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An MS-ROI based Detection and Segmentation of Erythemato-Squamous Disease

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Abstract *- Skins are the biggest part of the human body. It plays a vital role in our body. It regulates body temperature, sensing from touching heat and cold. However, there are a number of risks that affect the skin, one of which is a disease. Fungus, bacteria, allergies, enzymes, and viruses cause most skin diseases. Identify the disease on the basis of manual feature extractions or based on the symptoms is time-consuming and requires extensive knowledge for perfect identification. Diagnosing, detection, and classification of skin diseases are done by researchers previously. However, the recognition rate is still not enough and is dependent on feature selection, filtering, and segmentation methods. We also apply median filtering to remove noise and balance the intensity of the image. In segmentation, a lot of methods are available. So that this research mainly focuses on finding the best or new segmentation method for Erythemato-Squamous disease (ESD).*

Keywords: *ESD, Skin diseases, MS-ROI, Thresholding, Edges, Regions, Clustering, S-ROI.*

I. INTRODUCTION

Skin is the body's outer covering, which protects us from microbes and the elements. The skin can reduce the harmful effect of ultraviolet radiation (UV) due to the pigment melanin that absolves UV radiation, which protects the cell's nuclei from DNA damage. The skin regulates body temperature and also synthesizes vitamin D3. It allows for touch, cold, and heat sensations. The skin covers the human body around 1.8 m^2.

There are three layers to the skin. The epidermis, which is the outermost layer of skin, is the first layer. It produces our skin tone and acts as a waterproof barrier. The Dermis is the second layer of skin underneath the epidermis, and it contains Sweat glands, stiff connecting tissues, and hair follicles. The deeper subcutaneous tissue is the hypodermis, which is made up of fat and connective tissue. [1] Since our skin is the outermost layer of our bodies, it is often infected by bacteria, fungi, and viruses. The skin protects all of the organs in the human body.

As a result, it is critical to pay close attention to the skin's overall health. Since every disruption in its daily activities can have an impact on the rest of the body. The term "skin illness" refers to problems with the skin's surface layers only. Skin illnesses are the most frequent disease in people of all ages, and they are a major source of infection in Africa. [2] Common diseases that attack human skin are eczema, melanoma, vitiligo, mycosis, papillomas, impetigo, scabies, herpes, dermatitis, wart, psoriasis, acne, tinea capitis, tinea corporates, tinea pedies, etc. Skin disorders, whether bacteria, fungus, allergic, enzyme, or otherwise, are extremely destructive to the skin and can spread to other organs if not recognized precisely and as soon as feasible.

As a result, identifying these diseases is critical for accurately detecting the type of disease at an early stage. In developing countries like Ethiopia, diseases like tinea corporis, tinea pedies, tinea capitis, eczema, and scabies are widespread. More than 80% of randomly selected schoolchildren in western Ethiopia had at least one skin disease, which was typically caused by one of two conditions: scabies, capitis, tinea capitis, or pyoderma [3]. Dermatology is the medical specialty concerned with the diagnosis and treatment of skin problems in humans.

In Ethiopia, Dermatologists diagnosed using symptoms, and sometimes they used a blood test for further analysis. The diagnostic procedure is perceived to be extremely tedious, time-consuming, and necessitates a thorough grasp of the subject. In recent years there has been an increased interest in applying image processing techniques to the problem of skin disease identification. There are opportunities to improve skin disease identification through the design of a convenient disease identification system. Many different approaches are used to classify skin disease to its predefined classes using the features of the disease [4].

II. LITERATURE SURVEY

The process of splitting an image into non-overlapping constituent sections that are uniform in terms of characteristics like grey level, hue, texture, intensity, sharpness, and other (statistical) qualities is known as image segmentation. To begin, the digital image is divided into two sections: background and foreground, with the foreground consisting of the interesting objects and the background consisting of the rest of the image [5]. In terms of a particular feature, such as intensity, color, or texture, all of the pixels in the foreground are identical. Image segmentation creates a collection of parts that encompass the full image collectively. In images, recognition is the method of locating objects and borders (e.g., lines or curves). The output of image segmentation is a series of sections or contours taken from the image that together cover the entire image [6].

The segmented objects are often referred to as the foreground, while the rest of the image is referred to as the background. It's used to get rid of the unwanted parts of an image and locate the area of interest. We cannot, in general, speak of a single, correct segmentation for any given image. Rather, the right image segmentation is highly dependent on the types of entity or area we want to classify. To be allocated to one of two regions, the central question in image segmentation is what relationship a given pixel has with its neighbors and other pixels in the image [7].

