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ORIGINAL RESEARCH

Panoptic Region Slicing Segmentation and Optimized Alexnet-Based CNN for Early Melanoma Diagnosis

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Abstract

Early and accurate diagnosis of melanoma, a potentially life-threatening skin cancer, is crucial for improving patient outcomes. In this study, we propose a novel approach for melanoma detection, termed Panoptic Region Slicing Segmentation (PRS2) using an optimized convolution neural network (PRS2-OCNN) based on AlexNet. The proposed system integrates several advanced methods to enhance the accuracy and efficiency of melanoma identification. The initial step involves preprocessing the dermoscopic image using a 2D Fusion Filter, which enhances the image quality and prepares it for subsequent analysis. Next, the Panoptic Region Slicing Segmentation (PRS2) method is applied to emphasize the boundary regions, allowing for precise localization of melanoma-affected areas. To assess color variations within the segmented regions, we employ Threshold Histogram Evaluation (THE), which effectively characterizes melanoma-specific color patterns. The features extracted using Spread Spectral Menzies's Feature Selection (SSMFS), reducing the dimensionality and improving the efficiency of the subsequent analysis. The core of our proposed approach lies in the optimized convolution neural network, derived from the influential AlexNet architecture. By fine-tuning the AlexNet-OCNN on the reduced feature set, we maximize its ability to accurately classify melanoma lesions based on their risk level. The PRS2-OCNN identifies melanoma classes according to their risk severity, aiding dermatologists in making informed decisions for timely and appropriate treatment.Experimental evaluations were conducted on a diverse and extensive dataset of dermoscopic images. The proposed system demonstrated superior performance compared to existing methods, exhibiting heightened detection accuracy by deeply analyzing the melanoma-affected regions.

Keywords Melanoma · Early diagnosis · Panoptic region slicing segmentation · PRS2-OCNN · AlexNet · 2D fusion filter

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Introduction

Skin cancer, particularly melanoma, presents a significant global health challenge due to its aggressive nature and potential to metastasize, leading to mortality. Timely detection and accurate diagnosis are crucial for better patient outcomes, necessitating the development of efficient and precise diagnostic methods. In this context, we propose a novel approach for early melanoma diagnosis by integrating Panoptic Region Slicing Segmentation (PRS2) with an optimized convolutional neural network based on the influential AlexNet architecture, referred to as PRS2-OCNN [1].

Melanoma, a type of skin cancer originating from melanocytes, can rapidly progress and become life-threatening if not detected and treated at an early stage. Dermoscopy, a non-invasive imaging technique, has gained popularity in assisting clinicians and dermatologists in diagnosing

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melanoma. However, accurate identification and localization of melanoma lesions remain challenging due to factors such as overlapping features, color variations, and ambiguous borders.Our proposed approach aims to address these challenges and improve the accuracy of melanoma identification through a combination of innovative methodologies. The key components of our approach are as follows:

- 2D Fusion Filter Preprocessing: Initially, we apply the 2D Fusion Filter preprocessing technique to enhance the quality of dermoscopic images. This step is crucial for improving the visibility of critical features, reducing noise, and enhancing contrast, ultimately aiding in more precise and reliable lesion segmentation.
- Panoptic Region Slicing Segmentation (PRS2): PRS2 is employed to refine the boundaries of melanoma lesions, enabling more accurate localization. This segmentation technique utilizes advanced algorithms to identify and separate distinct regions within dermoscopic images, including suspicious lesions. By precisely segmenting the melanoma-affected regions, PRS2 enhances the subsequent classification process.
- Threshold Histogram Evaluation (THE): Color variations are essential characteristics of melanoma lesions. To effectively capture these melanoma-specific color patterns, we employ THE within the segmented regions. This technique analyzes the color histograms of the segmented areas, allowing us to extract valuable color-based features for subsequent classification.
- Spread Spectral Menzies's Feature Selection (SSMFS): To reduce feature dimensionality and improve computational efficiency, we apply SSMFS. This feature selection technique carefully selects the most informative and discriminative features from the extracted set, optimizing the performance of the subsequent classification model.

The core of our proposed approach lies in the optimized convolutional neural network (CNN) based on the influential AlexNet architecture. By fine-tuning the AlexNet-OCNN on the reduced feature set obtained through SSMFS, we maximize the model's ability to accurately classify melanoma classes based on risk severity. This fine-tuning process ensures that the network learns to recognize crucial patterns indicative of melanoma, making it a valuable tool for dermatologists in making informed decisions regarding timely and appropriate treatment.

