Detection and Removal of Assymmetrical Skin Lesions Using Dseg-Net for Patch Extraction

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Abstract

This study presents DSeg-net, a novel method for accurately identifying and removing pigmented skin lesions from dermoscopic images, crucial for timely diagnosis and management of melanoma. DSeg-net combines deep convolutional neural networks, particularly YOLOv5, for patch detection, asymmetrical patch contouring for edge preservation, and clustering techniques for patch extraction. Additionally, it employs De Trop Noise Exclusion with in-painting to eliminate hair from challenging dataset images. The method involves rigorous annotation of skin images with lesions of varying sizes and shapes using rectangle bounding, followed by fine-tuning YOLOv5 hyperparameters for high-confidence multiple lesion detection. Despite complex textures and unclear boundaries, DSeg-net consistently detects and labels patches, accurately segmenting areas of skin pathology. Evaluation on various datasets demonstrates that the proposed segmentation techniques achieve an overall average accuracy of approximately 92% to 94%.

Keywords: Skin Cancer, YOLOV5 Detection Algorithm, Image Labeling, Grouping, Removal of Skin Lesion Patches

1 Introduction

In recent years, there has been a significant increase in melanoma cases attributed to the effects of global warming. Melanoma, a highly aggressive form of skin cancer originating from malignant tumors in pigment cells, is responsible for over 70% of fatalities among individuals with skin cancer (**? ?**). Early detection is crucial for improving survival rates, as untreated melanoma can spread to vital organs like the liver, bones, lungs, and brain, posing considerable diagnostic challenges.

Clinical photography and dermoscopy are common techniques used for assessing melanoma lesions. Dermoscopy, in particular, provides detailed images of skin lesions and their vascular components, aiding in diagnosis. However, manual evaluation of these images by dermatologists is time-consuming, subjective, and prone to biases. To address these challenges, there is a pressing need for the development of Computer-Aided Diagnosis (CAD) systems for melanoma detection (**?**).

Accurate lesion segmentation is essential for improving diagnostic accuracy and classification performance in melanoma detection. However, the segmentation process is complex due to diverse lesion structures, varying boundaries, and additional elements such as hair and reflections in dermoscopic images. Existing segmentation techniques face difficulties in precisely isolating the region of interest from the background (**?**).

Various segmentation methods have been proposed, including k-means algorithms, CAD methods, and neural networks, but challenges persist due to factors like low contrast, blurred boundaries, and variations in lesion characteristics. Additionally, existing systems are computationally intensive and prone to inaccuracies (**?**).

This study introduces Dseg-Net, a novel segmentation pipeline combining YOLOV5 and clustering techniques for precise melanoma lesion segmentation. The approach involves denoising images, annotating skin images, detecting patches using YOLOV5, and applying thresholding and contouring for precise patch instance detection. Validation of the proposed method is conducted using established segmentation metrics on two separate datasets (**?**).

The remaining sections of the paper discuss existing approaches to skin cancer segmentation, detail the proposed segmentation process, present experimental validation results, and conclude with discussions on future research directions.

2 Related works

In the field of dermatology and medical imaging, various deep learning approaches have been proposed for skin lesion analysis and segmentation. These methods range from full-resolution recovery networks to instance segmentation models. Key techniques include dense deconvolutional layers, adversarial network segmentation, saliency detection, super pixel-level segmentation, and utilization of transformer prediction heads. While many models have achieved promising results on specific datasets, challenges persist in handling fuzzy boundaries, intricate textures, size variations, and detecting multiple lesions simultaneously. Advances such as combining segmentation and classification networks, depth-wise separable convolutions, and cross-connection layer modules aim to address these challenges. Overall, the field continues to evolve with a focus on improving segmentation accuracy, processing speeds, and adaptability to diverse clinical scenarios.

The table attached in annexure summarizes notable methods and techniques utilized in the domain of dermatology and medical imaging for skin lesion analysis and segmentation.

3 Proposed Methodology

This section outlines the methodologies utilized for segmenting input data, as illustrated in Figure 1. The process encompasses various steps including patch detection, grayscale conversion, binary mask creation, contouring, and k-means clustering for pixel grouping, ultimately resulting in the segmentation of skin cancer lesions.