While there are numerous segmentation strategies, they can be divided into two categories: detection of discontinuities & detection of similarities. The method of partitioning an image based on sudden changes in intensity is called segmentation based on the detection of discontinuities.

Both edge detection algorithms are examples of such algorithms. Detecting similarities, on the other hand, is dependent on continuities. These techniques use similarity rules to segment the entire image into sub-regions. Thresholding, area rising, and other algorithms are examples of such algorithms. Regardless of whether discontinuity or similarity is used as a segmentation technique, the end product of any segmentation process is a binary image [8,9]. Image segmentation approaches are divided into four categories: threshold-based, area-based, cluster-based, and edge-based [10,11]. The strategies for image segmentation are described in table 1.

Table 1: Analysis of different segmentation methods

Methods	**Info**	**Pros**	**Cons**	**Reference**
Methodology Based on Thresholding	To find related pixels, it focuses on finding peak values based on the image's histogram.	It doesn't necessitate any complex pre-processing, and it's really simple to do.	Much information can be overlooked, and Thresholding errors are common.	Figure 6
Methodology Based on Edges	Unlike similarity detection, discontinuity detection is based on Edges	It's ideal for images with more contrast between objects.	Not recommended for images with a lot of noise.	Figure 7
Methodology Based on Regions (S-ROI)	Centered on dividing an image into homogeneous areas	Works well for images with a lot of noise, and it accepts user markers for fast evaluation.	Memory is a valuable resource.	Figure 8
A methodology based on K-Means	Objects are obtained by dividing an image into k Means of homogeneous, mutually exclusive clusters.	Proven processes enhanced by fuzzy logic and more suitable for real-time use.	It can be difficult to determine a cost function for minimization.	Figure 9
The methodology based on Morphology	Based on gray image boundary topological interpretation	The obtained segments are more stable, and the detected boundaries are distinct.	The estimation of ridge gradients is difficult.	Figure 10

III. METHODOLOGY

Data acquisition, preprocessing, segmentation with future extraction, and classification are the four primary steps in the research for detecting affected areas. The overall architecture of the research is shown in Fig 1.

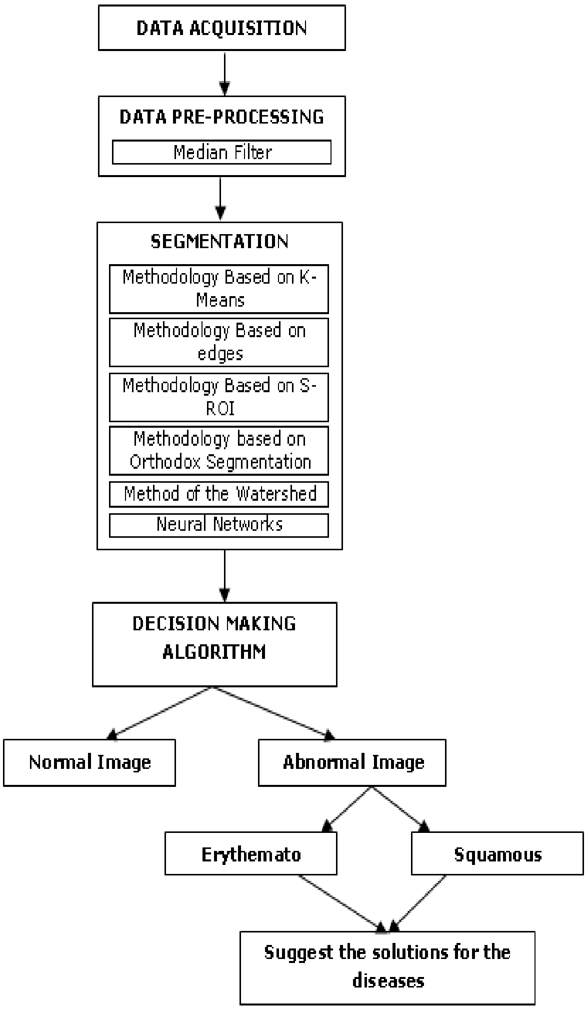


Fig 1: Architecture of the proposed model

A. DATA ACQUISITION

A collection of 1596 images are acquired from the [12] and [13] database also we have a different kinds of methods in image acquisition for screening the skin diseases such as Imagegraphy, Dermoscopy, Multispectral imaging, Laser-based enhanced diagnosis, Optical coherence tomography, Ultrasound imaging & magnetic resonance imaging. Fig 2 is the sample image for this process which is taken from the database.