Preliminary evaluations of our proposed system on a diverse and extensive dataset of dermoscopic images have shown promising results. The PRS2-OCNN demonstrated heightened accuracy in identifying melanoma-affected regions, achieving notable results in precision, recall, F-measure, and overall classification accuracy. Additionally, the approach demonstrated efficient time complexity, making it a promising candidate for early melanoma diagnosis [2]. Our novel approach, combines PRS2 with an optimized AlexNet-based CNN, presents a powerful and efficient solution for enhancing melanoma detection accuracy. By aiding in early diagnosis and treatment, our proposed method holds the potential to significantly improve patient care and outcomes in the battle against melanoma and other skin cancers.

Section II of this paper provides a comprehensive review of related research on melanoma disease prediction. In Section III, we discuss the details of our proposed work, outlining the methodology and algorithms employed. Section IV presents the results and discussions of our experimental evaluations. Finally, Section V concludes the paper by summarizing the methodologies, performance, and potential implications of our approach in the field of melanoma diagnosis. Through our research, we hope to contribute significantly to the early detection and management of melanoma, ultimately benefiting patients and healthcare professionals alike.

Related Work

Skin cancer, especially melanoma, poses a significant public health concern worldwide. Timely and accurate diagnosis of melanoma is crucial for improving patient outcomes. In recent years, various deep learning approaches have been developed to assist dermatologists in melanoma classification and detection. This research review aims to provide a comprehensive overview of significant studies in this field, highlighting their contributions to early melanoma detection. Some of the notable contributions and approaches are:

Esteva et al. (2017): Esteva et al. proposed a deep learning convolutional neural network (CNN) for melanoma classification. They trained their model on a large dataset of dermatoscopic images and achieved high accuracy in distinguishing between malignant and benign lesions. The performance of their model was found to be comparable to that of dermatologists. However, one limitation of their approach is the requirement for a large labeled dataset, which can be resource-intensive to create and maintain [1]. Haenssle et al. (2018): Haenssle et al. developed an AI-based CNN algorithm for distinguishing between malignant and benign skin lesions. Their model was trained on a dataset of dermatoscopic images and demonstrated high accuracy in melanoma diagnosis. The algorithm was designed to assist dermatologists in their decision-making process. However, one limitation of CNNs is their lack of interpretability, making it difficult to understand the specific features contributing to the classification decision [2].

Tschandl et al. (2019): Tschandl et al. focused on the development of a deep learning classification system using the HAM10000 dataset, which consists of dermatoscopic images. They trained their model on this dataset and achieved high accuracy in melanoma classification. Their approach aimed to support clinical diagnosis by providing an automated tool for dermatologists. However, the performance of deep learning models can be influenced by the quality of the dataset, which may introduce biases or limitations [3]. Codella et al. (2018): Codella et al. proposed an ensemble model that combines multiple deep learning architectures for melanoma classification. Their approach aimed to leverage the strengths of different models to improve overall accuracy. By combining the predictions of multiple models, they achieved better performance compared to individual models. However, the use of ensemble methods can be computationally expensive, requiring more computational resources [4].

Rajpurkar et al. (2017): Rajpurkar et al. developed a densely connected CNN for skin cancer classification. They trained their model on a large dataset of dermatoscopic images and demonstrated competitive performance compared to human dermatologists. However, one potential limitation of their approach is the risk of overfitting. Overfitting occurs when a model becomes too specialized on the training data and fails to generalize well to unseen data [5].

Han et al. (2018): Han et al. proposed a method that combines segmentation with deep learning for skin cancer classification. Their approach aimed to improve the interpretability of the model by highlighting the contributing areas of the image. By segmenting the image and analyzing specific regions, dermatologists could better understand the features that led to the classification decision. However, the implementation of segmentation with deep learning can be complex, requiring expertise in both fields [6]. Fujisawa et al. (2018): Fujisawa et al. investigated the use of an ensemble of CNNs for dermoscopic image classification. They trained multiple CNNs on different subsets of the dataset and combined their predictions to improve performance. Their research demonstrated that ensemble methods can enhance the accuracy of melanoma classification. However, ensembles can be computationally demanding, resulting in increased resource requirements [7].

