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SKIN LESION SEGMENTATION USING K-MEANS CLUSTERING WITH REMOVAL UNWANTED REGIONS

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ABSTRACT

The segmentation of skin lesions is crucial to the early and accurate identification of skin cancer by computerized systems. It is difficult to automatically divide skin lesions in dermoscopic images because of challenges such as hairs, gel bubbles, ruler marks, fuzzy boundaries, and low contrast. We proposed an effective method based on K-means and a trainable machine learning system to segment regions of interest (ROI) in skin cancer images. The proposed method was implemented in several stages, including grayscale image conversion, contrast image enhancement, artifact removal with noise reduction, skin lesion segmentation from image using K-means clustering, and ROI segmentation from unwanted objects using a trainable machine learning system. The proposed model has been evaluated using the ISIC 2017 publicly available dataset. The proposed method obtained a 90.09 accuracy rate, outperforming several methods in the literature.

Keywords: *Skin Cancer, Computer Aided Detection, Segmentation, Machine learning, K-means Clustering*

İSTENMEYEN BÖLGELERİN ÇIKARILMASI İLE K-ORTALAMA KÜMELEME YÖNTEMİ KULLANILARAK CİLT LEZYONU SEGMENTASYONU

ÖZET

Deri lezyonlarının bölütleme, bilgisayarlı sistemler tarafından cilt kanserinin erken ve doğru tanımlanması için çok önemlidir. Kıllar, jel kabarcıkları, cetvel işaretleri, bulanık sınırlar ve düşük kontrast gibi zorluklar nedeniyle dermoskopik görüntülerde cilt lezyonlarını otomatik olarak bölütleme zordur. Cilt kanseri görüntülerinde ilgilenilen bölgenin (ROI) bölütleme için K-ortalama kümeleme ve eğitilebilir makine öğrenme sistemine dayalı bir yöntem önerilmiştir. Önerilen yöntem, gri tonlamalı görüntüye dönüştürme, kontrast görüntü iyileştirme, gürültü azaltma ile artefaktların ortadan kaldırılması, K-ortalama kümeleme kullanılarak görüntüden cilt lezyonunun bölütlenmesi, eğitilebilir bir makine öğrenimi sistemine dayalı olarak istenmeyen nesnelerden ROI'nin ayrıştırılması gibi çeşitli aşamalara dayalı olarak uygulanmıştır. Önerilen model, ISIC 2017 kamuya açık veri seti kullanılarak değerlendirilmiştir. Önerilen yöntem, literatürdeki çeşitli yöntemlerden daha iyi performans göstererek 90.09 doğruluk elde etti.

Anahtar Kelimeler: *Cilt Kanseri, Bilgisayar Yardımlı Tespit, Bölütleme, K-ortalamalı Kümeleme*

1. Introduction

Skin cancer comprises one-third of all cancer forms, according to the World Health Organization (WHO) [1]. Cases of skin cancer are increasing as well as mortality rates are on the rise every year. Every year, roughly 3 million people are diagnosed with non-melanoma skin cancer and 132,000 people are diagnosed with melanoma skin cancer. The WHO estimates that 9,500 individuals in the United States are diagnosed with skin cancer each day, and two individuals die from the disease every hour [2].

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Treatment for these conditions costs, on average, USD 3.3 and USD 4.8 per year. Invasive melanoma categories have grown by 47% in the last 10 years, according to statistics [3,4]. There are around 100,000 diagnoses of melanomas detected each year in Europe. In contrast, 15,229 new instances of melanoma are diagnosed each year in Australia. As recent statistics have shown, skin cancer incidence has already been rising steadily since the year 1990. Sun exposure and the use of solariums and tanning beds have both increased in recent years, which may describe the existing trend [5].