Fig 2: Given input sample

B. PREPROCESSING

The goal of preprocessing is to improve the image by removing unwanted distortions and improving some key picture attributes in preparation for subsequent processing. Image preprocessing may be divided into three categories.

1) Conversion of grayscale
2) Noise removal
3) Image enhancement.

a) Gray-scale conversion

A grayscale image only includes brightness information. Each pixel in a grayscale image represents a different amount or quantity of light. A grayscale image shows the brightness gradient. Only the light intensity is measured in a grayscale picture. The brightness of an 8-bit picture ranges from 0 to 255, with 0 representing black and 255 representing white. As seen in Figure 1, grayscale conversion is the process of converting a color image to a grayscale one (3). Colored photographs require more time and effort to process than grayscale photos. Every image processing technique is applied to a grayscale picture [14].

$$Grayscale\ Intensity = 0.299\,R + 0.587\,G + 0.114\,B \qquad (3)$$

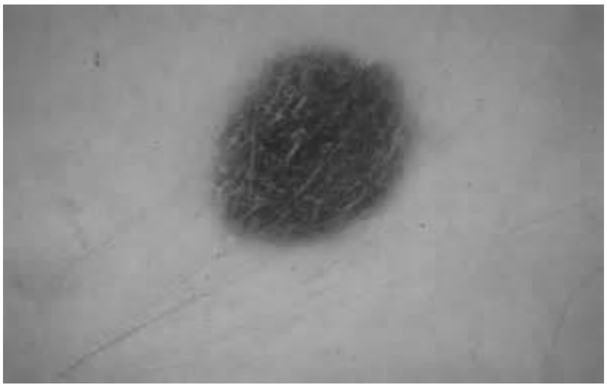


Fig 3: gray image

b) Noise removal

Noise reduction is the process of finding and removing undesirable noise from a digital picture. It is difficult to determine which characteristics of a picture are real and which are due to noise. The term "noise" refers to random changes in pixel values. As shown in fig. 1, we use a median filter to reduce extraneous noise in our suggested system (4). The median filter is a nonlinear filter that preserves edges. An odd-length sliding window is used to create the median filter [15]. The filter output is the sample's median within the window, and each sample value is ordered by magnitude.

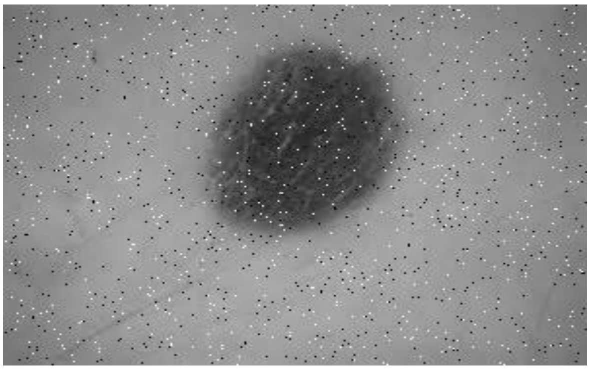


Fig 4: After noise remove

c) Image enhancement

The purpose of image enhancement is to make a topic of interest in an image more visible. Contrast enhancement is used in this situation to offer a higher quality result, as seen in fig (5).

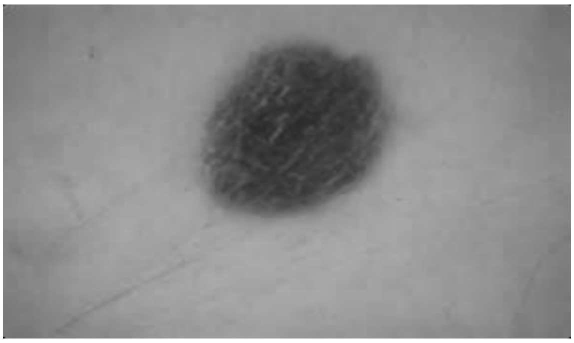


Fig 5: Enhanced Image

C. SEGMENTATION

The technique of removing an image's region of interest is known as segmentation. In a region of interest, each pixel has comparable attributes. We're using MS-ROI with the highest entropy for segmentation. To begin, we must first calculate the grey level of the original image, then compute the histogram of the greyscale images, and then segregate the foreground from the background using maximum entropy. According to the above survey, Most of the popular segmentation methods having some drawback in output sector but only the SROI provide the best result compare to others. From the SROI, we developed a new algorithm that is MS-ROI.

