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Melanoma Skin Cancer Segmentation using Robust Multi-View Fuzzy C- Means Algorithm

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Abstract: *Skin cancer has become a significant issue and the primary cause of death for people all over the world. Melanoma is one of the most serious types of skin cancer since it can spread to any area of the body. So, the prognosis of melanoma in its early stages is very important for figuring out how likely it is that the patient will get better. Because of this, clinical imaging science is a very important part of finding certain types of skin lesions quickly and correctly. In this study, we showed a new way to use digital image processing to separate skin lesions in dermoscopic images. First, the image is preprocessed with a median filter to eliminate extra hair, noise, and artefacts in order to create a better image for segmentation. To improve the accuracy of dermoscopic images, the preprocessed images are segmented based on an innovative method built on an improved robust Multiview Fuzzy C-Means clustering algorithm (RMV-FCM). Following segmentation, features are extracted using the ABCD rule to produce optimal features that may be used as input for classification. Lastly, the Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Nave Bayes classifiers use machine learning techniques to characterize skin lesions as malignant and benign (NB). The RMV-FCM algorithm exhibits more adaptability and higher clustering performance when compared to a variety of related clustering techniques. In terms of detection accuracy, as noted in the conclusion of this research, the novelty of the work shows that RMV-FCM is exceptional in comparison to numerous related clustering algorithms, and SVM is exceptional in comparison to other standard classifiers. The simulated outcome indicates that the suggested strategy accurately diagnoses skin tumors with a 97.5% accuracy rate. The results of the suggested segmentation are extremely accurate when compared to other algorithms in the same domain.*

Keywords: RMV-FCM, ABCD, SVM, and skin cancer

I. INTRODUCTION

Many people worldwide lose their lives each year as a result of the fatal skin cancer disease melanoma. The bodily components of the human that continue to be uncovered by daylight are its most essential objective locations, like the face, arms, legs, or necko be uncovered by daylight are its most essential objective locations, like the face, arms, legs, or neck. Unfortunately, melanoma also has the highest fatality rate (Siegel et al., 2017). The dermatologist should evaluate moles with a diameter of more than 6 mm and unusual coloration for the possibility of melanoma infection. Dermatologists first visually analyze such behavior by examining the shape, size, peculiar skin color, and diameter of the created moles (Nachbaret al., 1994). So, in order to overcome the difficulties in diagnosing melanoma, experts are now focusing on the automatic identification of this fatal disease (Burdick, Marques, Romero-Lopez, Giro Nieto, & Weinthal, 2017; Okur &Turkan, 2018). A number of techniques have been suggested for the computerized detection of a skin area afflicted by melanoma. First, manually created feature-based techniques for melanoma detection are added (Ballerini, Fisher, Aldridge, & Rees, 2013; Cheng et al., 2008; Stanley, Stoecker, & Moss, 2007). Due to variations in the melanoma moles' size, color, and shape, these approaches are no longer giving accurate results. The detection precision of these automatic systems is then improved by the addition of segmentation-based algorithms such as adaptive thresholding (Silveira et al., 2009) and iterative resolution thresholding (ISO) (Ridler & Calvard, 1978). Hence, when constructing the automated melanoma detection equipment, segmentation is the most crucial phase (Ganster et al., 2001; Garnaviet al., 2010; Schaefer, Krawczyk, Celebi, & Iyatomi, 2014). Fuzzy clustering methods are widely employed among them. The literature (Bezdek, 1981) initially proposed the FCM algorithm, and (Li et al., 2014) also proposed an optimized bias discipline estimation and tissue segmentation approach. It also introduced the concept of ambiguity into the clustering technique. The accuracy of the last segmentation is increased through the simultaneous release of the bias subject estimate and tissue segmentation, and the algorithm is particularly resilient to initialization. The FCM algorithm was first suggested in the literature (Chuang et al., 2006) and is mostly based on spatial correlations.