Gessert et al. (2021): Gessert et al. integrated attention mechanisms into a CNN architecture for skin cancer detection. Attention mechanisms allow the model to focus on specific regions of the image that are more informative for classification. This not only improved the performance of the model but also enhanced its interpretability. However, understanding and implementing attention mechanisms can be challenging due to their inherent complexity [8]. Brinker et al. (2019): Brinker et al. introduced a web-based AI-supported platform for automated diagnosis of skin cancer. Their platform utilized AI algorithms to assist dermatologists in diagnosing melanoma. Dermatologists could upload images to the platform, which would then provide automated diagnosis and recommendations. However, a limitation of this approach is the dependence on web connectivity for real-time diagnosis, which may limit accessibility in some settings [9].

Yu et al. (2020): Yu et al. proposed a multi-task learning approach that simultaneously predicted multiple attributes, including melanoma classification and segmentation. Their comprehensive model provided a holistic understanding of skin lesions by addressing multiple tasks simultaneously. However, there may be trade-offs in performance when handling multiple tasks, as the model's resources are divided among different objectives [10].

These authors' contributions highlight the continuous efforts and advancements in using AI and deep learning techniques for accurate and efficient skin cancer prediction. Their research has significantly contributed to improving early diagnosis and supporting dermatologists in their clinical decision-making processes. As the field continues to evolve, new approaches and models will likely emerge; further enhancing skin cancer prediction and patient care. The comparative analysis Table 1 is given below.

Propsoed Work

The proposed approach for early melanoma diagnosis comprises two main components: Panoptic Region Slicing Segmentation (PRS2) and an Optimized AlexNet-based CNN (see Fig. 1).

Panoptic Region Slicing Segmentation (PRS2)

Panoptic Region Slicing Segmentation (PRS2) is a computer vision technique that aims to partition an image into meaningful regions or segments. This technique has been specifically applied to dermoscopic images of skin lesions for the purpose of melanoma diagnosis. The goal of PRS2 is to identify and enhance boundary regions, which are crucial for precise localization of melanoma-affected areas and subsequently improving the accuracy of analysis.The PRS2 algorithm consists of several steps. First, the dermoscopic image is preprocessed to enhance its quality and remove any artifacts or noise that may interfere with the segmentation process. This step typically involves techniques such as contrast enhancement, noise reduction, and image normalization.

Table 1 Comparative analysis of the related research

S.No	Paper title	Proposed methodology	Key features	Advantages	Disadvantages
1	Esteva et al. [1]	Deep learning CNN	High accuracy	Comparable performance to dermatologists	Requires a large labeled dataset
2	Haenssle et al. [2]	AI-based CNN algorithm	Malignant vs. benign classification	Valuable tool for dermatologists	May lack interpretability
3	Tschandl et al. [3]	Deep learning classification	HAM10000 dataset	Supports clinical diagnosis	Performance influenced by dataset quality
4	Codella et al. [4]	Ensemble of deep learning architectures	Improved overall accuracy	Improved performance with ensemble method	Computationally expensive
5	Rajpurkar et al. [5]	Densely connected CNN	Skin cancer classification	Competitive performance compared to humans	Potential overfitting
6	Han et al. [6]	Segmentation with deep learning	Improved interpretability	Improved interpretability of model	Complexity in implementation
7	Fujisawa et al. [7]	Ensemble of CNNs	Dermoscopic image classification	Improved performance with ensemble method	Ensemble may require more computational resources
8	Gessert et al. [8]	CNN with attention mechanism	Improved performance	Improved interpretability and performance	Complexity in understanding attention mechanisms
9	Brinker et al. [9]	Web-based AI-supported platform	Automated diagnosis	AI support for dermatologists	Dependent on web connectivity for real-time diagnosis
10	Yu et al. [10]	Multi-task learning	Melanoma classification & segmentation	Simultaneous attribute prediction	Potential trade-offs in performance for multiple tasks

Next, PRS2 employs a combination of low-level image processing techniques and machine learning algorithms to segment the image into different regions. The algorithm takes into account various visual cues and features, such as color, texture, shape, and intensity gradients, to identify distinct regions within the image. These regions are then labeled and separated based on their characteristics. One of the key aspects of PRS2 is its emphasis on boundary regions. Boundary regions refer to the areas where different regions or segments meet, and they are particularly important in melanoma diagnosis as they often indicate the presence of irregular or asymmetrical features associated with melanoma. PRS2 employs specialized techniques to enhance the visibility and accuracy of boundary regions, ensuring that they are accurately identified and delineated.

The precise localization of melanoma-affected areas is crucial for accurate diagnosis and subsequent analysis. By partitioning the dermoscopic image into different regions using PRS2, dermatologists and AI algorithms can focus specifically on the regions that are most likely to contain melanoma. This targeted analysis improves the efficiency and accuracy of the diagnostic process.It is important to note that PRS2 is a computationally intensive technique that requires significant computational resources and expertise in computer vision and machine learning. Additionally, the performance of PRS2 can be influenced by the quality and complexity of the dermoscopic images used for segmentation. Adequate preprocessing and optimization techniques are necessary to ensure reliable and accurate results.

