et al.</i> [46]	0.873	0.792	0.934	0.936
	Ibtehaz <i>et al.</i> [47]	-	0.803	-	-
	Proposed	0.951	0.943	0.9510	0.9810

The experimental analysis shows that the proposed approach achieves better performance when compared with existing schemes. The mean Dice score performance is obtained as 0.9610, 0.991 and 0.951 for PH2, ISIC2017 and HAM1000, respectively. Figure 5 demonstrates the qualitative results for PH2, ISIC 2017 and HAM dataset. The SegNet model suffer from the blurriness issue which is further resolved by employing UNet however contextual information issue still remains challenging issue. In order to resolve this issue DoubleUNet architecture is developed which is able to resolve this issue but fail to handle the complex boundaries. Therefore, we presented a attention based mechanism which covers these issues and improves the segmentation performance which is validated by quantitative and qualitative analysis.

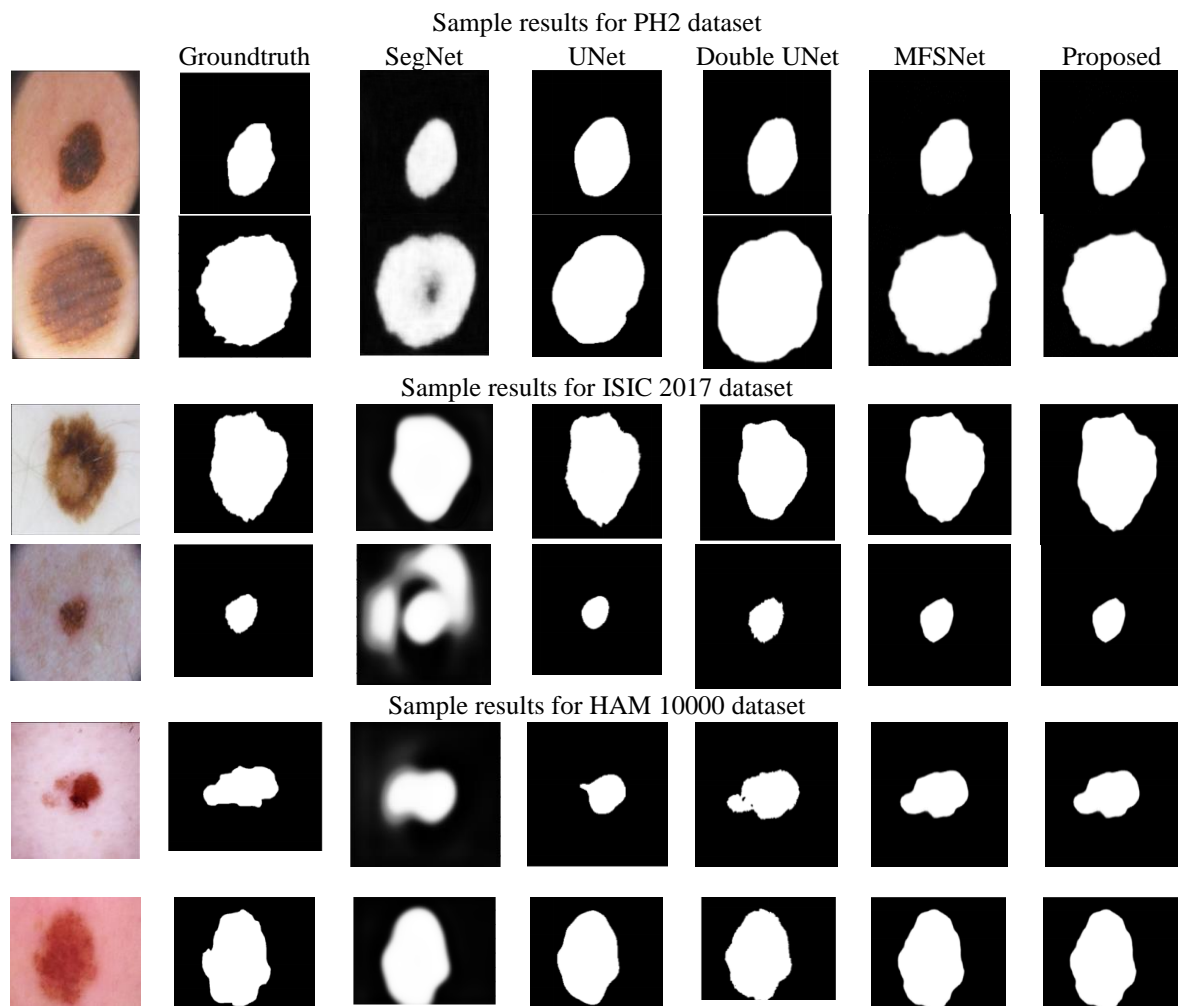


Figure 5. Sample outcome for PH2, ISIC 2017 and HAM 10000 dataset

5. CONCLUSION

In this work, we have focused on improving the segmentation accuracy of melanoma skin cancer. Traditional methods are based on the computer vision-based tasks however the accuracy of these systems is highly dependent on the expert skills. Deep learning-based schemes have gained huge attention recently. Therefore, we present UNet based deep learning architecture which uses low and high statistics attention information with feedback