Skin Cancer Detection using Deep Learning Architectures and Fuzzy K-Means Clustering

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***Abstract*—Melanoma, a type of skin cancer, is regarded as the most perilous and fatal within the spectrum of skin malignancies. Nevertheless, the task of automating the localization and segmentation of skin lesions at their nascent stages presents a formidable challenge, primarily due to the minimal contrast between melanoma-affected moles and adjacent skin regions, along with the heightened resemblance in coloration between melanoma-affected and unaffected areas of the skin. This research endeavors to elucidate a fully automated method designed for the early-stage segmentation of melanoma skin lesions. It leverages a deep learning approach, explicitly employing the Faster Region-Based Convolutional Neural Networks (RCNN) and Fuzzy K-Means Clustering (FKM). The efficacy of this proposed approach is assessed using a range of clinical photographs, offering potential support to dermatologists in the timely identification of this potentially life-threatening condition. As an initial step, the suggested technique preprocesses the dataset images to mitigate noise, rectify lighting issues, and amplify the visual information before employing the Faster-RCNN to construct a feature vector of fixed dimensions. Subsequently, the Fuzzy K-Means (FKM) algorithm delineated the melanoma-affected skin, accommodating diverse sizes and boundary contours. The performance of the proposed methodology was rigorously evaluated against the established ISBI-2016 dataset which is available at https://challenge.isic-archive.com/data/, and the results unequivocally demonstrate its superiority over cutting-edge techniques. Remarkably, when applied to the ISIC-2016 dataset, this approach attains an impressive average accuracy of 95.40%, underscoring its resilience in the realm of skin lesion detection and segmentation. Our code is available is at https://colab.research.google.com/drive/1kZej3D2OxL0uUg3H2rNxXzfEpSjqD6eJ?usp=sharing**

***Index Terms*—deep learning, faster-RCNN, fuzzy k-means clustering, melanoma, skin cancer**

I. Introduction

Melanoma, an insidious form of skin cancer, takes a tragic toll, claiming the lives of numerous individuals across the globe annually. This malignancy primarily targets exposed body areas that receive sunlight, encompassing regions like the face, arms, legs, and neck. Regrettably, melanoma holds the dubious distinction of having the highest fatality rate among skin cancers [5]. It stems from the abnormal proliferation of skin pigment-producing cells within the body (as indicated by the American Cancer Society in 2016). Melanoma lesions manifest a diverse array of shapes and hues, spanning a spectrum from pink, red, and black to brown, reflecting the varying degrees of severity associated with this affliction. Moles exceeding a diameter of 6 millimeters and displaying abnormal colors warrant assessment by a dermatologist to explore the potential presence of melanoma. Dermatologists undertake a thorough physical examination, scrutinizing aspects like the mole's shape, size, unusual pigmentation, and diameter. However, the scarcity of dermatologists can elongate this diagnostic process, diminishing an individual's prospects for survival [10]. Nonetheless, early detection of the disease not only spares individuals from the discomfort of biopsies but also significantly enhances their chances of survival. To address the diagnostic challenges associated with melanoma, experts are now directing their efforts toward the automated diagnosis of this life-threatening ailment.

Numerous methods have been proposed for the automatic identification of melanoma-affected skin. Initially, techniques rooted in handcrafted features are introduced for melanoma detection. However, these methods fail to deliver satisfactory results, primarily due to the variations in the shape, size, and color of melanoma lesions. Subsequently, in an effort to enhance the precision of these automated systems, segmentation-based approaches, such as adaptive thresholding and iterative selection thresholding (ISO), are presented. These strategies isolate the region of interest (ROI) [8], representing a segmented portion of the melanoma. The rationale behind their improved performance lies in effectively identifying the afflicted area when the feature extraction process places greater emphasis on the pathological region. The primary reason for segregating the nonaffected portion from the affected area lies in the potential compromise of the feature vector's strength, which, in turn, can detrimentally impact the detection capabilities of the system. Consequently, segmentation stands as the foundational step in the development of an automated melanoma detection system. Nevertheless, the effectiveness of region-of-interest or thresholding-based algorithms is contingent on image content remaining constant in contrast and experiencing minimal illumination variations. This approach thrives when the image depicts a uniform distribution of chrominance. However, in practical scenarios, it is often challenging, if not impossible, to entirely mitigate changes in lighting and chrominance within photographs. Con-