A timely diagnosis of melanoma is critical to the patient's prognosis. The five-year average life expectancy for melanoma is 92% if detected early. Nevertheless, the greatest issue in identifying melanoma is the apparent similarity between benign and malignant skin lesions. As a result, even a highly qualified professional may have difficulty identifying melanoma. Identifying the type of lesion with the human eye is quite difficult [6]. As a result, a variety of imaging techniques have been employed over the years, including dermoscopy. Using light magnification equipment and immersion fluid, dermoscopy is a non-invasive imaging technique that allows us to see the outer layer of skin. Using this imaging technology, dermatologists are able to detect 50% more malignant cases than they could with previous imaging methods. There may be a problem with relying solely on the human eye to detect melanoma in dermoscopic images if the dermatologist's expertise varies from person to person. An untrained specialist can diagnose melanoma from dermoscopic pictures with an accuracy of 75% to 84% [3, 7]. The use of Computer Aided Diagnosis (CAD) tools is required to help experts diagnose melanoma and overcome the challenges they face. Preprocessing, segmentation, feature extraction, and classification are the four phases in CAD methods for detecting a lesion as melanoma. Lesion segmentation is a critical phase in CAD systems for correctly diagnosing melanoma. In dermoscopic images, skin lesions vary widely in color, texture, and size, making it difficult to divide them. Furthermore, the image's poor contrast inhibits nearby tissues from differentiating. The segmentation of lesions is further complicated by the presence of supplementary elements including blood vessels and color illimitation such as air bubbles, hair, and black [8].

Skin lesion identification was carried out by a CAD system employing a segmentation approach and a classification of skin lesion types. In the first stage, the position of the tumor is determined either by using the traditional segmentation method or a deep learning method. The excised tumor, on the other hand, must be categorized as nevi, benign, or malignant in the second stage. Nevertheless, both activities are difficult because of the following factors: (i) Tumors have low contrast, making it difficult for the segmentation method to correctly identify them; and (ii) despite their similar appearance, there appear to be visual distinctions among intra-type skin lesions. In an attempt to tackle these problems, numerous strategies have been presented [9,10], but none have been able to attain considerable accuracy.

Since it influences the precision of the future steps, the segmentation stage is one of the most crucial. Nevertheless, segmentation is challenging because of the wide range of lesion sizes, colors, and forms, as well as various skin types and textures. Additionally, many lesions possess uneven borders, whereas in other instances, the border between the lesion and the skin is smooth. The presence of dark hair concealing the lesions and the appearance of specular reflections present further challenges. In this work we apply and evaluate two segmentation techniques including thresholding and K-means. Based on the results it is shown that K-means has better ability tosegment skin cancer. Thus, this work build a model to segment skin cancer in different stages: pre-processing, initial segmentation, and post-segmentation. Pre-processing has been applied using different methods to improve the quality of image that can help to make an accurate segmentation. Pre-processing followed by initial segmentation that has been done based on K-means method. The output of K-means shown that it still suffer from segmentation problem which motivated us to improve the model by applying post- segmentation method to remove small unwated objects. These model is evaluated using dermoscopic images and compared with the expected lesion segmentation (ground truth).

In general, the contribution of this study to the literature is that, unlike other studies in the literature, the bottom-hot filter is used as a pre-process before segmentation. In addition to this, in order to eliminate the errors in the result obtained with the K-Means algorithm, unwanted objects are removed as post processing operation.

In the rest of the article; In the second part, similar studies are summarized, in the third part, the proposed pre-processing method is explained, the proposed segmentation algorithm is explained and the results obtained are discussed in the next parts.

2. Related Work

The identification of melanoma relies heavily on the appearance of lesions and the details present inside them. In order to obtain these features, the skin tumor must be properly segmented from the surrounding tissue. In order to make a reliable and accurate diagnosis, it is critical to separate the tumor from the surrounding healthy tissue and extract more relevant aspects of the tumor. Tumors can be automatically or semi-automatically segmented using a variety of segmentation techniques. Skin lesion identification was made easier with the help of a new method given by Khan et al. [11]. The lesion region is segmented using normal and uniform distributions. These segmented images will have their features retrieved and will then be fused with one another in parallel, utilizing a fusion approach. The entropy-based method is used in combination with the Bhattacharyya distance and variance formulation for feature selection. An accuracy of 93.2%, 97.75%, and 97.50% is achieved using the introduced method on three publically available datasets, including the combined ISBI 2016 and ISBI 2017, ISIC, and PH2.