module. Moreover, the proposed approach uses channel and spatial attention blocks to improve the channel attributes. The proposed approach is tested on publically available dataset and extensive experimental study is presented which shows that the proposed approach realizes average performance as 0.991, 0.981, 0.991, and 0.999 in terms of DSC, IoU, Sensitivity and Specificity.

REFERENCES




- [1] D. N. H. Thanh, V. B. S. Prasath, L. M. Hieu, and N. N. Hien, "Melanoma skin cancer detection method based on adaptive principal curvature, colour normalisation and feature extraction with the ABCD rule," *Journal of digital imaging*, vol. 33, no. 3, pp. 574–585, Jun. 2020, doi: 10.1007/s10278-019-00316-x.
- [2] Y. N. Fu'adah, N. K. C. Pratiwi, M. A. Pramudito, and N. Ibrahim, "Convolutional neural network (CNN) for automatic skin cancer classification system," *IOP Conference Series: Materials Science and Engineering*, vol. 982, no. 1, p. 12005, 2020, doi: 10.1088/1757-899x/982/1/012005.
- [3] D. Crisan, S. Kastler, K. Scharffetter-Kochanek, M. Crisan, and L. Schneider, "Ultrasonographic assessment of depth infiltration in melanoma and non-melanoma skin cancer," *Journal of Ultrasound in Medicine*, vol. 42, no. 7, pp. 1609–1616, 2023, doi: 10.1002/jum.16180.
- [4] S. Majumder and M. A. Ullah, "Feature extraction from dermoscopy images for an effective diagnosis of melanoma skin cancer," *2018 10th International Conference on Electrical and Computer Engineering (ICECE)*. IEEE, 2018. doi:

- 10.1109/icece.2018.8636712.
- [5] American Cancer Society, "Melanoma skin cancer." Accessed: Apr. 25, 2023. [Online]. Available: <https://www.cancer.org/cancer/melanoma-skin-cancer.html>
 - [6] International Agency for Research on Cancer, "Cancer topics." Accessed: Apr. 25, 2023. [Online]. Available: <https://www.iarc.who.int/cancer-topics/>
 - [7] American Cancer Society, "Key statistics for melanoma skin cancer." Accessed: Apr. 07, 2023. [Online]. Available: <https://www.cancer.org/cancer/types/melanoma-skin-cancer/about/key-statistics.html>
 - [8] L. Rahib, M. R. Wehner, L. M. Matrisian, and K. T. Nead, "Estimated projection of US cancer incidence and death to 2040," *JAMA network open*, vol. 4, no. 4, pp. e214708–e214708, Apr. 2021, doi: 10.1001/jamanetworkopen.2021.4708.
 - [9] K. D. Miller *et al.*, "Cancer treatment and survivorship statistics, 2016," *CA: A Cancer Journal for Clinicians*, vol. 66, no. 4, pp. 271–289, 2016, doi: 10.3322/caac.21349.
 - [10] R. Kaur, H. GholamHosseini, R. Sinha, and M. Lindén, "Melanoma classification using a novel deep convolutional neural network with dermoscopic images," *Sensors (Basel, Switzerland)*, vol. 22, no. 3, p. 1134, Feb. 2022, doi: 10.3390/s22031134.
 - [11] K. Hu *et al.*, "A skin lesion segmentation method based on saliency and adaptive thresholding in wavelet domain," *Cognitive Internet of Things: Frameworks, Tools and Applications*. Springer International Publishing, pp. 445–453, 2019, doi: 10.1007/978-3-030-04946-1_43.
 - [12] J. L. Garcia-Arroyo and B. Garcia-Zapirain, "Segmentation of skin lesions in dermoscopy images using fuzzy classification of pixels and histogram thresholding," *Computer Methods and Programs in Biomedicine*, vol. 168, pp. 11–19, 2019, doi: 10.1016/j.cmpb.2018.11.001.
 - [13] B. S. Lin, K. Michael, S. Kalra, and H. R. Tizhoosh, "Skin lesion segmentation: U-Nets versus clustering," *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, 2017, doi: 10.1109/ssci.2017.8280804.
 - [14] Y. Guo, A. Ashour, and F. Smarandache, "A novel skin lesion detection approach using neutrosophic clustering and adaptive region growing in dermoscopy images," *Symmetry*, vol. 10, no. 4, p. 119, 2018, doi: 10.3390/sym10040119.
 - [15] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Lecture Notes in Computer Science*. Springer International Publishing, pp. 234–241, 2015, doi: 10.1007/978-3-319-24574-4_28.
 - [16] Y. Ren, L. Yu, S. Tian, J. Cheng, Z. Guo, and Y. Zhang, "Serial attention network for skin lesion segmentation," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 2, pp. 799–810, 2021, doi: 10.1007/s12652-021-02933-3.
 - [17] R. Baig, M. Bibi, A. Hamid, S. Kausar, and S. Khalid, "Deep learning approaches towards skin lesion segmentation and classification from dermoscopic images - A review," *Current Medical Imaging Formerly Current Medical Imaging Reviews*, vol. 16, no. 5, pp. 513–533, 2020, doi: 10.2174/1573405615666190129120449.
 - [18] M. K. Hasan, L. Dahal, P. N. Samarakoon, F. I. Tushar, and R. Martí, "DSNet: Automatic dermoscopic skin lesion segmentation," *Computers in Biology and Medicine*, vol. 120, p. 103738, 2020, doi: 10.1016/j.compbiomed.2020.103738.
 - [19] S. N. Hasan, M. Gezer, R. A. Azeez, and S. Gulsecen, "Skin lesion segmentation by using deep learning techniques," *2019 Medical Technologies Congress (TIPTEKNO)*. IEEE, 2019, doi: 10.1109/tiptekno.2019.8895078.
 - [20] L. Liu, L. Mou, X. X. Zhu, and M. Mandal, "Skin lesion segmentation based on improved u-net," *2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*. IEEE, 2019, doi: 10.1109/ccece.2019.8861848.