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sequently, under such circumstances, threshold-based methods exhibit a decline in their ability to detect melanoma-affected regions. Notably, deep-learning-based techniques are gaining prominence in medical imaging, representing an increasingly significant trend. Convolutional Neural Networks (CNNs) [6] employ small image segments containing melanoma-affected regions for instructing the automated detection system. Drawing from the knowledge acquired through this training process, these methodologies segment the test images. Notably, deep-learning-based algorithms surpass their handcrafted feature-based counterparts when it comes to the tasks of melanoma identification and segmentation. These advanced techniques have the capability to automatically derive intricate and representative sets of features directly from the input images. This results in an enhanced ability to precisely locate and detect areas of melanoma-affected skin. Furthermore, deep-learning methods effectively detect skin lesions of varying sizes, even with challenges like blurriness, noise, and fluctuations in lighting conditions and color. As a result, these methods are capable of better coping with the difficulties associated with handmade and segmentation-based melanoma recognition systems, and they have captured the attention of researchers in order to be used for the automated detection of skin lesions.

Current approaches, whether reliant on manual techniques or deep learning, confront two potential challenges: (a) a substantial computational burden and (b) the risk of model overfitting. In this paper, we endeavor to address the constraints of established methods by introducing an innovative approach for the automated identification of melanoma lesions. This method leverages a deep-learning technology, specifically the Faster Region-Based Convolutional Neural Networks (RCNN), in conjunction with Fuzzy K-Means Clustering (FKM). The images utilized as input are frequently subject to fluctuations in lighting and illumination, alongside issues of noise and blurriness. In this research, we initiate the process by subjecting the input images to a preprocessing stage before feeding them into a well-trained model, utilizing the Faster Region-Based Convolutional Neural Networks (Faster-RCNN). Our deep-learning algorithm, with enhanced precision, generates a feature vector of fixed dimensions that distinguishes between melanoma-affected and unaffected regions. These identified sections then undergo Fuzzy K-means clustering (FKM) to segment the affected areas, which vary in size and boundary contours, thereby facilitating the detection of melanoma. To evaluate the efficacy of our approach, we conducted a comparative analysis against other contemporary methods, employing commonly used dataset such as ISIC-2016. The qualitative and quantitative results clearly demonstrate the superiority of our system, primarily attributed to the exceptional localization capabilities of the Faster-RCNN and FKM's proficiency in handling overfitting issues in training data.

Following are the main contributions of the presented method:

1) Accurate and exact identification of skin lesions employing the precise localization power of faster-RCNN.
2) The robust segmentation of melanoma-affected pictures employing competence and the capacity of the FKM method to deal with overfitted training data.
3) The procedure here can also be used for other skin problems.
4) To the best of our knowledge, faster-RCNN is being used for skin lesion identification for the first time in medical image analysis. The reported findings demonstrate the usefulness of faster RCNN in detecting melanoma moles and computing a profound and discriminative collection of features with enhanced performance outcomes.

The rest of the sections of this paper are structured as follows: II presents the related work. In III, the presented method is explained in detail. IV presents the evaluation results, while V presents the conclusion of the presented method.

II. Related Works

Dildar et al. [4]The significance of early diagnosis is emphasized as a key factor in improving patient outcomes. The utilization of diverse and high-quality image datasets, such as the ISIC dataset, plays a pivotal role in training and evaluating deep learning models. Various model architectures, including transfer learning and ensemble models, are explored to enhance accuracy. Deep learning is applied to segment lesions and extract features, with clustering methods facilitating region-of-interest identification. Ultimately, the review underscores the potential for deep learning to assist dermatologists in making more accurate and timely skin cancer diagnoses, offering the promise of enhanced patient care and treatment. Vidya et al. [11] Machine learning techniques are showing great promise in the field of skin cancer detection. By analyzing dermatological images, these methods can assist in early diagnosis, potentially improving patient outcomes. However, challenges such as the quality of image datasets, model interpretability, and clinical validation need to be addressed for widespread adoption in clinical practice. Despite these challenges, machine learning holds the potential to enhance skin cancer management by aiding dermatologists in making more accurate and timely diagnoses.