This study by Ali et al. [12] presents a Fuzzy C-Means (FCM)-based method for the detection of melanoma. There are three steps to the methods: preprocessing (contrast stretching), main processing (FCM), and post-processing (morphological erosion). The contrast stretching stage aims to increase the dynamic range of the source images by stretching the source image's pixel intensity range. After that, the FCM method splits the contrast-stretching data into two clusters: lesions and skin. It does this automatically. Finally, the segmented image is eroded morphologically, with the structural element being transferred over each pixel of the object to overcome usual abnormalities between lesion and skin (e.g., irregular boundaries, dark hair covering the lesions, specular reflections, among others). Semi-supervised skin tumor segmentation is described by Jaisakthi et al. [13]. Segmentation makes use of grab-cut and K-means clustering together. After the melanoma has been segmented using graph cuts, the final step is to fine-tune the lesion's boundaries. Prior to feeding the input images to the pixel classifier, preprocessing procedures including image normalization and noise removal strategies are performed. In order to segment tumors, Mohanad Aljanabi et al. [14] developed an artificial bee colony (ABC) technique. There are fewer parameters in the model because it is built on top of a swarm-based approach that starts with preprocessing digital images before determining the best threshold value for melanoma to use when segmenting the lesion, similar to Otsu thresholding. Three stages were taken in this study to identify the melanoma in the dermoscopy images. The colored dermoscopy image's red channel was chosen for preprocessing. To smooth the data, morphological filtering based on the Gaussian kernel and a 2D median filter with a size of 20 by 20 were used. The ABC algorithm was then utilized to determine the ideal threshold value for the segmentation of melanoma in the following step. Finally, the predicted optimal threshold value was applied for the segmentation of melanoma using the Otsu method's thresholding technique. This algorithm has high specificity and the Jaccard Index.

3. Proposed Method

In this section, we presented details of the proposed segmentation method as well as presented and discussed the results of the proposed method. Before the segmentation stage, this method applies some preprocessing techniques to improve the quality of the image.

First, the RGB image has been converted to a grayscale image; then, histogram equalization and median filter are performed to improve the contrast of the image and reduce the existing noise in the image, respectively. Morphological bottom- hat- filtering has been employed to remove hair. Then the Region of Interest (ROI) has been extracted from the image based on using the K-means clustering method. The proposed method has been trained and tested on the ISIC 2017 datasets. Throughout training, the introduced method predicts the segmentation mask and its corresponding edge from a source image of a skin lesion concurrently. Only the segmentation mask can be utilized for prediction during the testing stage. Initially, datasets and subsequent findings are discussed and presented. At the outset, it is important to mention that we proposed a method that outperformed other similar methods. Figure 1 depicts a schematic representation of the proposed method.