In this study (RMV-FCM), we tried to fix the problems with the way things are done now by coming up with a new way for computers to find melanoma lesions using a segmentation method, specifically the improved robust Multiview fuzzy c-Means clustering.Typically, noise and blurring, as well as adjustments for lighting and lightning, challenge the input photographs.So, in this work, the expanded image utilised in segmentation was first preprocessed using a median filter to remove unwanted hair, noise, and artefacts. The preprocessed image is completely split using a revolutionary method that is designed for the more desirable RMV-FCM technique, which uses robust multiview fuzzy c-Means clustering, improves the accuracy of dermoscopic images. Following segmentation, the ABCD rule is used for characteristic extraction to produce an optimal function to feed classification. Lastly, using SVM, the classifiers divide skin lesions into benign and malignant categories. We compared the newly developed method to other current methodologies using the chosen databases, namely ISIC-2016, ISIC-2017, and PH2. Because of the increased robust multiview fuzzy c-Means clustering's (RMV-FCM) environment-friendly localization power to handle the overfitted coaching data, both the qualitative and quantitative results show that our framework outperforms other approaches.

The following are some of the method's significant contributions:

Skin lesions can be accurately and precisely diagnosed using enhanced RMV-FCM with a specific localization strength.

The effective segmentation of melanoma-affected images using the prowess and power of the SVM algorithm to handle the overfitted training data.

The suggested strategy can also be extended to treat other skin conditions.

To the best of our knowledge, the use of enhanced RMV-FCM for skin lesion detection in scientific picture evaluation is a first. The results show that the improved RMV-FCM is good at finding melanoma moles and coming up with a rich set of points that can be used to tell them apart. This gives the model a better overall performance.

II. RELATED WORKS

A serious skin cancer illness called melanoma is to blame for the hundreds of fatalities that have occurred in people around the world. To keep the victims safe, significant work has been done from the past to the present for its earliest stage detection. In 2013, Barata, Ruela, Francisco, Mendonça, and Marques proposed work for the localization of melanoma skin tumors utilizing two distinct approaches that incorporate local and global imaging elements. Laplacian pyramids and the gradient histogram are used to collect information about the color, shape, size, and texture of the melanoma lesion for the global image features. After that, the collected data is used to train a binary classifier. A method to categorize melanoma lesions was suggested by Daghrir, Tlig, Bouchouicha, and Sayadi (2020). The scale-invariant feature transform (SIFT) and histogram of oriented gradients (HOG) have been used to compute the optimal set of features after preprocessing input data. The computed elements were then used to train two classifiers, the support vector machine (SVM) and the k-nearest neighbor (KNN), to categorize the melanoma moles. An approach for segmenting and recognizing skin lesions was introduced by Rehman et al. in 2020. Lesion segmentation from the input pictures was completed after the preprocessing step was completed utilizing the seed location developing and graph-cut techniques. Then, using the accelerated strong features (SURF) and HOG descriptors, the features of the segmented lesions were computed. The SVM classifier had been taught to categorize lesions using the retrieved elements. The method shows improved lesion segmentation and classification accuracy but is burdened by high computing costs. The majority of contemporary picture segmentation techniques use approaches including threshold, regional, side detection, and clustering. Due to its fundamental performance, the FCM clustering algorithm may be the most widely used among clustering techniques for picture segmentation (J. Oliveira, and W. Pedrycz,).

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Clustering is a way to divide a set of data into separate groups so that all of the groups share the same common features based on a certain distance metric. The popular crisp C-Means clustering algorithm is used for sample recognition. P. Hart, D. Stork, and R. Duda. A generalization of the general crisp c means scheme, the fuzzy c means (FCM), allows an information factor to belong to all instructions with particular ranges of membership. (J.Bezdek,) A prognosis method for dermoscopic pictures has been devised by Stolz et al. and R. Johr to evaluate the asymmetry (A), border (B), color (C), and dimension (D) of distinct structures. Dermoscopy now routinely stages PSL into benign, suspect, or malignant moles according to the ABCD criteria (melanoma). By using an innovative mechanism, we attempted to get around this problem in our proposed approach.

III. METHODOLOGY

In this study, we developed a unique method for recognizing and segmenting skin lesions from input photos using enhanced robust clustering with multiview fuzzy c-Means (RMV-FCM). First, preprocessing is done on the input photos to get rid of any artefacts that can fool the median filter's detection. The next step is to submit the processed photos to the RMV-FCM segmentation technique in order to separate the damaged area from the images. Once the lesion has been separated from the historical skin, the ABCD is used to determine whether it is cancerous or benign. The characteristic vector is then sent to SVM classifiers to look for cancerous and non-cancerous cells. Figure 1 illustrates the complete method used in conjunction with this strategy. Due to their high efficacy and accurate findings, our method demonstrated that using RMV-FCM produced the best results for segmenting and identifying skin malignancies