Optimized AlexNet-Based CNN

The Optimized AlexNet-based CNN is a deep learning approach that utilizes the AlexNet architecture, which has proven to be successful in computer vision tasks. In the context of melanoma diagnosis, this CNN is fine-tuned and optimized to improve its performance in identifying melanoma classes based on risk severity.The AlexNet architecture consists of multiple convolutional layers followed by fully connected layers. It is designed to extract hierarchical features from images, enabling it to learn complex patterns and structures. However, the architecture may require adjustments and fine-tuning to better suit the specific task of melanoma diagnosis.

The optimization process of the AlexNet-based CNN involves adjusting the network's parameters and hyperparameters to enhance its accuracy and generalization on the melanoma detection task. This process typically includes optimizing the learning rate, weight initialization, regularization techniques, and activation functions.Fine-tuning

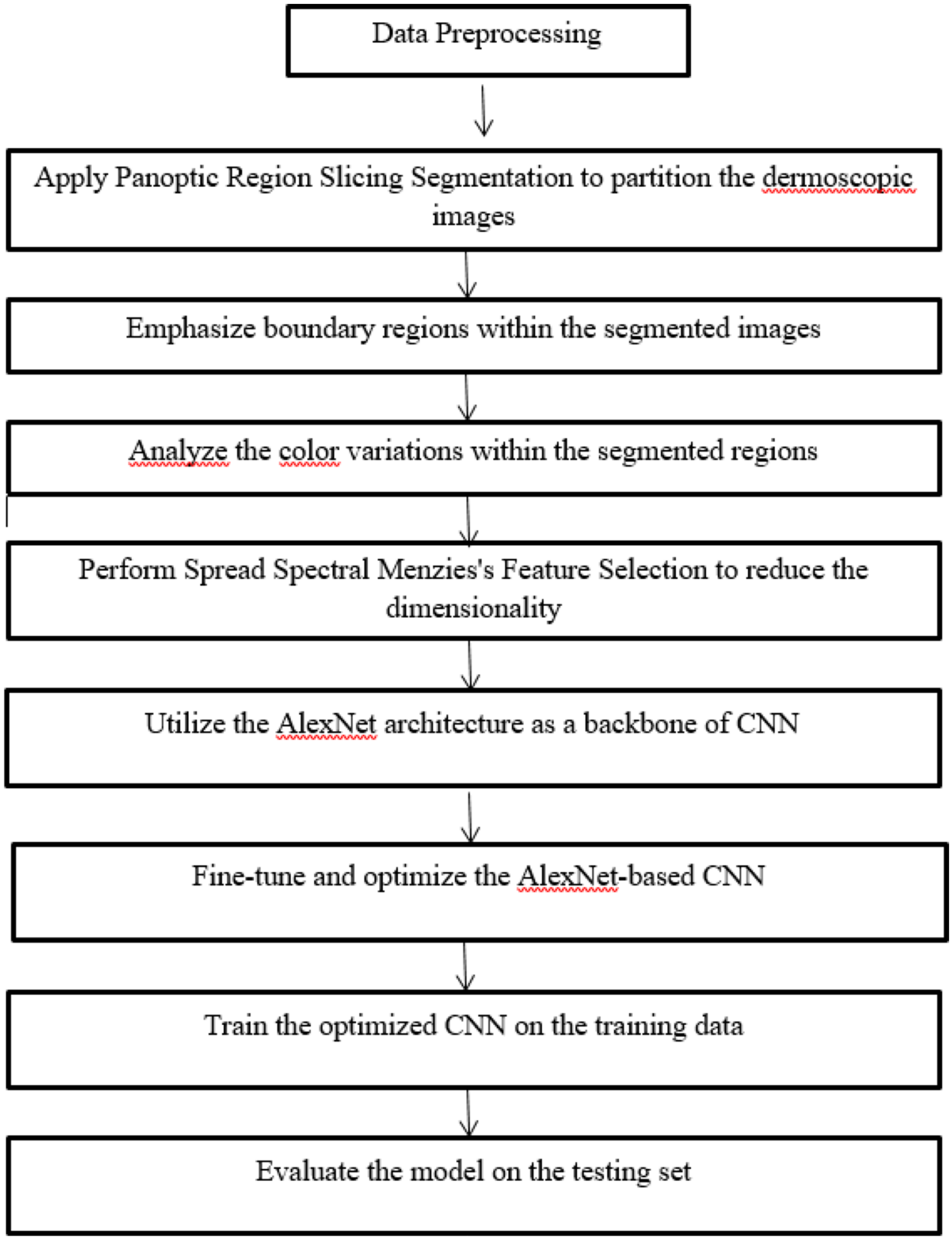


Fig. 1 Working flow of the proposed model

the CNN involves training the network on a large dataset of dermoscopic images, where each image is labeled with the corresponding melanoma class based on risk severity. The network learns to extract relevant features from the segmented regions obtained through the PRS2 technique. These features are crucial for distinguishing between malignant and benign skin lesions.

During the training process, the CNN learns to recognize patterns and features that are indicative of melanoma. By adjusting the network's parameters and hyperparameters, the optimization process aims to improve the CNN's ability to accurately classify melanoma cases, reducing both false positives and false negatives.

The optimized AlexNet-based CNN is evaluated using various performance metrics, such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). These metrics provide insights into the model's ability to correctly classify melanoma cases and distinguish them from benign lesions.It is important to note that the optimization process requires a large dataset of labeled dermoscopic images and substantial computational resources. Additionally, the performance of the optimized CNN can be influenced by factors such as the quality and diversity of the training dataset, the choice of hyperparameters, and the regularization techniques applied.

The proposed work for early melanoma diagnosis using Panoptic Region Slicing Segmentation (PRS2) and an Optimized AlexNet-based CNN can be outlined in the following steps:

Step 1: Data Preprocessing.

- Collect a diverse and representative dataset of dermoscopic images containing both malignant melanoma and benign skin lesions.