 - [21] P. Tang *et al.*, "Efficient skin lesion segmentation using separable-Unet with stochastic weight averaging," *Computer Methods and Programs in Biomedicine*, vol. 178, pp. 289–301, 2019, doi: 10.1016/j.cmpb.2019.07.005.
 - [22] C. Zhao, R. Shuai, L. Ma, W. Liu, and M. Wu, "Segmentation of skin lesions image based on U-Net + +," *Multimedia Tools and Applications*, vol. 81, no. 6, pp. 8691–8717, 2022, doi: 10.1007/s11042-022-12067-z.
 - [23] R. Arora, B. Raman, K. Nayyar, and R. Awasthi, "Automated skin lesion segmentation using attention-based deep convolutional neural network," *Biomedical Signal Processing and Control*, vol. 65, p. 102358, 2021, doi: 10.1016/j.bspc.2020.102358.
 - [24] X. Tong, J. Wei, B. Sun, S. Su, Z. Zuo, and P. Wu, "ASCU-Net: Attention gate, spatial and channel attention U-net for skin lesion segmentation," *Diagnostics (Basel, Switzerland)*, vol. 11, no. 3, p. 501, Mar. 2021, doi: 10.3390/diagnostics11030501.
 - [25] Y. Dong, L. Wang, S. Cheng, and Y. Li, "FAC-Net: Feedback attention network based on context encoder network for skin lesion segmentation," *Sensors (Basel, Switzerland)*, vol. 21, no. 15, p. 5172, Jul. 2021, doi: 10.3390/s21155172.
 - [26] E. K. Aghdam, R. Azad, M. Zarvani, and D. Merhof, "Attention Swin U-Net: Cross-Contextual Attention Mechanism for Skin Lesion Segmentation," in *2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI)*, IEEE, Apr. 2023, pp. 1–5, doi: 10.1109/ISBI53787.2023.10230337.
 - [27] Y. Jiang, J. Dong, Y. Zhang, T. Cheng, X. Lin, and J. Liang, "PCF-Net: Position and context information fusion attention convolutional neural network for skin lesion segmentation," *Heliyon*, vol. 9, no. 3, pp. e13942–e13942, Feb. 2023, doi: 10.1016/j.heliyon.2023.e13942.
 - [28] T. Lee, V. Ng, R. Gallagher, A. Coldman, and D. McLean, "Dullrazor®: A software approach to hair removal from images," *Computers in Biology and Medicine*, vol. 27, no. 6, pp. 533–543, 1997, doi: 10.1016/s0010-4825(97)00020-6.
 - [29] M. A. Al-masni, M. A. Al-antari, M.-T. Choi, S.-M. Han, and T.-S. Kim, "Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks," *Computer Methods and Programs in Biomedicine*, vol. 162, pp. 221–231, 2018, doi: 10.1016/j.cmpb.2018.05.027.
 - [30] M. Z. Alom, C. Yakopcic, T. M. Taha, and V. K. Asari, "Nuclei segmentation with recurrent residual convolutional neural networks based U-Net (R2U-Net)," *NAECON 2018 - IEEE National Aerospace and Electronics Conference*. IEEE, 2018, doi: 10.1109/naecon.2018.8556686.
 - [31] R. Azad, M. Asadi-Aghbolaghi, M. Fathy, and S. Escalera, "Attention deeplabv3+: Multi-level context attention mechanism for skin lesion segmentation," *Computer Vision – ECCV 2020 Workshops*. Springer International Publishing, pp. 251–266, 2020, doi: 10.1007/978-3-030-66415-2_16.
 - [32] M. D. Alahmadi, "Multiscale Attention U-Net for skin lesion segmentation," *IEEE Access*, vol. 10, pp. 59145–59154, 2022, doi: 10.1109/access.2022.3179390.
 - [33] O. Oktay *et al.*, "Attention U-Net: Learning where to look for the pancreas," *ArXiv.org*, Apr. 2018, doi: 10.48550/arXiv.1804.03999.
 - [34] D. Jha, M. A. Riegler, D. Johansen, P. Halvorsen, and H. D. Johansen, "DoubleU-Net: A deep convolutional neural network for medical image segmentation," *2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS)*. IEEE, 2020, doi: 10.1109/cbms49503.2020.00111.
 - [35] M. Goyal, A. Oakley, P. Bansal, D. Dancey, and M. H. Yap, "Skin lesion segmentation in dermoscopic images with ensemble deep learning methods," *IEEE Access*, vol. 8, pp. 4171–4181, 2020, doi: 10.1109/access.2019.2960504.
 - [36] Ş. Öztürk and U. Özkaya, "Skin lesion segmentation with improved convolutional neural network," *Journal of digital imaging*, vol. 33, no. 4, pp. 958–970, Aug. 2020, doi: 10.1007/s10278-020-00343-z.