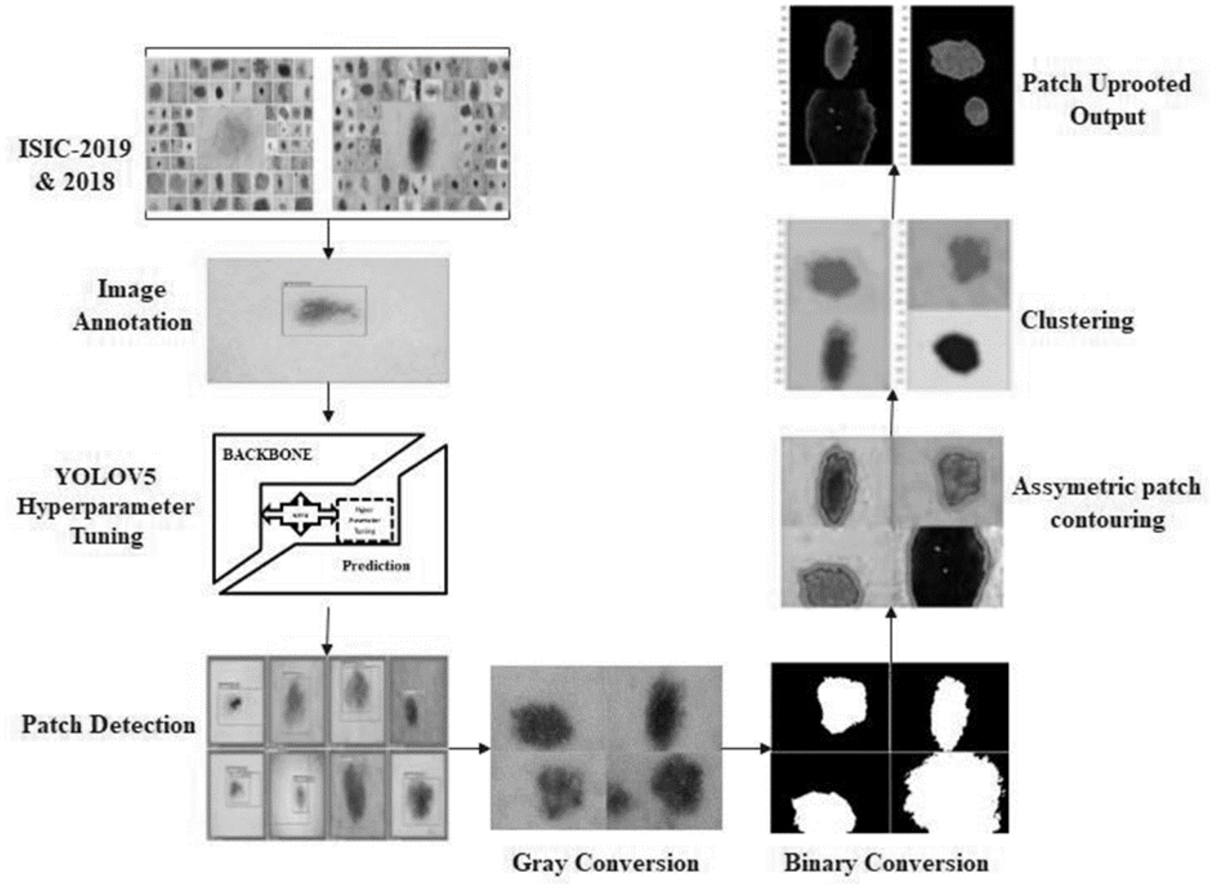

FIGURE 1
Proposed Flow Diagram.

3.1 Input Image

Our approach begins by preprocessing input images sourced from the ISIC challenging datasets. These datasets often contain images captured under various conditions, leading to potential noise and inconsistencies. To address this, we employ several preprocessing techniques:

Vintage Boosting: This technique enhances the color and contrast of images, making features more discernible, particularly useful for improving the visibility of subtle details.

Grey Contrast Stretching: By expanding the dynamic range of grayscale images, this step further enhances visibility, aiding in the detection of relevant features.

Filtering: Median filtering or Gaussian blurring techniques are utilized to remove noise and smooth out image textures, thereby improving the quality of the images.

Mask Construction and Noise Exclusion: These steps involve constructing masks to segregate relevant components from the background and employing in-painting techniques to exclude noise. This ensures accurate extraction of lesion information.