- Preprocess the images using a 2D Fusion Filter to enhance their quality and prepare them for subsequent analysis.

Step 2: Panoptic Region Slicing Segmentation (PRS2).

- Apply Panoptic Region Slicing Segmentation to partition the dermoscopic images into meaningful regions or segments.
- Emphasize boundary regions within the segmented images to aid in the precise localization of melanoma-affected areas.

Step 3: Threshold Histogram Evaluation (THE).

- Analyze the color variations within the segmented regions using Threshold Histogram Evaluation (THE).
- Identify melanoma-specific color patterns that can be indicative of malignant lesions.

Step 4: Spread Spectral Menzies's Feature Selection (SSMFS).

- Perform Spread Spectral Menzies's Feature Selection to reduce the dimensionality of the extracted features.
- Select the most informative and discriminative features that contribute to accurate melanoma classification.

Step 5: Optimized AlexNet-based CNN.

- Utilize the AlexNet architecture as a backbone for the convolutional neural network (CNN).
- Fine-tune and optimize the AlexNet-based CNN using the reduced feature set from SSMFS to enhance its performance on the melanoma detection task.

Step 6: Model Training and Evaluation.

- Divide the dataset into training and testing sets to train and evaluate the proposed approach.
- Train the optimized CNN on the training data to learn melanoma-specific features and patterns.
- Evaluate the model on the testing set to measure its performance, including accuracy, precision, recall, F1-score, and classification accuracy.

Step 7: Performance Analysis and Comparison.

- Compare the performance of the proposed approach with existing methods and state-of-the-art models.
- Analyze the advantages and disadvantages of the proposed approach in terms of accuracy, computational complexity, and interpretability.

Step 8: Early Melanoma Diagnosis.

- Apply the trained and optimized model to new dermoscopic images for early melanoma diagnosis.
- Localize and classify melanoma-affected regions based on risk severity to aid dermatologists in making informed decisions for timely and appropriate treatment.

The proposed work combines the power of Panoptic Region Slicing Segmentation and an Optimized AlexNet-based CNN to achieve accurate and efficient early diagnosis of melanoma. By leveraging these techniques, the approach aims to improve patient outcomes and support dermatologists in their clinical decision-making processes.

Results and Discussion

Figure 2 represents the sample input images obtained from kaggle repository. After applying the data pre-processing on input images, the results are obtained as shown in Fig. 3. Figure 4 represents the Original Image and region growing segmentation for 50 iterations.