Daghrir et al. [3] A hybrid approach combining deep learning and classical machine learning techniques is explored to detect melanoma skin cancer. This approach leverages the strengths of both methodologies to enhance accuracy and reliability in diagnosis. Integrating these techniques presents a promising strategy for improving melanoma detection, potentially aiding clinicians in early and accurate diagnosis. Nahata et al. [10] Deep learning solutions for skin cancer detection and diagnosis represent a cutting-edge approach to improving the accuracy and efficiency of identifying skin lesions. These methods, primarily based on convolutional neural networks (CNNs), leverage the power of artificial intelligence to automatically analyze dermatological images, allowing for the early detection of skin cancer. Using large, diverse datasets, such as the ISIC dataset, is crucial for training and validating these deep-learning models. Challenges include the need for interpretable models and clinical validation, but these solutions have the potential to significantly enhance diagnostic accuracy and assist dermatologists in making more timely and accurate skin cancer diagnoses, ultimately improving patient care and outcomes.

VijayaLakshmi et al. [12] Melanoma skin cancer detection through image processing and machine learning involves the analysis of dermatological images to identify potentially cancerous lesions. By extracting features and patterns from these images, machine learning algorithms assist in early diagnosis. This approach shows promise in improving detection accuracy and aiding clinicians in making timely and informed decisions regarding melanoma, ultimately enhancing patient care and outcomes. Hasan et al. [5] Skin cancer detection using Convolutional Neural Networks (CNNs) is a cutting-edge approach that harnesses the power of deep learning to identify skin lesions accurately. CNNs, well-suited for image analysis, automatically extract meaningful features from dermatological images, aiding in early diagnosis. By utilizing large and diverse datasets, such as ISIC, these models are trained and validated to achieve high accuracy. The key advantage is the potential for early and accurate skin cancer diagnosis, which can significantly improve patient care and outcomes. However, challenges like model interpretability and clinical validation must be addressed for broader clinical adoption. Anas et al. [2] Skin cancer classification using K-means clustering involves a data-driven approach to categorizing skin lesions. By grouping similar data points into clusters, K-means aids in the identification of patterns within dermatological images. Although traditionally more associated with data segmentation, when applied to skin cancer, K-means clustering can help differentiate between benign and malignant lesions. This method contributes to the development of diagnostic tools, but its effectiveness may be enhanced when integrated with machine learning or deep learning techniques, considering factors like texture, color, and shape for more accurate classification and diagnosis.

Kumar et al. [8] The "De-ANN" (De-Artificial Neural Network) inspired skin cancer detection approach using Fuzzy C-Means clustering employs a data-driven technique to detect and classify skin lesions. By applying Fuzzy C-Means clustering, the method groups similar data points within dermatological images to facilitate lesion differentiation. This approach draws inspiration from artificial neural networks and aims to enhance skin cancer detection. By incorporating Fuzzy C-Means clustering, the technique can improve the accuracy and efficiency of classification, offering a potential tool for early and accurate skin cancer diagnosis. Ahmed et al. [1] The early prevention and detection of skin cancer risk using data mining involves applying data-driven techniques to identify and predict the likelihood of skin cancer development. Data mining algorithms analyze various data sources, including medical records, patient histories, and environmental factors, to identify patterns and risk factors associated with skin cancer. By extracting meaningful insights from large datasets, this approach aids in early risk assessment and preventive measures. It provides valuable information for clinicians and patients to make informed decisions and take proactive steps in skin cancer prevention and early detection. Kaur et al. [6] The method of enhanced and automatic skin cancer detection employs K-means clustering and Particle Swarm Optimization (PSO) techniques to improve the accuracy and efficiency of skin cancer diagnosis. K-means clustering helps identify distinct patterns in dermatological images, while PSO fine-tunes the detection process. This approach enhances the precision of skin cancer detection, offering a potential tool for early and automated diagnosis.Mhaske et al. [9] the fusion of supervised and unsupervised learning techniques holds significant promise for the detection and classification of melanoma skin cancer. Supervised methods harness the power of labeled data to accurately identify melanoma lesions, while unsupervised methods contribute to data preprocessing, feature extraction, and the exploration of data structures. The synergy between these two approaches can lead to more robust and effective diagnostic systems, ultimately benefiting patients and clinicians in the early and accurate diagnosis of melanoma. Khan et al. [7] The classification of melanoma and nevus in digital images for the diagnosis of skin cancer involves the use of computer-based methods to distinguish between malignant melanoma and benign nevi in dermatological images. Machine learning techniques, particularly deep learning, are commonly employed to analyze image features and patterns automatically. This approach contributes to early and accurate skin cancer diagnosis by providing clinicians with a reliable tool to differentiate between potentially harmful melanomas and harmless nevi. It is a critical development in dermatology, aiming to improve patient care and outcomes through enhanced diagnostic accuracy.