3.2 Image Annotations

Annotation is a critical process in training deep learning models for lesion detection. We utilize a Python script to label skin patches and lesions with rectangle bounding boxes. These annotations provide valuable training data, allowing the model to learn the spatial characteristics of lesions, including size and shape variations.

3.3 YOLOv5 and Patch Detection

For patch detection, we employ the YOLOv5 network, renowned for its speed and accuracy in object detection. This network architecture comprises backbone, neck, and output components, enabling efficient feature extraction and object detection. Modules like Bottleneck CSP and SPP enhance the model's ability to capture rich visual information and detect objects at various scales.

YOLOv5 outputs bounding box coordinates and confidence scores for detected objects. The confidence score represents the model's confidence in the presence of an object within a bounding box. This aids in filtering out false positives, ensuring accurate patch detection.

3.4 Two-Dimensional Otsu Algorithm

Following patch detection, we utilize the Otsu algorithm to convert color images into grayscale. Grayscale conversion simplifies subsequent analysis while preserving relevant information. The algorithm determines an optimal threshold for binarizing the image based on the histogram of pixel intensities, effectively separating the lesion from surrounding tissue.

3.5 Patch Detection using K-means Clustering Algorithm

We employ k-means clustering, an unsupervised learning technique, for patch detection. This algorithm groups similar pixels together based on their characteristics, effectively delineating the lesion from surrounding tissue. The iterative nature of the algorithm ensures convergence to stable cluster centroids, optimizing segmentation accuracy.

In summary, our proposed methodology combines various preprocessing techniques, deep learning models, and unsupervised learning algorithms to achieve accurate and reliable segmentation of skin cancer lesions. Each step contributes to enhancing image quality, extracting relevant features, and facilitating further analysis and diagnosis.

4 Results and Discussion

This section presents a detailed comparison between the proposed segmentation techniques and existing methods for dermoscopic image analysis. The analysis includes both quantitative and qualitative performance metrics. The proposed system is implemented using Python and PyTorch on a system equipped with 8GB RAM, a 1TB hard drive, and a 3.0GHz Intel i5 processor. For evaluation purposes, a manual ground truth is established.

4.1 Description of Datasets

Two challenging datasets are utilized for evaluation:

A) ISIC 2019: Derived from the ISIC 2019 challenge dataset archive, comprising dermoscopy images of both benign and malignant skin lesions. It consists of 2637 training images and 660 testing images.

B) ISIC 2018: Sourced from the ISIC 2018 challenge dataset archive, containing dermoscopy images of both benign and malignant skin lesions. It comprises 2650 training images and 712 testing images.

4.2 Performance Metrics

To assess the performance of the segmentation techniques, five evaluation measures are employed: Jaccard Similarity Coefficient (JSC), Dice Similarity Coefficient (DSC), precision

(ACC), specificity (SPE), and sensitivity (SEN). The mathematical expressions for these metrics are provided.

4.3 Performance Analysis of Proposed Segmentation Techniques on ISIC-2018

Initial output for the first five images of ISIC-2018 using different segmentation techniques is presented. Figure 2 illustrates the visual segmented output images, while Table 1 and Figure 3 present the validated outcomes in terms of ACC, DSC, JSC, SEN, and SPE.