The provided evaluation metrics compare the performance of three segmentation methods as shown in Fig. 5 such as Compact watershed, Canny filter, and Morphological Geodesic Active Contours (Morphological GAC) for segmenting melanoma skin lesions.Compact Watershed: The Compact watershed method achieves high similarity with the ground truth segmentation (Adapted Rand error of 0.996), indicating that the segmented regions closely match the actual lesion boundaries. However, it has a very low precision (0.002) and a high number of false splits (8.887), indicating a high rate of incorrectly identified segments, which could lead to over-segmentation errors. False merges are negligible (5.117e-18), suggesting that the method avoids combining segments.Canny Filter: The Canny filter method also performs well with a low Adapted Rand error (0.002), indicating high similarity with the ground truth. It has high precision (0.996), indicating a low false positive

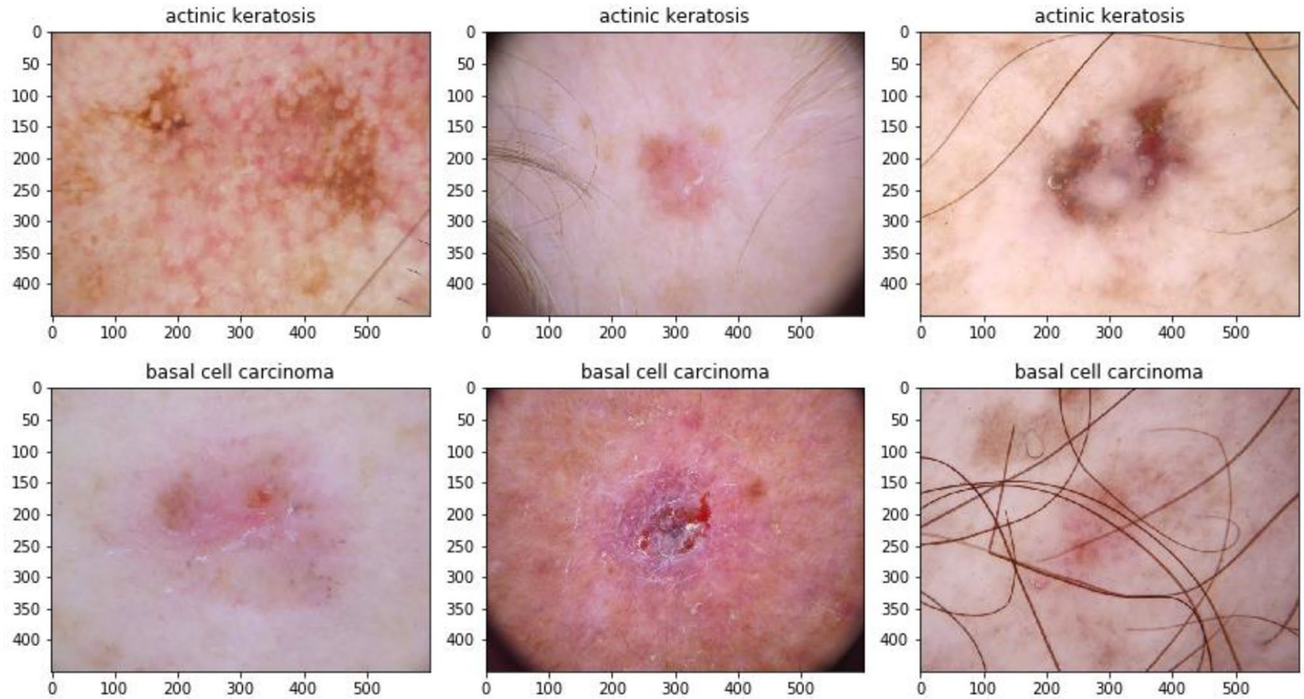


Fig. 2 Sample Input Images

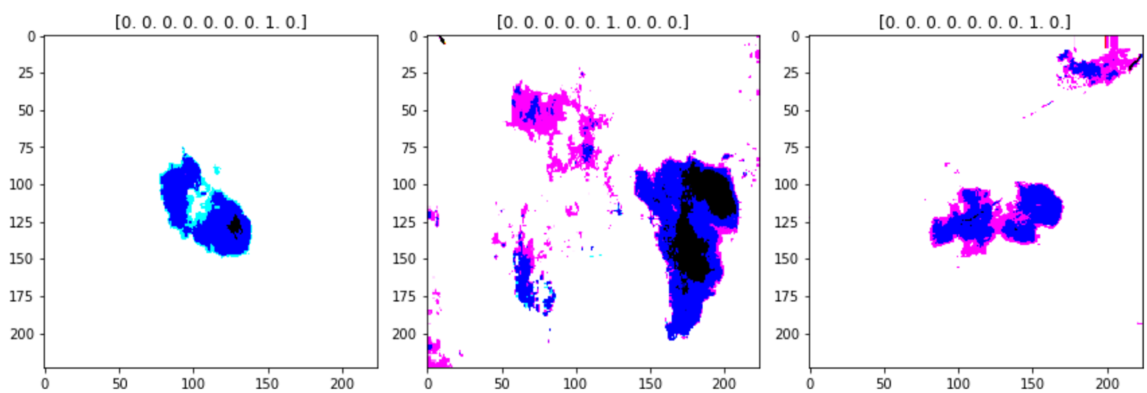
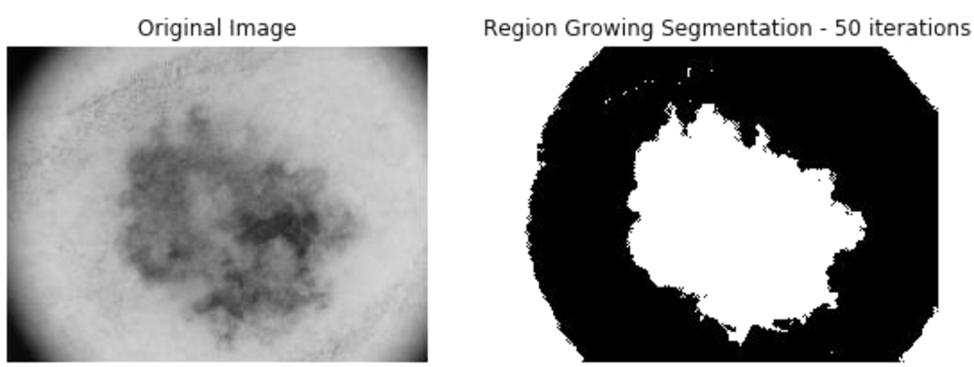