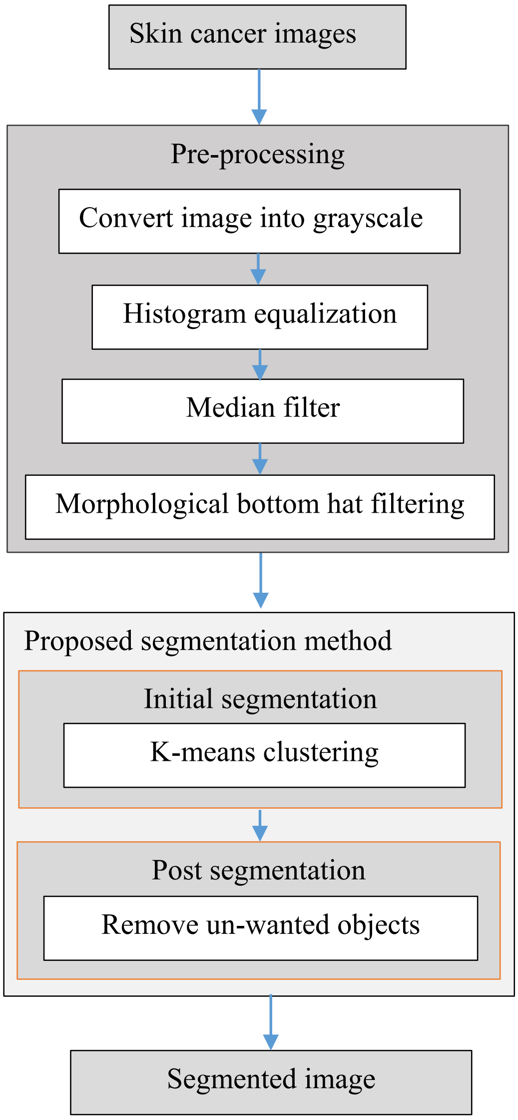

Figure 1. General Framework of the Proposed Segmentation Method

3.1. Dataset

An extensive collection of, in total, 2750 samples of ISIC 2017 dermoscopy images is included in this dataset [4]. Each image is divided into three groups: A total of 2000 images are used to train the algorithm, 150 to validate it, and 600 to put it to the test. Also obtainable are the dataset's ground truth samples, which are being utilized to verify the segmentation technique. The segmentation method has been validated with a few examples of images. Figure 2 displays a few examples of these types of images. Seborrheic keratosis (254), melanomas (374), and nevi (1372) were the three classifications used for the classification task.

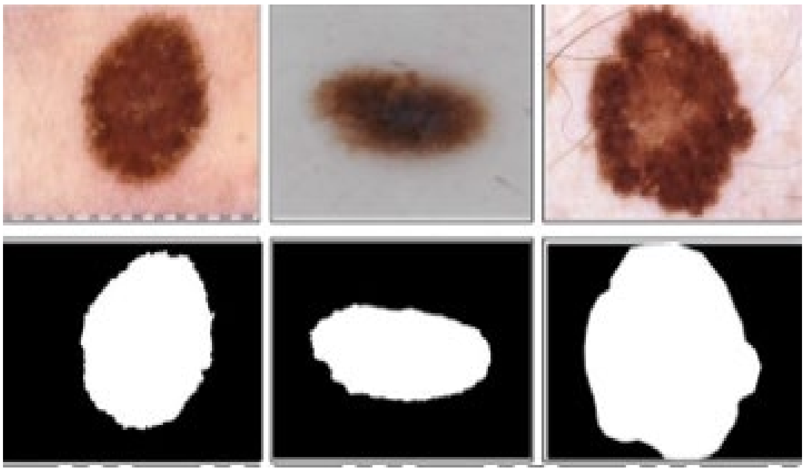

Figure 2. Original ISIC 2017 Sample Images

3.2. Preprocessing Operations

In dermoscope images, hair, gel, and air bubbles can be visible. As a result, image enhancement approaches such as image resizing, grayscale conversion, contrast enhancement, hair removal, and noise removal are used to prepare the dermoscope images for further processing. The practice of resizing images before feeding them to the neural network is sound. That saves computational power and takes care of memory constraints by allowing the model to convolve faster. It is necessary to downsample to 256×256 resolution of dermoscopic images and their corresponding ground truths to achieve uniformity across individuals.

Grayscale images are created by converting the original color image to black-and-white. Luminance values of 8 bits are used to indicate a grayscale image. The RGB (24-bit) values of a color image are converted to grayscale values to create a grayscale image (8 bits). Image transformation to grayscale is followed by image reversal and comparison with the reverted image and the grayscale image in order to determine cancer symmetry. Figure 3 shows converting an image from RGB to grayscale.