- [37] F. Xie, J. Yang, J. Liu, Z. Jiang, Y. Zheng, and Y. Wang, "Skin lesion segmentation using high-resolution convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 186, p. 105241, 2020, doi: 10.1016/j.cmpb.2019.105241.
- [38] H. M. Ünver and E. Ayan, "Skin lesion segmentation in dermoscopic images with combination of YOLO and GrabCut algorithm," *Diagnostics (Basel, Switzerland)*, vol. 9, no. 3, p. 72, Jul. 2019, doi: 10.3390/diagnostics9030072.
- [39] L. Bi, J. Kim, E. Ahn, A. Kumar, M. Fulham, and D. Feng, "Dermoscopic image segmentation via multistage fully convolutional networks," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 9, pp. 2065–2074, 2017, doi: 10.1109/tbme.2017.2712771.
- [40] L. Bi, J. Kim, E. Ahn, A. Kumar, D. Feng, and M. Fulham, "Step-wise integration of deep class-specific learning for dermoscopic image segmentation," *Pattern Recognition*, vol. 85, pp. 78–89, 2019, doi: 10.1016/j.patcog.2018.08.001.
- [41] H. Basak, R. Kundu, and R. Sarkar, "MFSNet: A multi focus segmentation network for skin lesion segmentation," *Pattern Recognition*, vol. 128, p. 108673, 2022, doi: 10.1016/j.patcog.2022.108673.
- [42] A. Saha, P. Prasad, and A. Thabit, "Leveraging adaptive color augmentation in convolutional neural networks for deep skin lesion segmentation," *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*. IEEE, 2020. doi: 10.1109/isbi45749.2020.9098344.
- [43] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A deep convolutional encoder-decoder architecture for image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 12, pp. 2481–2495, 2017, doi: 10.1109/tpami.2016.2644615.
- [44] N. Abraham and N. M. Khan, "A novel focal Tversky loss function with improved attention u-net for lesion segmentation," *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019. doi: 10.1109/isbi.2019.8759329.
- [45] A. H. Shahin, K. Amer, and M. A. Elattar, "Deep convolutional encoder-decoders with aggregated multi-resolution skip connections for skin lesion segmentation," *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019. doi: 10.1109/isbi.2019.8759172.
- [46] A. Bissoto, F. Perez, V. Ribeiro, M. Fornaciali, S. Avila, and E. Valle, "Deep-learning ensembles for skin-lesion segmentation, analysis, classification: Recod titans at ISIC challenge 2018," *ArXiv.org*, Aug. 2018, [Online]. Available: <http://arxiv.org/abs/1808.08480>
- [47] N. Ibtihaz and M. S. Rahman, "MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation," *Neural Networks*, vol. 121, pp. 74–87, 2020, doi: 10.1016/j.neunet.2019.08.025.

BIOGRAPHIES OF AUTHORS



Soumya Gadag    completed her B.E degree in Electronics and Communication Engineering from Visvesvaraya Technological University, India in 2008. She received her M.Tech. from Visvesvaraya Technological University in 2012. Currently working as Assistant Professor in the Department of Electronics and Communication Engineering, S.G. Balekundri Institute of Technology, India. Her research interests include wireless communication, image processing, machine learning and artificial intelligence. She can be contacted at email: soumya.gadag5@gmail.com.



Dr. Pradeepa Palraj    received the B.E. degree in Electrical and Electronics Engineering from Government College of Technology, Coimbatore in 2001 and pursued her masters in Applied Electronics from Government College of Engineering, Salem in 2004. Ph.D. degree from Anna University, Chennai in the year 2017. Currently she is Professor and Head of the Electrical and Electronics Engineering Department, Faculty of Engineering and Technology, Jain Deemed to be University. Her research interests are image processing registration and segmentation of medical images. She can be contacted at email: p.pradeepa@jainuniversity.ac.in.