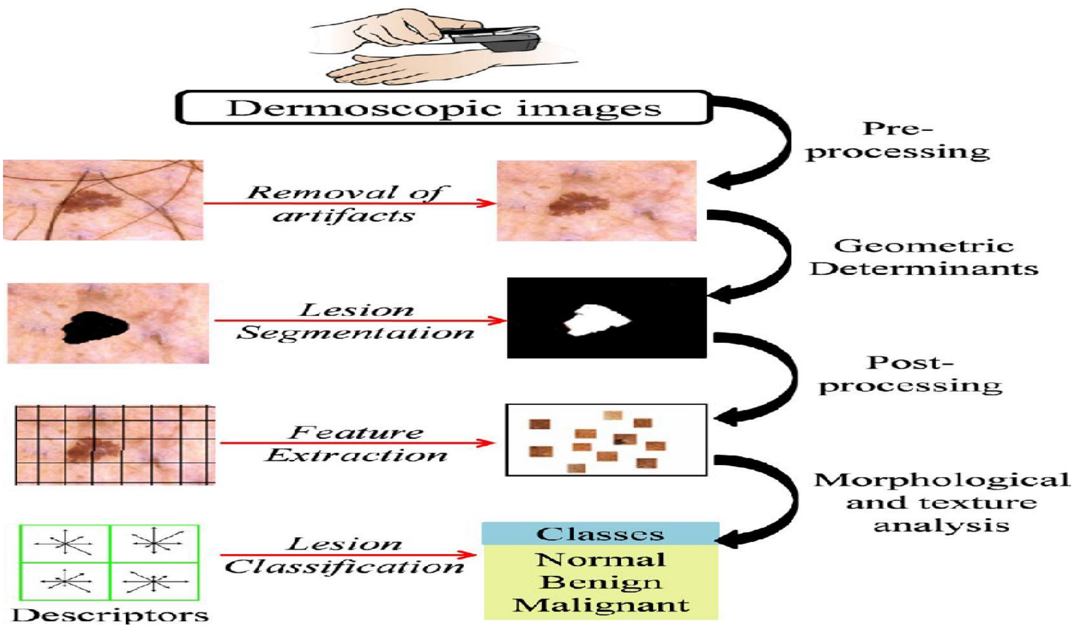

Figure1: Melanoma detection using dermoscopic images

3.1 Preprocessing

First, the image is preprocessed with a median filter to eliminate extra hair, noise, and artefacts in order to create a better image for segmentation.

The following are the preprocessing methods: i)conversion to color, the saturation is altered after converting a color image to the Hue Saturation Value (HSV) color space as part of the histogram equalization technique. With HSV, every nook and cranny is lit. (ii) Then, channel separation is utilized to render each color channel in grayscale. (iii) The grayscale image is then processed for noise removal using median filtering, which creates an image of skin lesions. The median filtered image is then used for hair removal. It uses median filtering, which is far more effective at reducing noise than maintaining edges.

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Figure 2. Example images from the ISIC dermoscopy dataset, frist row is malignant and second row is benign

The working principle of the median filter is to use an element to travel over the picture factor. The median of nearby pixels should therefore be used in place of each pixel. The window is a representative sampling of nearby areas that traverses the entire image, element by element. After the first sorting of all the medians, the factor values from the window are arranged numerically. The hair is removed using a location filling morphology with inward interpolation on the pixel.

3.2 Segmentation

One of the fundamental aspects of image processing is segmentation. It is employed to separate the image's subject matter for processing. In image analysis, segmentation is crucial since it makes the subsequent steps' technical processing easier. Segmentation is essential for the examination of medical images. The subsequent stages of image processing are more precise and effective if segmentation is successful. Segmenting images according to interest areas is necessary for medical image analysis. The right results are derived from the interest pixels using the proper segmentation technique. For picture segmentation, a variety of techniques and algorithms are available. This article suggests a ground-breaking method for identifying and segmenting the skin lesion from the dermoscopy image. Every view receives the highest weight according to its contribution to the cluster thanks to the view weight adaptive learning method used by RMV-FCM. The standard clustering performance can be enhanced by giving a high weight to perspective-based view facts with a high degree of contribution and a low weight to perspective-based view facts with a low degree of contribution. Hence, a multiview fuzzy clustering approach with capabilities for adapting viewing attitude is adopted in this study, and its primary objective is to