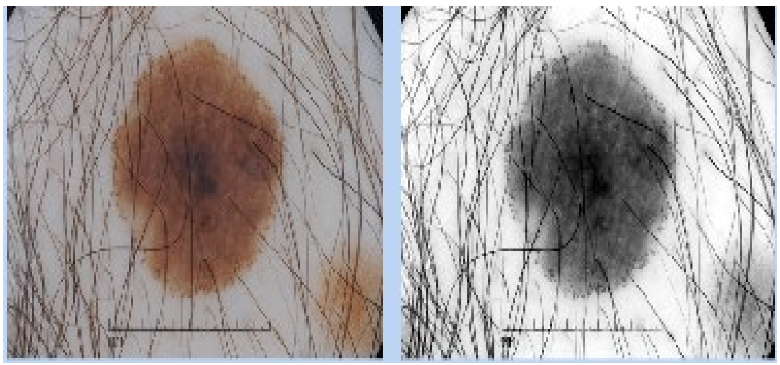

Figure 3. A Sample of RGB and grayscale image

Increasing the contrast in an image is a technique for bringing out the details. The range of intensity of the image is changed to increase contrast for better quality through contrast manipulations. Contrast stretching, also known as normalization, enlarges the dynamic range of the output image by stretching the range of pixel intensities in the source images. The top and bottom image pixel restrictions on which an image should be normalized, before we can perform stretching. For an 8-bit image, the top and bottom bounds of the pixel quantization range are 255 and 0, respectively. Context stretch begins by scanning an image for the maximum and minimum pixel values currently present. The image pixel range is stretched using the following formula:

$$I_{output}(i,j) = \left(I_{output}(i,j) - c\right)\left(\frac{b-a}{d-c}\right) + a \tag{1}$$

I_{output} is the image after pre-processing, then it is fed to the next step.

Most of the time, during the photographic process (particularly in medical imaging), various noises are generated as a result of oscillations, and unwanted alterations are shown in the recorded signals as a result of this. Noise is a severe concern in image processing activities, and it can cause serious problems. This phenomenon has a negative impact on image processing, namely on image edge recognition, and should be avoided. Given the requirement for edge detection distinction, it enhances the impact of high-frequency pixels, in particular noise, on the edge identification process [15]. The employment of a median filter is a straightforward method of alleviating this difficulty. This technique is critical for removing the noise that has been produced in the medical images that have been input. The primary benefit of median filtering is that it removes noise while retaining edges at the same time. This filter is a nonlinear low pass filter, which means that it requires extra processing time to complete the filtering operation. When using median filtering, an m × n neighborhood is taken into account. Finally, the center element of the sorted numbers is selected and replaced with the center pixel. This process is repeated until all of the neighborhoods have been organized in ascending order. The median filter is an effective filter for removing salt and pepper. A 3 × 3 mask has been used in this paper to filter the input images in a moderately effective manner. While raising the mask size reduces image noise, it sacrifices some critical edges in the process. Table 1 gives the results of some samples-based median filters. This strategy is modeled by the following equation:

$$y_{(m,n)} = median\{x_{(i,j)}, (i,j) \epsilon\ C\} \tag{2}$$

Centered neighborhood around position (m, n) of the image is represented by C.

Table 1. Median Filter Results for Some Samples

Samples	PSNR
Sample 1	29.14
Sample 2	31.33
Sample 3	31.71
Sample 4	32.26
Sample 5	28.79

In image processing, morphological filtering is a nonlinear process that is associated with the morphological properties of the image being processed. When working with binary images, it is useful for both removing and recovering the undesirable portions of the image that are segmented as foreground or background in a binary image. An operation on a binary image called a morphological operation introduces a new binary image where the pixel has a value that is not zero. Erosion, dilation, opening, and closing are just a few of the fundamental morphological operations. The bottom-hat transformation is a morphological algorithm that is used in many applications. These transformations are employed in the removal of items from an image by employing a structural element in the opening operation and do not fit the objects to be removed in the closing operation when utilized in the opening operation. There are various sorts of morphological algorithms to choose from. The bottom hat filtering technique is applied to this input image. The top-hat filtering technique is used only for light things on a dark backdrop, and the bottom-hat filtering technique is used only for dark objects on a light background in a photograph. Using bottom-hat filtering, you may take an input image and remove it from the result by morphologically closing on the same input image.