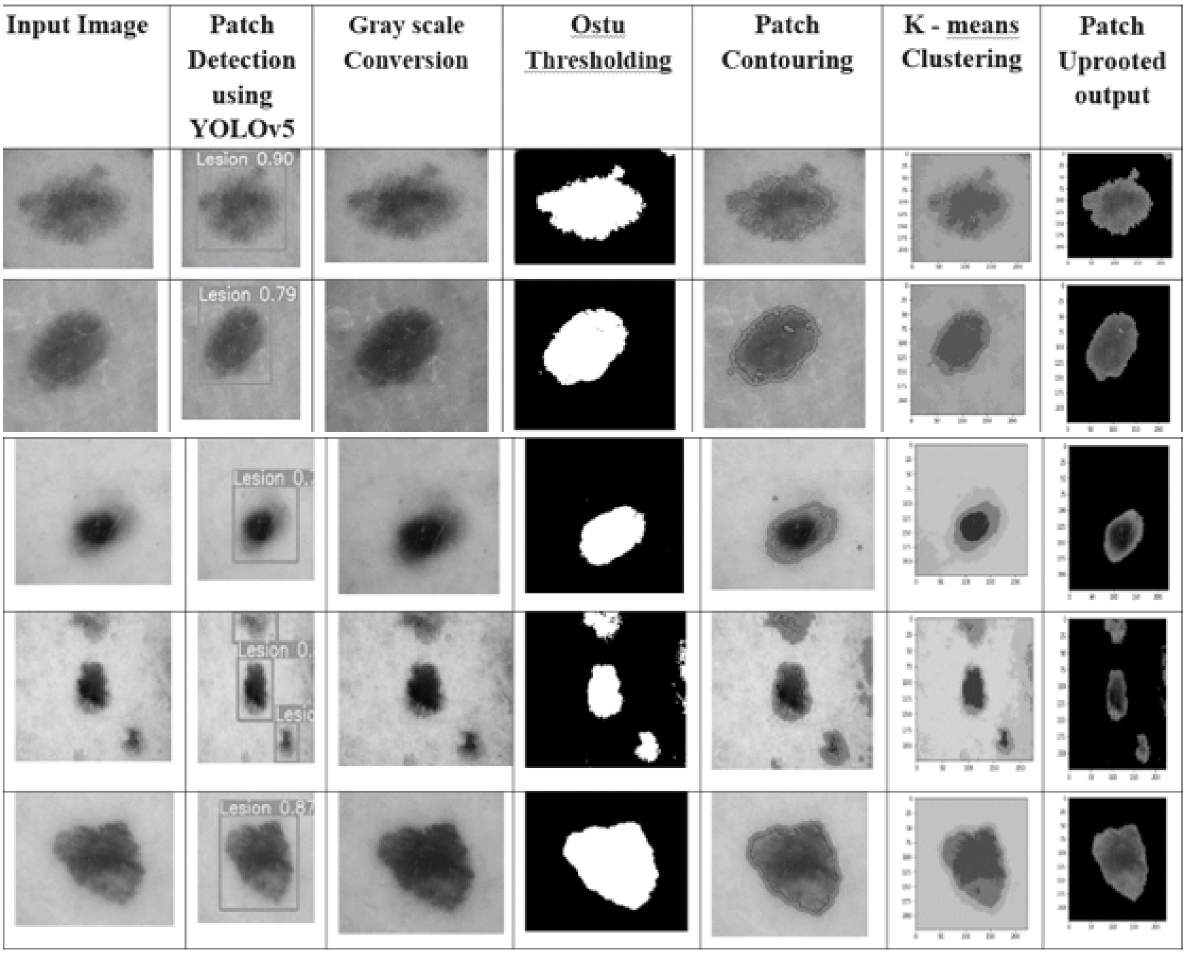

FIGURE 2

Visual Segmented Output images of ISIC-2018 dataset usingdifferent segmentation techniques.

4.4 Performance Analysis of the Proposed Segmentation Techniques on ISIC-2019

Outputs for the first five images from the ISIC-2019 dataset using different segmentation methods are provided in Figure 4. Table 2 and Figure 5 depict the experimental results of the proposed segmentation technique for the ISIC-2019 dataset.

TABLE 1

Experimental Results of the Proposed Segmentation Technique for the First Five Images on the ISIC-2018 Dataset.

Image	Accuracy	Dice	Jaccard	Sensitivity	Specificity
Image 1	93.40	84.90	76.5	82.5	97.5
Image 2	90.14	76.27	61.64	67.15	97.24
Image 3	94.03	87.08	77.11	85.40	96.69
Image 4	93.60	87.80	78.20	81.60	98.30
Image 5	94.70	88.06	82.03	89.80	96.44