$$J= \sum_{v=1}^{V} \sum_{i=1}^{C} \sum_{j=1}^{N} \sum_{t=1}^{V} W_v\ ,\ t^{u_{ij}^{m}}, t^{d_{ij}^{2}}, v + \gamma \sum_{v=1}^{V} \sum_{t=1}^{V} W_v , t \log (W_v , t)$$

$$\sum_{i=1}^{C} u_{ij\,,} v = 1, u_{ij}, v \in [0,1] \qquad (1)$$

$1 \le i \le C$, $1 \le j \le N$, $1 \le v \le V$

$$\sum_{t=1}^{V} w_{v,t} = 1, w_{v,t\in[0,1],1\le v\le V}$$

where $d_{ij,v}^{2} = \left\|x_{j,v} - z_{i,v}\right\|^{2}$ and $U_v = \left[u_{ij,v}\right]$ is the division matrix corresponding to the ith view. $\widetilde{u_{ij,v}} = \sum_{t=1}^{V} w_{v,t}\, u_{ij,t}^{m}$ is the division fusion item, which realizes the view fusion of different views in the vth view clustering task. At this time, the importance of each view is reflected by the weight wv,t . wv,t represents the importance of the t[th] view in the v[th] view cluster. W is the weight matrix of all views. The Lagrange multiplier method is used to solve the extreme value of Eq. 1, and the expression of each variable is obtained as follows:

$$Z_{i,v} = \frac{\sum_{j=1}^{N} \sum_{t=1}^{V} w_{v,t}\, u_{ij,t}^{m} x_{j,v}}{\sum_{j=1}^{N} \sum_{t=1}^{V} w_{v,t}\, u_{ij,t}^{m}} \qquad (2)$$

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$$u_{ij,t} = \frac{1}{\sum_{h=1}^{C}\left[\frac{\sum_{v=1}^{V} w_{v,t} d_{ij,v}^{2}}{\sum_{v=1}^{V} w_{v,t} d_{hj,v}^{2}}\right]^{\frac{1}{(m-1)}}} \tag{3}$$

$$w_{v,t} = \frac{exp\left[\frac{-\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij,t}^{m} d_{ij,v}^{2}}{\gamma}\right]}{\sum_{g=1}^{V} exp\left[\frac{-\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij,g}^{m} d_{ij,v}^{2}}{\gamma}\right]} \tag{4}$$

The following ensemble method is used to obtain the final Partition matrix:

$$\bar{U} = max\left(\sum_{t=1}^{V}\left(\frac{\sum_{v=1}^{V} w_{v,t}}{\sum_{t=1}^{V}\sum_{v=1}^{V} w_{v,t}} U_t\right)\right) \tag{5}$$

Using the fusion method in Eq. 5, the final global membership matrix is made by giving each membership matrix a weight (w) that is the same as the weight of the other membership matrices.

The RMV-FCM algorithm's precise stages are listed in the RMV-FCM algorithm.

Multiview sample set, views, clusters, iteration threshold, fuzzy index, iteration number, and parameter are the inputs.

The final division matrix U, the clustering center of each view Zl, and the view fusion weight matrix W =Wv,t are the outputs.

Step 1: Make fuzzy membership matrices uij,t (1, t, V) and view fusion weight matrices W = Wv,t at random for each view.

Step 2: Update each view's cluster centers (zj, v) in accordance with Eq. 2.

Step 3: Each view's membership degree uij,t is changed in accordance with Eq. 3.

Step 4: Using Eq. 4, the view fusion weight matrix W = Wv,t is updated.

The method ends at Step 5 if J(l+1) = J(l); otherwise, it loops back to Step 2.

Step 6: The fuzzy membership of each view is output after the algorithm converges.

Step 7: Use Eq. 5 to figure out the final division matrix based on each view's fuzzy membership degree, which was found in Step 6.