III. METHODOLOGY

In our research, we have unveiled a novel method for detecting and isolating skin lesions in input images, employing a combination of faster-RCNN and FKM. To begin, we carry out preprocessing to eliminate any artifacts within the input images that could potentially hinder the effectiveness of faster-RCNN detection. Subsequently, these processed images are fed into the deep learning algorithm faster-RCNN, which identifies the melanoma-affected regions. These identified areas are then used to segment the affected portions of the images, which can be further employed to detect melanoma disease. (Fig. 1) Illustrates the comprehensive workflow of this methodology. Our approach has demonstrated that the combination of faster RCNN and FKM delivers outstanding outcomes in terms of both efficiency and performance when it comes to the detection and segmentation of skin cancer. Detailed descriptions of each step in this process are provided in the subsequent sections.

A. Preprocessing

Even when using high-quality cameras, obtaining images utterly devoid of light or noise interference in real-world scenarios is often an impractical feat. Such interference typically arises from significant fluctuations in lighting or the reflection of light off the skin's surface. To mitigate the influence of these

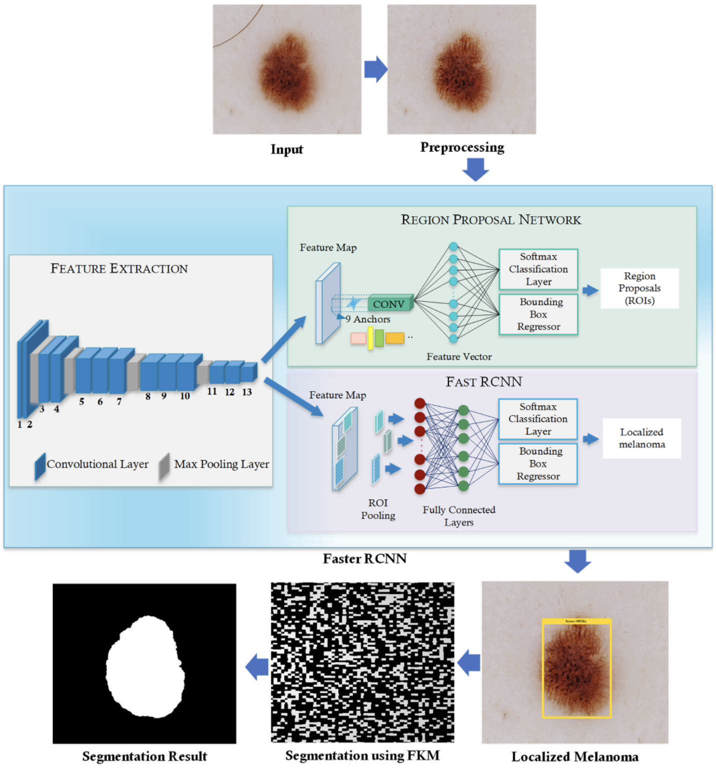

Fig. 1. Framework of our proposed method

variables during the training phase, the initial images undergo a light correction process. Furthermore, tiny blood vessels and hair can disrupt the accurate categorization and segmentation of melanoma lesions. In our proposed solution, we employ a morphological closure technique to eliminate these mentioned artifacts. The resulting image is then subjected to a smoothing process, followed by applying an unsharp filter to enhance its overall quality. The performed morphological operation on the input image is given by the following equation:

$$Img_{mor}(a,b) = (Img(a,b) \oplus S_1) \ominus S_2$$

In the given context, $Img(a,b)$ symbolizes the initial input image, and S_1 and S_2 denote specific neighborhoods consisting of 10 pixels oriented at angles of 90 and 180 degrees from each pixel. Meanwhile, $Img_{mor}(a,b)$ represents the resultant morphed image, which has been purged of any irregular anomalies like hair or minuscule blood vessels, albeit at the cost of a slight loss in image sharpness due to the morphological closing process. To counteract this blurring effect, we employ an un-sharp filter on the combined images in the subsequent manner.

$$Img_u(a,b) = Img_{mor}(a,b) \times \omega(a,b)$$

$$\omega(a,b) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{a^2+b^2}{2\sigma^2}\right] e^{\frac{a^2+b^2}{2\sigma^2}}$$

Finally, the obtained un-sharp image $Img_u(a,b)$ is subtracted from the input image $Img(a,b)$ to obtain the final sharp image $Img_s(a,b)$, which is accessible from the hair and tiny vessels and also preserves the details required for detecting the melanoma lesion

B. Feature Extraction using faster-RCNN

In this section, we offer an elaborate explanation of the process of feature extraction through the utilization of the faster RCNN. To effectively differentiate among various classification groups, it is essential to employ an efficient and distinctive set of features. However, a potential issue arises when dealing with an excessive number of identified features, as it may introduce undesired complexities into the proposed system. Conversely, if we restrict the set of features used in the system, there is a risk of omitting essential descriptors, which could impact the system's performance adversely. Hence, it becomes imperative to utilize a feature extraction descriptor that can autonomously derive an effective and distinctive set of features from input images, relying on labeled training data, as opposed to employing a manually crafted feature selection method.

In our approach, we harnessed the power of the faster RCNN, a deep learning framework tailored for the automatic localization of melanoma lesions. This method utilizes convolutional filters to meticulously examine the structural elements within the input image, enabling it to capture the primary characteristics of the input efficiently. The primary rationale behind our selection of faster-RCNN over alternatives like RCNN or fast-RCNN is rooted in the fact that both of these algorithms rely on generic object proposals generated using hand-crafted models like EdgeBox or selective search. This leads to two potential issues: (a) the automatic learning of features tends to outperform manually designed features, and (b) it incurs a higher computational cost due to the creation of object proposals. To address the limitations posed by RCNN and fast-RCNN, a more sophisticated approach, known as faster-RCNN, is introduced. This method comprises two essential modules. The first module, referred to as the regional proposal network (RPN), is a fully convolutional network with the ability to autonomously generate object proposals, which subsequently serve as input for the subsequent steps. The second module, named fast R-CNN, is tasked with refining the object proposals initially generated by the first module. An important feature is that both modules share a common convolutional layer, allowing the input image to traverse the convolutional neural network (CNN) just once for the generation and enhancement of object proposals. Within the domain of medical imaging, the task of identifying objects of interest within input images frequently presents two prominent challenges. The first pertains to precisely localizing multiple objects, while the second relates to categorizing each of these objects. In the context of detecting skin lesions from input photographs, the faster-RCNN method replaces the conventional selective search algorithm with the Regional Proposal Network (RPN) and the fast R-CNN. The RPN module plays a crucial role in pinpointing the lesion's location based on factors such as its color, size, and texture. This approach is designed to achieve a higher recall rate while minimizing the number of selected windows, thus reducing computational complexity. Interestingly, this study reveals that melanoma lesions identified by the faster-RCNN contribute to concealing information. The faster-RCNN method encompasses four distinct phases.