Any color space of the filtered image is subjected to a morphological bottom-hat filtering operation. The structural element is then obtained as a result of this. It improves the contrast between normal skin and hair in dermoscopy images by enhancing the contrast between normal skin and hair. The transformation of the image to a binary image is then carried out, with a threshold of 5% being used. To achieve NewImage, we conduct element-wise multiplication of each multiplied array of binarized hair and in each color space of RGB, respectively, and then divide the result by the number of elements in the array. Additionally, we convert the output image NewImage into a binary image using a 2% threshold for the binary image.

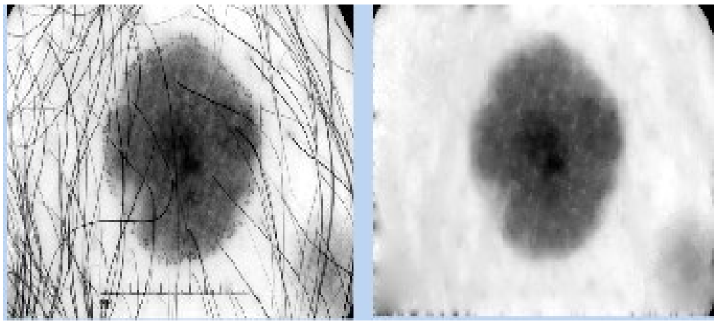

Figure 4. Obtained Image After Hair Removal Process

4. Proposed Segmentation Method

The main purpose and contribution of this work is to build a fully automatic trainable method based on K-means and a machine learning system, where this method is able to segment Regions of Interest (ROI) from skin cancer images accurately. because ROI extraction from dermoscopic skin cancer images is still considered a difficult task. Thus, this work proposes a segmentation method based on two main stages called initial segmentation and post-segmentation. In the first step, we used the K-means method to extract the region of interest from the image.

One of the most common segmentation techniques that is utilized in the literature is called K-means clustering. This technique is considered an unsupervised clustering method in machine learning. It is utilized to cluster and differentiate data into different groups. Because an image consists of different regions such as a Region of Interest (ROI), background, and artefacts, K-means can be utilized in a segmentation task to isolate wanted regions from unwanted regions. The K value should be determined in the K-means technique, where this value represents the group number or image regions that could be divided. The K-means technique can work based on two main steps. The first one is to calculate the mean of all group numbers or clusters. Second, calculate the distance of each point from each group or cluster by calculating its distance from the corresponding cluster mean. Each point in the image is determined by the nearest cluster of them. K-means runs through the two processes until the sum of squared points inside each group reaches a user-defined minimal error threshold. To cluster randomly, the initial points must be defined. During iteration, the k-means technique tries to minimize the sum across all groups and the sum of squared errors inside each group, as well as changing the center of each group dynamically during run time.

The image which has been obtained from the previous stage (pre-processed image) is subjected to the K-means clustering algorithm for segmenting ROI in skin cancer. K-means is considered one of the most popular for color-based image segmentation. Each pixel in the image is first assigned to a cluster with the goal of minimizing the cluster sum of squares, and then cluster pixels are updated using the new mean for each cluster.

The pixel assignment to a special cluster is performed based on using Equation (3).

$$S_i^{(t)} = \left\{x_p : \left\|x_p - m_i^{(t)}\right\|^2 \leq \left\|x_p - m_j^{(t)}\right\|^2 \ \forall j, 1 \leq j \leq k\right\} \tag{3}$$

Where, $s^{(t)}$ represents cluster, x_p is observation, $m_i^{(t)}$ and $m_j^{(t)}$ are indicate initial means. Based on the utilizing a new mean the cluster has been updated by the Equation (4).

$$m_i^{(t+1)} = \frac{1}{\left|S_i^{(t)}\right|} \sum_{x\, j\, \epsilon\, S_i^{(t)}} x_j \tag{4}$$

Where, $s^{(t)}$ represents cluster, x_j is observation, $m_i^{(t+1)}$indicates updated mean.

In this study, we have determined the cluster number as two. This is because this work tries to segment and differentiate the image into wanted and non-wanted regions. The output of the results of K-means in an image that has pixels classified into various clusters.