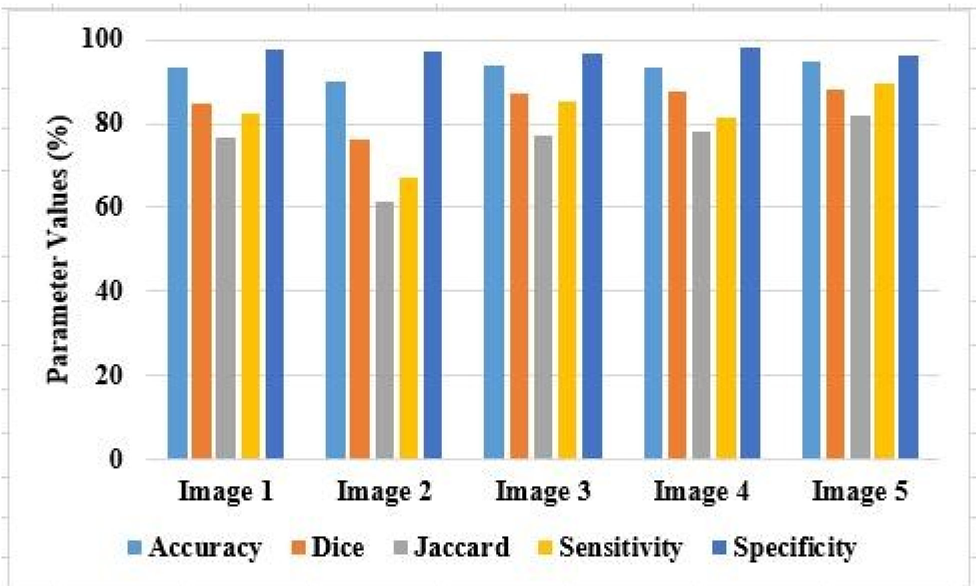

FIGURE 3

Graphical Representation of the Performance of the Proposed Segmentation Technique on the ISIC-2018 Dataset