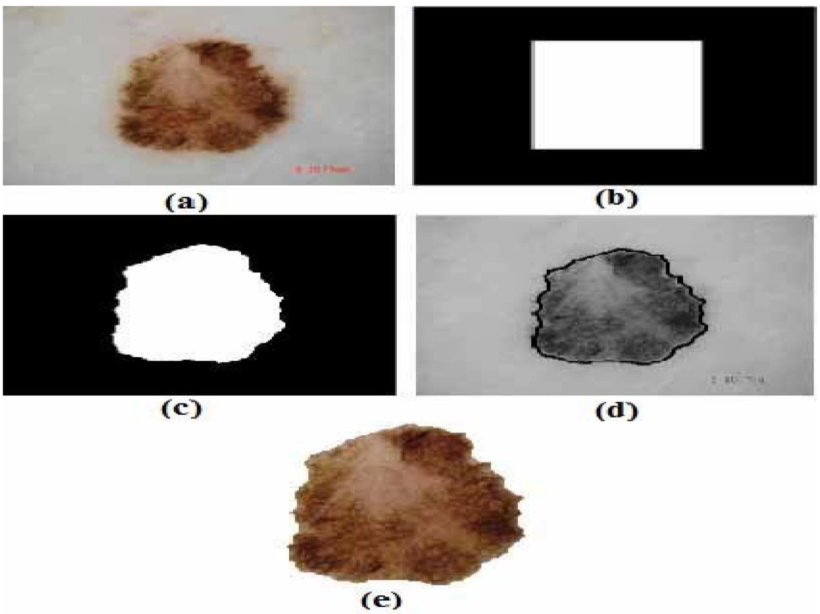

Figure 3. Preprocessing steps for malignant lesion. original image (a), initia lsegmentation (b), active countor model segmentation (c), border of the sementation on gray scale image (d), colored ROI (e)

3.3 Feature Extraction

The technique used to extract useful information from dermoscopy images is called feature extraction. In order to distinguish between benign and malignant lesions, a number of features from a specific dermoscopy image are extracted using computer-aided diagnosis (CAD) systems. Due to its effectiveness, efficiency, and simplicity of

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performance and implementation, the ABCD rule of dermoscopy pictures has been the primary methodology for extracting the feature in many early detection systems for the skin lesion. The capability of using computer algorithms can be used to assess how well the ABCD rule extracts necessary characteristics of the malignant lesion like asymmetry, border irregularity, color, and diameter.

Asymmetry: The lesion area is divided in half so that one half of the melanoma lesion does not match the other half in size and shape in order to extract the features based on asymmetry. Typically, a melanoma lesion is thought to be asymmetric along both axes (horizontal and vertical).

The calculation of the vertical axis (AS2) and horizontal axis (AS1) asymmetry scores

$AS1=\frac{\Delta X}{\Delta T}$, $AS2=\frac{\Delta Y}{\Delta T}$

Border Irregularity: The border of a melanoma lesion is said to be ragged, uneven, blurry, and irregular. In this equation, the circularity index is utilised to calculate the border irregularity (B). This score is between 0 and 1. This score approaches 0 when a lesion's border is uneven, jagged, and irregular. $B = \frac{4\pi A}{P^2}$

Color Variation: White, red, black, light brown, dark brown, and blue-gray are the six colours that best capture the hues in the lesion region. Each hue that is present in the lesion area is given a point, which is then added together and multiplied by a weight factor of 0.5 to create the following equation: [(white + red + black + light brown + dark brown + blue-gray) 0.5]. When the lesion has six different colours, the maximum score is 3. A minimum of three hues are present in melanoma illness. The colours in the area of interest are represented statistically. Nine features for each lesion were retrieved using the RGB colour system's values, contrast, standard deviation, and mean. These characteristics enable accurate diagnosis of the lesions.

Lesion Diameter: One of the characteristics used to recognise and diagnose a skin lesion is its diameter. One of the qualities in the ABCD rule that accepts the weight 0.5 as (0.5 diameter) is the diameter. It is malignant if the diameter is more than 6 mm. It is benign if its diameter is less than 6 mm.

$$D_{Image} = \sqrt{\frac{4A}{\pi}}$$

IV. CLASSIFICATION

To categorize segmented images, numerous classification techniques are currently available. To categorize the segmented lesion as melanoma or non-melanoma in our research, we employed four classifiers: KNN classifier, Navie Bayes (NB),Random Forest (RF), and Support Vector Machine (SVM) classifier. The impacts on classification accuracy are contrasted and discussed in the section that follows.

With their default parameter settings, these classification algorithms are trained and tested to reach the above-average accuracy we'll talk about below.