The output of the initial segmentation was ROI with some unwanted objects. Deleting these unwanted objects was still challenging. A machine-learning-based trainable model was established to solve this issue. The goal of this work was to develop a method for obtaining the ROI from an image. In this section, the Gabor feature was employed in the proposed method to extract ROI from the image background and unwanted objects. Several images are selected as training samples for the proposed approach. Samples taken from both within and outside the ROI were utilized to select different blocks. The ROI and non-ROI classes were identified in these blocks. The Gabor feature was extracted from these regions. A Gabor function can be utilized for edge detection in image processing. The two-dimensional Gabor filter is capable of achieving the best localization in both the spatial and frequency domains, making it well suited to express the local structure data of an image that corresponds to the spatial size, spatial position, and direction selectivity. A Gabor filter is frequently used to represent and describe texture aspects because its frequency and direction representations are similar to those of the human visual system. The two-dimensional Gabor kernel form that we select is as follows:

$$\psi_{u,v}(Z) = \frac{||k_{u,v}||^2}{\sigma^2} e - \left(\frac{\left||k_{u,v}|\right|^2 ||x||^2}{2\sigma^2}\right) \left[e^{ik_{u,v^2}} - e^{-\left(\frac{\sigma^2}{2}\right)} \right] \tag{5}$$

Finally, the obtained features were fed into a Support Vector Machine (SVM) classifier. Similar to a neural network, the SVM is a mathematical computing unit that builds hyperplanes to define the categorization decision border. SVM configurations are primarily motivated by the desire to maximize separation between categorized labels. Binary classification is applicable to SVM. The original SVM was designed for linear classification, but a kernel function was used to produce a non-linear classification. Kernel functions convert low-dimensional data into high-dimensional spaces that allow for linear data separation. The supervised learning model is used to train SVM, which is developed from statistical learning. Solving a quadratic equation with linear constraints is translated into a quadratic programming issue [18].

5. Experimental Results

At the outset of this section, we provide details of the implementation of our strategy. The dataset and performance measures utilized for evaluation were then discussed. To demonstrate the significance of each parameter and module, the work conducts experiments involving parameter setting and ablation study. Eventually, the method's effectiveness is assessed and compared to other available options. The International Skin Imaging Collaboration (ISIC) 2017 served as a testing ground for our skin imaging model. We used the ISIC 2017 training set of skin lesion images to develop our method. Only the segmentation mask is required for evaluating the proposed method's efficiency during the testing stage. Data from ISIC 2017 was used for model validation and testing, respectively. Figure 5 shows some examples of the proposed model's segmentation results. The proposed model's performance could be compared to the available ground truth. All images were preprocessed before being fed into the segmentation model.

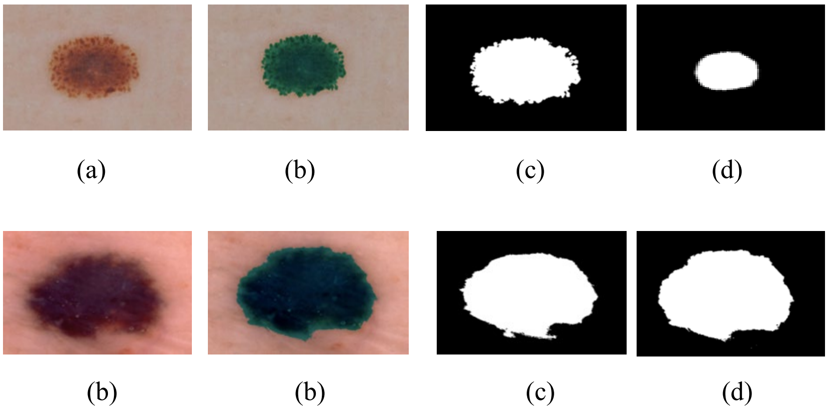

Figure 4. Segmentation Results based Proposed Method, (a) Original image (b) Masking Image (c) Segmented Image (d) Ground truth