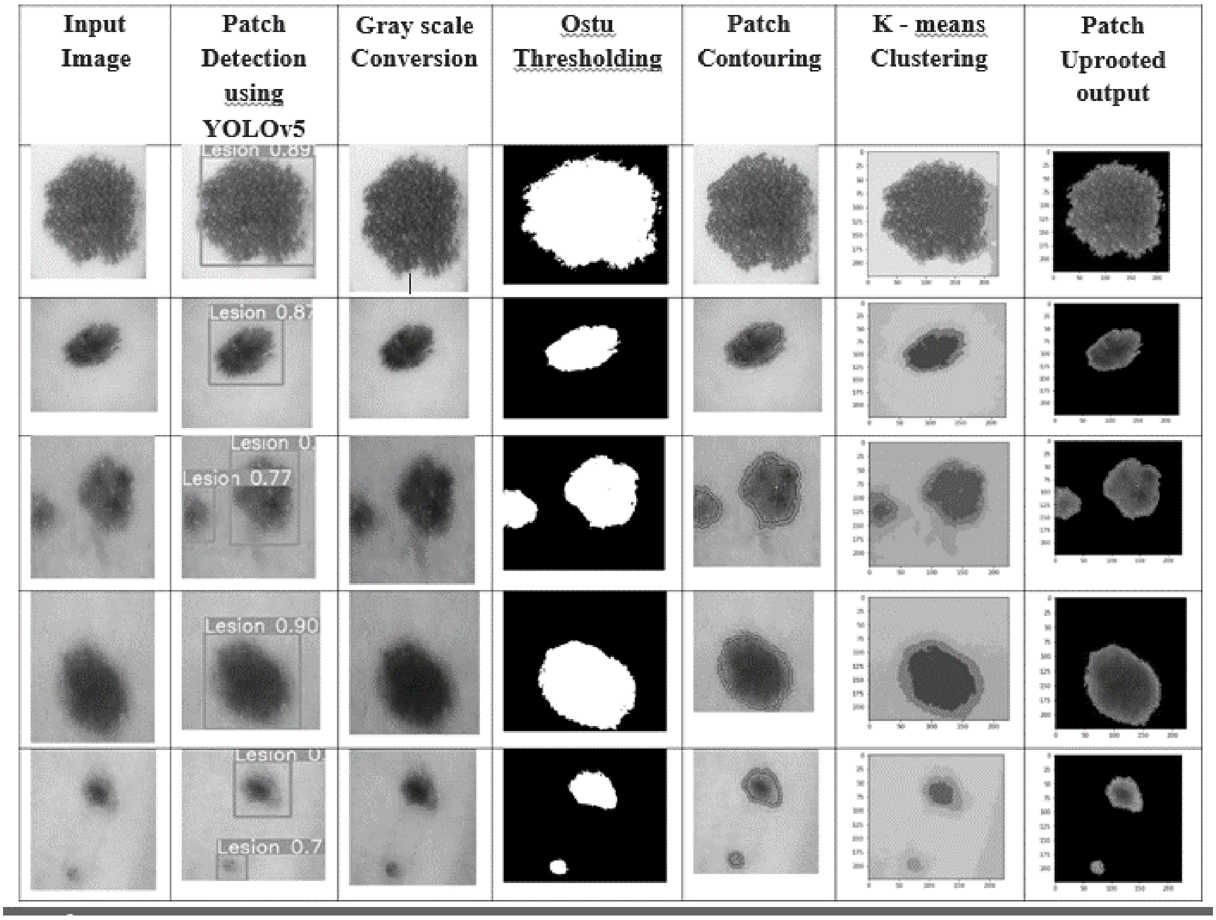

FIGURE 4

Visual Segmented Output Images of the ISIC-2019 Dataset Using Different Segmentation Techniques.

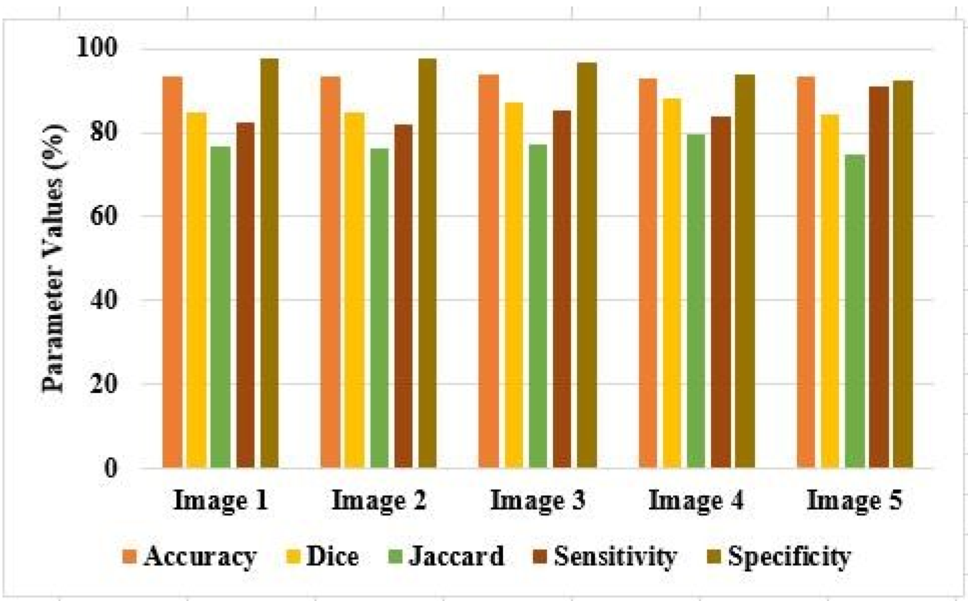

FIGURE 5

Graphical Representation of the Performance of the Proposed Segmentation Technique on the ISIC-2019 Dataset

TABLE 2

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Image 2	93.20	84.70	76.20	82.00	97.80
Image 3	94.03	87.08	77.11	85.40	96.69
Image 4	92.99	88.13	79.54	83.63	94.02
Image 5	93.39	84.26	74.81	90.82	92.68

4.5 Comparative Analysis of the Proposed Segmentation Technique with Existing Techniques

Comparison of the proposed segmentation method with existing techniques is presented in Table 3. Various methodologies are considered, and the performance metrics are compared, emphasizing the superiority of the proposed techniques.

From the results analysis, it's evident that the proposed segmentation techniques outperform existing methods. However, there's room for improvement in the Dice and Jaccard coefficients, which could be addressed in future work. The overall accuracy achieved demonstrates the effectiveness of the implemented pipeline for segmenting lesions in dermoscopic images.