- S-ROI (Statistical - Region Of Interest)
- MS-ROI (Multilevel S-ROI)

D. S-ROI

The region of skin image that provides diagnostically relevant information is ROI. The ROI is further subjected to segmentation, where the images are demarked into fixed-size squared shape regions, also called SROI's, to attain a comprehensive database for the next step. Researchers generally use manual, semi-automatic, fully automatic, and interactive segmentation approaches. The Dermato images usually suffer from (i) low brightness contrast, (ii) gray level discontinuity, (iii) strong speckle noise, and (iv) attenuated artifacts, which may affect the outcomes of automatic or semi-automatic segmentation. Besides, SROI's should also be free from the portions of hepatic vessels, artifacts, and other nearby structures.

This necessitates the requirement of an expert interaction, and hence, the present research used interactive segmentation where an expert who had experience of more than 20 years in skin imaging helped in marking the ROI seed point. The application of interactive segmentation helped the study to gather clear and specific image data.

a) Selection of the Size of Segmented Regions-of-Interest

Segmented regions-of-interest contains the region of the image with the most diagnostic information and makes it a good ‘representative’ of the image. Additionally, SROI's reduce the computational time for feature extraction. Thus, the selection of an appropriate size of SROI's is a crucial process. It was observed that the images with 75×75 pixels and 100×100 pixels were not suitable as they included blood vessels. Further, SROI's of 10×10 pixels and 25×25 pixels were also not advisable, as they were too small to have sufficient information for a reliable statistical analysis, which can signpost the diffused skin disease (i.e., where whole skin gets infected). This reduced the choice to 64×64 pixels and 32×32 pixels. However, it was observed that both 32×32 pixel SROI's and 64×64 pixel SROI's contained similar information. Thus, 32×32 pixel non-overlapping SROI's were used to build a large dataset.

Additionally, 227×227 pixel SROI's were used in deep learning as the input image size was 227×227x3 pixels as per the requirement of architecture that is Alexnet. Here, all the grayscale images were transformed into Color images via reproducing one to three-channel RGB Images.

b) Parameters used in SROI

The following parameters are basically used to find the SROI in an image.

- Median intensity
- Minimum and Maximum Feret's diameter
- Perimeter

E. MS-ROI

Based on the above analysis, the SROI providing better output, but it takes too much time to provide the output. So that this is research is focused on implementing the new MSROI model. We obtained a color image after achieving maximum entropy, as shown in fig (11).

The MSROI model consisting of the following parameters in Affected Area

- Perimeter
- Mean
- Standard deviation
- Minimum and Maximum image intensity
- Median intensity
- Minimum and Maximum Feret's diameter

a) Follow of MSROI

- The image's rows are examined one by one.
- If the row crosses the ROI at any point, each pixel in that image row is examined separately.
- The ROI is intersected with each pixel.
- The overall ROI area is equal to the sum of all crossed forms' areas. The area is 0 for Text, Marker, and Line ROIs. Let I_i represent the intensity of pixel I with a non-zero intersected area, ∂_i represent the intersected area of pixel I and A represent the total area of all crossed forms $(i.e., \Sigma(\partial_i))$.
- The average pixel intensity is

$$\frac{\Sigma(\partial_i \times I_i)}{A} \qquad (1)$$

- The mean pixel intensity for a Text or Marker ROI is the intensity of the pixel in the center of the text or under the marker. Assume that μ is the average pixel intensity.
- The pixel intensity standard deviation is:

$$\sqrt{(((\Sigma(\partial_i \times I_i \times I_i) - \mu \times \mu \times A) / A).)} \qquad (2)$$

- Text and Marker ROIs are the only ones where the standard variation in pixel intensity is always zero.
- The least pixel intensity in any intersected form with an area greater than zero is the minimum pixel intensity. The only exception is in the case of Text and Marker ROIs, where the minimum pixel intensity is equal to the intensity of the pixel in the text's center or under the marker.
- The greatest pixel intensity in any intersected form with an area larger than zero is the maximum pixel intensity. The only exception is text and marker ROIs, where the maximum pixel intensity is the pixel in the center of the text or under the marker.