SVM: The SVM is the most prevalent type of classifier. The main advantage is the unified framework, which allows for the construction of various computing device study architectures by selecting a kernel. The information gathered from carcinogenic and non-cancerous skin and pore lesions is presented to an SVM classifier.

KNN is the best way to do things because it is the quickest, easiest, and clearest.The majority votes of an image's neighbors are used to categorize it. The training and test samples are delivered to the KNN classifier, and each classification is made using the closest distance. The malignant and non-cancerous characteristics are classified using the KNN classifier.

NB: The prior chance belief, which is entirely based on Bayes theorem, is the cornerstone of NB evaluation. The main advantages are that it is rapid, doesn't require large amounts of data, and that the characteristics are conditionally unbiased (i.e. there is no reliance between them). It uses NB's supervised computer studying approach.

RF: RF is made up of a number of selection trees, each of which has an effect on function association due to the use of multiple categorization.This method allows sampling allocation to be taken into account when using the random pattern method, which is very helpful for some small models.

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V. EXPERIMENTAL RESULTS AND DISCUSSIONS

In particular, we used the ISIC-2016 (Gutman et al., 2016), ISIC-2017 (Codella et al., 2018), and PH2 datasets in this section (Mendonca, Celebi, Mendonca, & Marques, 2015).. The ISIC datasets were chosen for our research because they are the most challenging database for melanoma segmentation since their samples contain a variety of abnormalities, such as variations in the measurement and texture of skin moles, the presence of hair, and microscopic blood vessels. Images also contain a variety of modifications, such as changes in brightness, intensity, colour, presence of blurring, and noise, which makes them a challenging dataset for melanoma segmentation. In the quantitative evaluation of the introduced approach, comparison matrices are used for both segmentation and classification, along with evaluation parameters and experimental results.Four metrics—pixel degree accuracy, pixel degree sensitivity, pixel degree specificity, and precision—are used to assess segmentation. Sensitivity:

RMV-FCM groups the melanoma detected pixels as foreground (shown with white colour), while the non-affected pixels are grouped as heritage. This is done to test the segmentation overall performance of the introduced technique (represented with black color). Table 1 shows the segmented output together with the relevant characteristic values.

Table.1 Proposed segmented skin cancer images with observed feature values

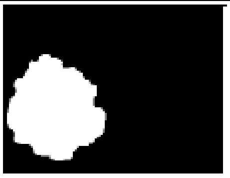
Input image	Segmented output image	Asymmetric	Border Irregularity	Color variance	Lesion Diameter	output
		AS1=0.16 AS2=0.18	0.86	1	D1=4.2 D2=0.45	Benign
		AS1=0.23 AS2=0.17	0.5	4	D1=8.6 D2=1.5	Malignant

Table 2.Confusion matrix for various classifier based on proposed segmented feature values

Model Description	TP	TN	FP	FN
SVM	240	99	6	4
KNN	235	90	6	9
RF	237	85	14	9
NB	235	82	12	8

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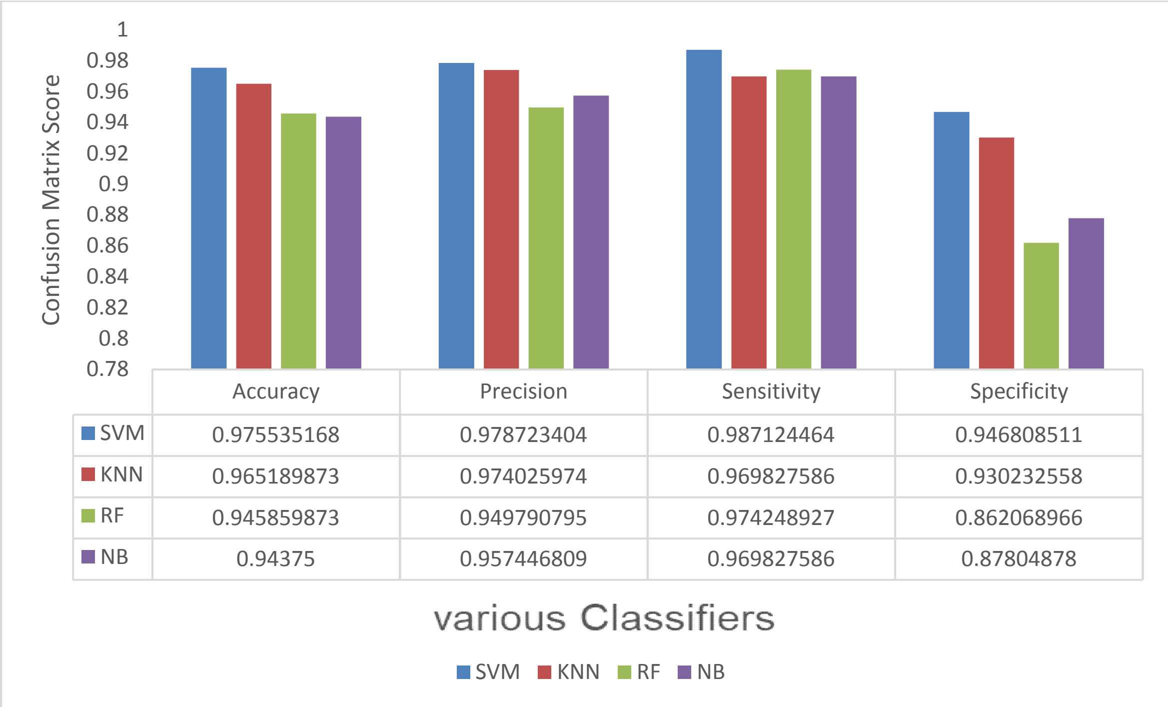