1) Convolutional Networks: 13 Conv+13 relu+pooling layers are used to extract feature maps from the input image. The generated picture feature map is distributed throughout the RPN and linked layers.

2) Regional Proposal Networks: It is used to generate proposals for picture objects (skin lesions). The RPN module employs 3*3 convolutional layers to generate anchors and bounding box regression offsets, which are then used to estimate object proposals.

3) ROI Pooling: This phase entails using the output of the previous two processes, such as the feature map and object proposals, to estimate the pro-proposal feature maps and passing them to all completely linked layers.

4) Classification: The classification phase of faster-RCNN uses the outcome of the preceding step to identify the kind of proposal. Finally, it employs bounding box regression to determine the precise position of the test box.

C. Skin lesion segmentation using FKM

To culminate the process, Fuzzy K-means (FKM) segmentation is applied to the obtained collection of pixels corresponding to melanoma lesions. The fundamental reason for selecting FKM over the traditional K-Means clustering lies in the nature of the two approaches. K-Means is a rigid type of clustering where each instance can belong to only one cluster. In contrast, FKM permits a single instance to be associated with multiple clusters, making it particularly well-suited for handling situations where data points may overlap or have multiple attributes.

The melanoma regions are acquired from the localization step and input into the FKM method for segmentation. The FKM method splits the image into k regions related to the cluster centered. FKM has the "fuzzy" or "soft" correlation between ROIs and images, and reduces distortion by using the given formula:

$$L = \sum_{j=1}^{N} \sum_{i=1}^{N} b_{i,j}^{f} g_{i,j}$$

where k is the number of clusters while f is the fuzzifier parameter that manipulates the data points and resultant clusters, and $b(i,j) \in [0,1]$ represents the relationship between the cluster's center and datapoints, while $g(i,j)$ represents the Euclidean distance among clusters and data points.

IV. Experimental Results and Discussions

Within this section, we shall delve into the dataset employed and the set of evaluation parameters utilized to assess the effectiveness of the method we have introduced.

A. Details of Dataset

The ISIC-2016 dataset contains 1,280 images, of which 900 images are for training purposes, while the remaining 380 images are used for testing the presented method. The dataset's ground truth photos are also accessible, which were collected by a panel of dermatologists. The ISIC datasets were chosen for our investigation because they are the most difficult database for melanoma segmentation since their samples contain various artefacts, such as differences in the size and texture of skin moles, the presence of hair, and microscopic blood vessels. Furthermore, photos contain many modifications such as brightness, intensity, color variations, and blurring and noise, making them a difficult dataset for melanoma segmentation.

B. Experimental results

To create an effective framework for the automated diagnosis of skin lesions, the exact location of multiple skin moles is required. We designed an experiment to test the recognition capacity of the provided approach for this aim. We assessed the accuracy of our proposed technique using test photos from the standard dataset, ISIC-2016. The faster-RCNN approach's excellent localization capacity enables it to precisely recognize and locate skin moles of all sizes and forms. To quantitatively quantify the localization performance of the current technique, we used a measure called mAP, which helps to determine how effectively the presented method can recognize skin moles. With mAP scores of 0.945 for ISCI-2016, the faster RCNN localized the melanoma areas at the regression layer. The FKM algorithm groups the melanoma-diagnosed pixels as foreground (shown with white color) and the non-affected pixels as background (represented with black color) to test the segmentation performance of the proposed technique. (Fig. 2) Depicts how the segmentation performance is assessed by computing the accuracy, sensitivity, and specificity of test pictures at the pixel level. The average value of accuracy in our provided technique for the ISIC-2016 dataset is 0.954, while the average values of sensitivity and specificity are 0.90 and 0.971, respectively. The given data demonstrate the effectiveness of the suggested strategy in segmenting skin lesions.