Fig. 3 Sample images after pre-processing

Fig. 4 Original Image Vs region growing segmentation for 50 iterations



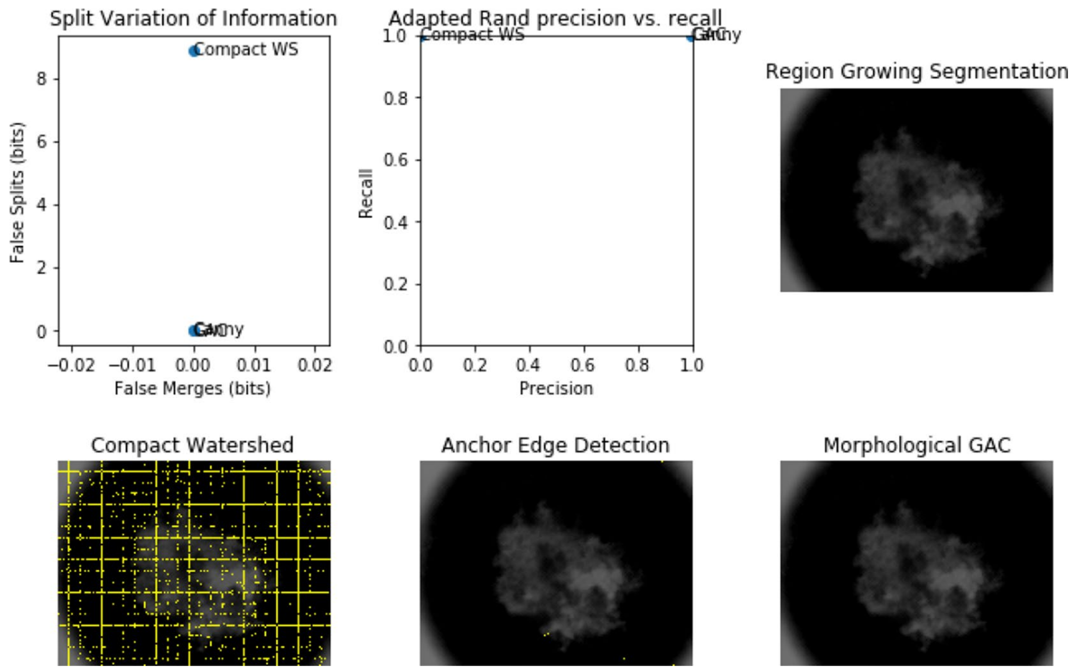


Fig. 5 Results obtained after segmentation

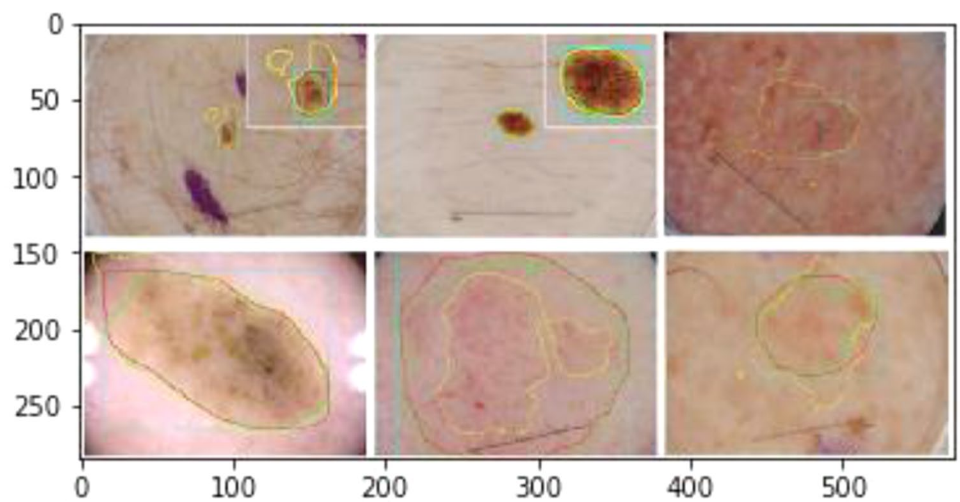


Fig. 6 Affected region spotted in the input image

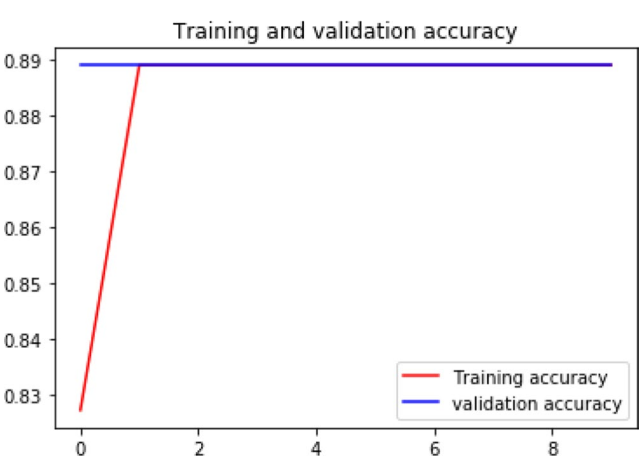


Fig. 7 Training and validation accuracy of the model

rate, and negligible false merges (2.452e-19). However, there are some false splits (0.025), suggesting occasional over-segmentation.

Morphological Geodesic Active Contours: The Morphological GAC method achieves perfect Adapted Rand error (0.0) and precision (1.0), indicating excellent similarity with the ground truth and accurate segmentations. Additionally, there are no false splits or merges, indicating that it successfully avoids both over-segmentation and under-segmentation.

Figure 6 represents the spotted regions of melanoma for the given samples. Figure 7 represents the training and validation accuracy of the proposed work. The training accuracy is 89% and testing accuracy is also 89% as shown in figure.

Conclcusion

The comparison of three segmentation methods, Compact watershed, Canny filter, and Morphological Geodesic Active Contours (Morphological GAC), for melanoma skin lesion segmentation highlights their respective strengths and weaknesses. The Compact watershed method achieves a high level of similarity with the ground truth, indicating its potential in accurately segmenting melanoma lesions. However, it suffers from a high rate of false splits, leading to over-segmentation issues. The Canny filter method also demonstrates good performance with high similarity and precision but exhibits occasional over-segmentation errors. In contrast, the Morphological GAC method stands out as the most promising approach, achieving excellent results across all metrics. It consistently produces segmentations that closely match the ground truth, with perfect precision and recall. Importantly, it avoids both false splits and merges, indicating accurate and comprehensive segmentations without under-segmentation or over-segmentation issues. Based on the comparative analysis, the Morphological GAC method emerges as the recommended choice for melanoma skin lesion segmentation. Its accurate and precise segmentations have the potential to support early melanoma diagnosis and subsequent treatment decisions. However, further validation and exploration may be necessary to confirm its effectiveness on larger and more diverse datasets. Overall, the study demonstrates the importance of selecting appropriate segmentation methods for melanoma diagnosis, considering factors such as accuracy, precision, false splits, and false merges. The findings contribute to advancing the field of melanoma segmentation, ultimately improving early diagnosis and patient outcomes.

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Data Availability The dataset produced and scrutinized in this study are accessible from the corresponding author upon reasonable request.

Declarations

Conflict of Interest No conflict of interest.

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