	Accuracy	Precision	Sensitivity	Specificity
SVM	0.975535168	0.978723404	0.987124464	0.946808511
KNN	0.965189873	0.974025974	0.969827586	0.930232558
RF	0.945859873	0.949790795	0.974248927	0.862068966
NB	0.94375	0.957446809	0.969827586	0.87804878

Figure 4. Performance evaluation result for predicting skin cancer based on proposed segmentation feature values

Evaluation of the new technique's effectiveness RMV-FCM Values for Segmented Characteristics:

The classification outcome indicates that segmentation accuracy using RMV-FCM, ABCD rule via SVM is 0.9753, which is higher than segmentation accuracy using the existing KNN, NB, and RF.

With SVM, the proposed RMV-FCM segmentation characteristic values are 0.9753, which is much higher than the values for KNN, RF, and NB.Similarly, the precision may be computed as the variety of an enormous prediction divided by the total quantity of an effective prediction. Sensitivity and specificity are the key variables for assessing the overall performance of skin cancers. With the use of the entire range of positive predictions in the dataset, the sensitivity is calculated as an exact positive prediction. In comparison to other classifiers like KNN, RF, and NB, the suggested RMV-FCM segmented characteristic values using SVM have a superior sensitivity of 0.9871. The segmented RMV-FCM characteristic values with SVM are 0.9468, which is somewhat higher than KNN, NB, and RF.

Comparing the results of 4 classifiers shows that our method does better than the other methods because the other methods use very deep models, which can lead to a problem called "model overfitting."Our method, however, employs the RMV-FCM algorithm, which creates a more effective set of picture elements and is better able to handle the model overfitting issue. Moreover, the comparison methods are more expensive than our method economically. As a result, we can state that our newly presented method is more accurate and environmentally friendly for segmenting and detecting skin lesions.

VI. CONCLUSION

The cells (melanocytes) that make melanin, the pigment responsible for your skin's colour, grow into melanoma, the most dangerous type of skin cancer. Moreover, melanoma can develop in your eyes and, very rarely, inside your body, like in your throat or nose. Melanoma risk appears to be rising among those under 40, particularly women. The detection and treatment of malignant alterations prior to the progression of the disease can be made possible by being aware of the warning symptoms of skin cancer. If melanoma is found early on, it can be successfully treated. Despite recent advancements in the identification and prevention of cancer, it is still challenging to automatically identify and separate cancer-affected areas from the subject's skin due to poor contrast and high similarity between afflicted and unaffected skin patches. In particular, Robust Multiview Fuzzy C Means Clustering, a novel technique that uses a

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segmentation-based approach, is presented in the study (RMV-FCM). Even in the presence of a number of artefacts, the experimental results of the newly proposed technique demonstrate significant improvements in melanoma detection and segmentation. The results show that the newly developed melanoma detection method performs better in terms of accuracy than current procedures for detecting skin lesions. As a result, this method may be crucial for the precise detection, segmentation, and identification of skin lesions at their early stage.

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