C. Performance comparison with state-of-the-art techniques

In this paper, we undertake a comparative analysis of our proposed method against contemporary algorithms designed for skin lesion segmentation; all applied to the same datasets. Our performance assessment involves a meticulous evaluation of the average highest results obtained from our technique when juxtaposed with the average outcomes documented in prior research, specifically in the context of the ISIC-2016 dataset. (Fig. 4) serves as a visual representation of this quantitative comparison, considering two crucial assessment parameters: specificity and accuracy. The accuracy scores in previous research studies are reported as 0.82, 0.91, 0.82, 0.693, and 0.94, all registering lower performance levels than our proposed method. Figure 5 distinctly illustrates that our

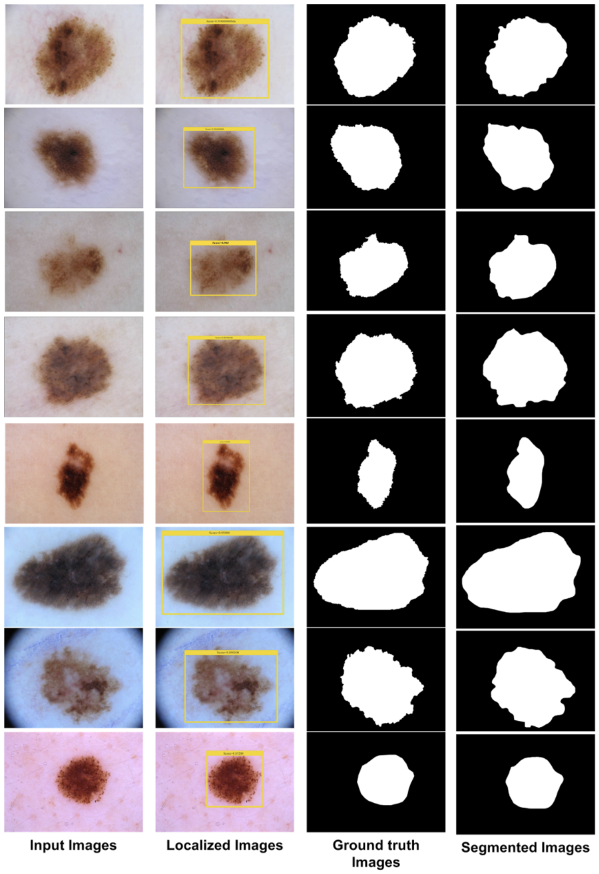

Fig. 2. Test results of the presented method over the ISIC-2016 dataset

Technique	Sensitivity	Specificity	Accuracy
Mahmudur	0.88	0.969	0.952
ExB	0.91	0.965	0.95
TMUteam	0.832	0.987	0.946
SFU-mial	0.915	0.955	0.944
CUMED	0.911	0.957	0.94
UNIST	0.876	0.954	0.94
UiT-Seg	0.863	0.974	0.939
Presented method	0.90	0.971	0.954

Fig. 3. Performance comparison of the presented method with previous studies of ISBI 2016

suggested approach outperforms its counterparts. Our framework attains an average accuracy rating of 95.4%, whereas the comparable techniques exhibit an average accuracy rating of 95.3%.

V. Conclusions

Melanoma, a highly life-threatening form of skin cancer that affects individuals worldwide, remains a formidable challenge for automated detection and segmentation. The difficulty lies in distinguishing cancer-affected areas from healthy skin due to minimal contrast and high visual similarity. This article introduces an innovative approach utilizing advanced deep learning, specifically the faster RCNN combined with FKM. Experimental results demonstrate substantial enhancements in

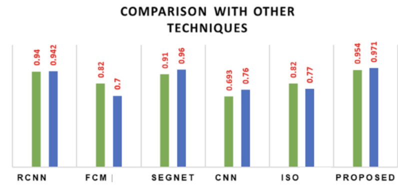

Fig. 4. Performance comparison of the presented method with previous studies of ISBI 2016

melanoma detection and segmentation, even in the presence of complicating factors like lighting variations, noise, and small blood vessels or hair. The outcomes highlight the superiority of this melanoma detection method over existing approaches in terms of accuracy, thanks to its more streamlined neural network. As a result, this method holds significant promise for the early and accurate detection, segmentation, and recognition of skin lesions.

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