Sensitivity, specificity, and accuracy were utilized as performance measures to assess our proposed model. The percentage of properly segmented pixels in the tumor region is represented by sensitivity, while the percentage of properly segmented non-tumor regions is shown by specificity. Finally, the accuracy metric shows how well the segmentation algorithm performed pixel by pixel. To check the matched and unmatched pixels in both the automatic segmentation method and ground truth, the Jaccard similarity coefficient has been used, which compares the pixel’s similarity between both images. In contrast, the Dice similarity coefficient computes the similarity between both ground truth image and segmented image based on the proposed method [16, 17]. The following equations are used to evaluate all of the previously stated evaluation measures:

$$Accuracy(Ac) = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Sensitivity(Sn) = \frac{TP}{TP+FN} \tag{7}$$

$$Specificity(Sp) = \frac{TN}{TN+FP} \tag{8}$$

$$Jaccard(JD) = \frac{|X \cap Y|}{|X \cup Y|'} \tag{9}$$

$$Dice = \frac{2TP}{FP \cup 2TP \cup FN} \tag{10}$$

True positives, false positives, false negatives, and true negatives are represented by the letters TP, FP, FN, and TN, respectively. Images with properly segmented lesion pixels are classified as TPs; alternatively, they are classified as FNs. When a non-lesion pixel's estimation is non-lesion, it is regarded as a TN. Otherwise, it is a false positive. In Equation (8), X represents the number of pixels in ground truth and Y represents the number of pixels in the segmented image. The performance evaluation of the proposed method for skin cancer segmentation has been presented in Table 2 using the machine learning field. Here, the K-means clustering algorithm is introduced after the preprocessing stage. To remove unwanted objects, this study presents model-based machine learning, which shows improved results than K-means clustering. The performance evaluation of the proposed method has been calculated based on using three different metrics. Here we have used 215 images for testing data. The segmentation performance of the proposed method based on the ISIC 2017 dataset was obtained with 90.09 % accuracy. The proposed method failed in segmentation on 215 images, whereas 198 images were segmented correctly. As it is shown in Table 2, the proposed method obtained an 89.33% sensitivity rate and a 91.04% specificity rate.

The classification of skin lesions as melanoma relies heavily on the ability of CAD systems to automatically segment the lesions. Particularly in the case of traditional methods, which necessitate the use of an effective segmentation method. This research did not use any data augmentation strategies. Here, 2000 images were used to train the proposed model. It was found that the proposed method performed better than k-means and thresholding segmentation models. High spatial resolution images can be used to segment skin lesions in the proposed method. The segmented region of the lesion thus yields more detailed characteristics, which improves classification accuracy. Table 2 shows a comparison of the proposed method's robustness with that of current approaches. This table compares our method's performance with other traditional techniques, including K-means and the thresholding method. Based on the results that have been presented in Table 2, our proposed method has improved k-means after removing unwanted objects. It is shown that our proposed model is more robust than K-means and thresholding.

Table 2. The comparison of the proposed method with previous studies.

Method	Ac	Sn	Sp	JD	Dice
K-means	83.12	85.83	87.41	81.22	86.03
Thresholding	81.02	79.65	82.75	80.07	83.8
Proposed Method	**90.09**	**89.33**	**91.04**	**85.71**	**91.12**

6. Conclusion

This study proposed an effective and reliable method for skin lesion segmentation. The proposed method was able to overcome several challenges where there were no issues with the system's ability to handle skin lesion borders that were both irregular and fuzzy. In the preprocessing stage, we have used histogram equalization, median filter, and morphological bottom hat filtering to enhance the contrast of the image, noise reduction, and hair removal. The proposed segmentation method has been performed in two stages. In the initial stage, we used the K-means method to extract skin lesions from the background. Then, to obtain an accurate ROI and remove unwanted objects, we have built a machine learning system based on Gabor feature and SVM classifier. Accuracy was significant when the proposed model was evaluated on a publicly available dataset. Metrics like sensitivity and specificity showed that the new system outperformed when compared to the current state-of-the-art methods.

In future studies, the classification of the types of skin lesions obtained as a result of this study will be carried out. This study will play an important role in increasing the classification success.

Conflict Of Interest

The authors declare that they have no conflict of interest

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