TABLE 3

Comparative Analysis of the Proposed Segmentation Technique with Existing Techniques

Method	Accuracy (%)	Dice (%)	Jaccard (%)	Specificity (%)
Maglogianis (**?**)	92.8	-	-	97
FAN (**?**)	93.6	-	-	-
Sparse Coding (**?**)	91	80	67	86
PSPN (**?**)	85	86	81	85
DeepLan-v3 (**?**)	87	85	80	85
YOLOv4-DarkNet (**?**)	94	-	-	94
Proposed Segmentation Techniques	**94.70**	**88.06**	**82.03**	**97.50**

5 Conclusion

In conclusion, this study introduces Dseg-Net, a fusion segmentation approach that utilizes YOLOv5's deep convolutional neural network and clustering techniques to detect and annotate diverse lesions in dermoscopic images. Unlike previous methods, our approach effectively handles lesions of varying sizes and shapes through hyperparameter tuning and focused foreground region detection. By employing patch detection and clustering strategies, we surpass state-of-the-art methods in accurately segmenting skin lesions.

Our evaluation on the ISIC 2018 and ISIC 2019 datasets demonstrates promising results, with patch detection accuracies reaching 97% and 91%, respectively, and an overall average accuracy ranging from 92% to 94%. As a future direction, we aim to further enhance our method by integrating a Deep Convolutional Neural Network for feature extraction and classification, particularly to differentiate melanoma from segmented skin lesion images.

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Method	**Year**	**Reference**	**Key Features**	**Datasets**	**Achievements**
Full-Resolution Recovery Network (FrCN)	2018	[16]	Full architectural resolution, high accuracy rates	PH2, ISBI 2017	High accuracy rates on PH2 and ISBI 2017 datasets
Dense Deconvolutional Network (DNN)	2018	[17]	Dense deconvolutional layers, residual chained pooling, hierarchical supervision	2017 ISBI	Competitive results on 2017 ISBI dataset
Adversarial Network Segmentation	2018	[18]	Generative Adversarial Network with U-network generator, Convolutional Neural Network discriminator	2016 ISBI	High accuracy on 2016 ISBI dataset but needs effective clustering models for accurate segmentation
Saliency Detection and Sparse Representation	2017	[19], [20]	Saliency detection, sparse representation, challenges in handling fuzzy boundaries and intricate textures	-	-
Superpixel-level Segmentation	2016	[21]	Contextual information at superpixel level, challenges in managing size variations in identified borders	-	-
Pyramid Scene Parsing Network (PSPN)	2017	[21]	Captures global contextual information, utilizes atrous convolutions, spatial pyramid pooling	-	-
DeepLab V3	2017	[22]	Utilizes atrous convolutions and spatial pyramid pooling to improve segmentation accuracy	-	-
Transformer Prediction Heads YOLOv5 (TPH-YOLOv5)	2021	[23]	Transformer Prediction Heads, Convolutional Block Attention Model for improved prediction accuracy	Drone-captured scenes	Improved prediction accuracy on drone-captured scenes
Mutual Bootstrapping Deep Convolutional Neural Network (MB-DCNN)	2021	[24]	Combination of segmentation and classification networks using mutual bootstrapping	ISIC-2017, PH2	Promising results on ISIC-2017 and PH2 datasets but requires improvement in discriminatory ability
Depth-wise Separable Network (DSNet)	2020	[25]	Utilizes depth-wise separable convolutions, achieves superior results compared to U-Net and FCN8s	ISIC-2017, PH2	Superior results compared to U-Net and FCN8s
You Only Look At Coefficients of Transformations (YOLACT)	2021	[26]	Instance segmentation, high mAP rates and FPS, lack testing on varied psoriasis severity photos	Psoriasis photos	High mAP rates and FPS, but lacks testing on varied psoriasis severity photos
Dermoscopic Skin Network	2020	[27]	Combines Open Neural Network Exchange (ONNX), squeeze net, and Residual Network (ResNet-18) models	MICCAI ISIC	Promising results on MICCAI ISIC datasets but struggles with detecting multiple lesions
Deep Saliency Segmentation	2019	[28]	Multiclass skin lesion classification utilizing Local Contrast and Homogeneity-based Intensity Variation enhancement and Convolutional Neural Network-based saliency estimation	HAM10000	High segmentation and classification accuracies on HAM10000 dataset
Convolutional Neural Network with Cross-Connection Layer Module	2018	[29]	Segmentation and edge prediction simultaneously, high Jaccard Index, Accuracy, and Sensitivity	-	High Jaccard Index, Accuracy, and Sensitivity
You Only Look Once (YOLO) Approaches	2016	[30]	Object detection, rapid processing speeds, outperforms other real-time detectors	-	Rapid processing speeds, outperforms other real-time detectors