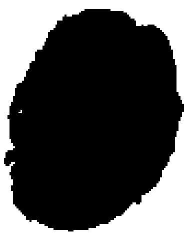


Fig 6: Thresholding method output

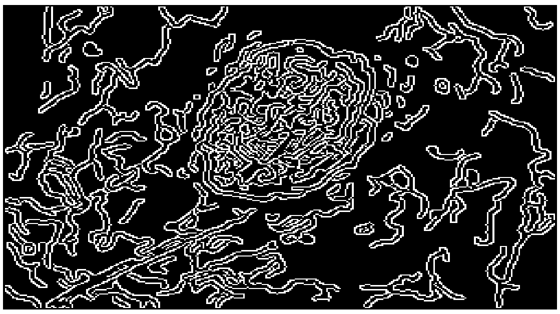


Fig 7: Edge detection (Canny) method output

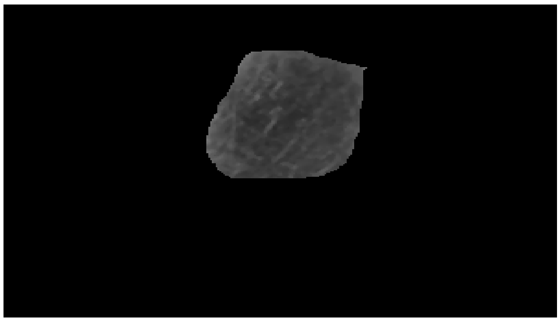


Fig 8: S-ROI method output

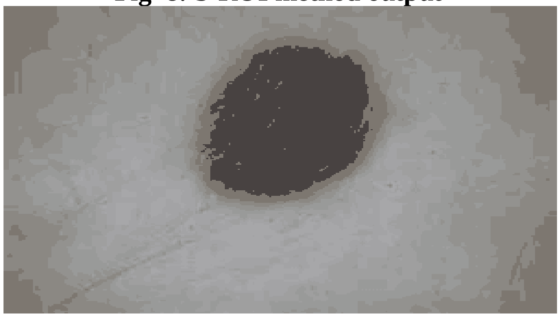


Fig 9: K-Menas method output

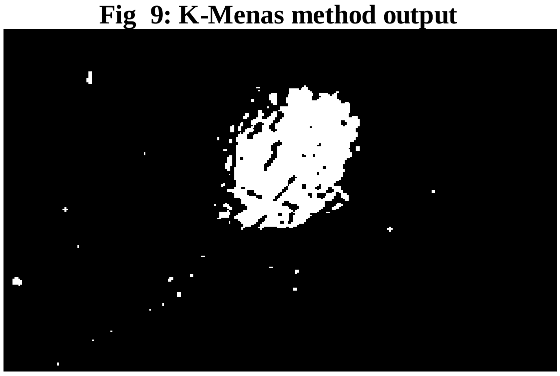


Fig 10: Morphology method output

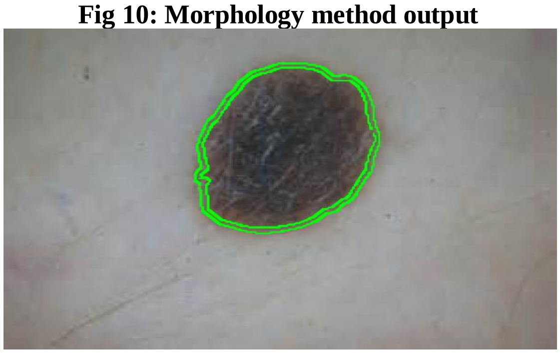


Fig 11: MS-ROI method output

b) Feature extraction

Feature extraction is critical for extracting information from a given image. We're using GLCM (Gray Level Co-occurrence Matrix) for texture image analysis. To capture the spatial connection between image pixels, the GLCM approach is utilized. GLCM uses the grey level image matrix to store the most common properties such as contrast, mean, energy, and homogeneity [16]. The purpose of feature extraction (GLCM) is to minimize the size of the original image data set by measuring certain values or features that aid in image classification [15].

IV. RESULT AND DISCUSSION

Computer-based classification systems can assist in finding skin abnormalities. In the previous sections, texture features were extracted by using S-ROI methods and MS-ROI methods. The success of a computer-based system depends jointly on the features and segmentation method. An efficient set of textural features decides the correct detection of skin abnormalities area; also, parameters are analyzed with S-ROI. It has been listed in table 2.

Table 2: Parameters comparison

Parameters	MS-ROI	S-ROI
Affected Area	42%	37%
Perimeter	185.4760	151.5440
Mean	9.845	6.4178
Standard deviation	29.564	20.0677
Minimum image intensity	37	28
Maximum image intensity	180	174
Median intensity	145	138
Minimum Feret's diameter	280.35	276.36
Maximum Feret's diameter	321.56	309.65

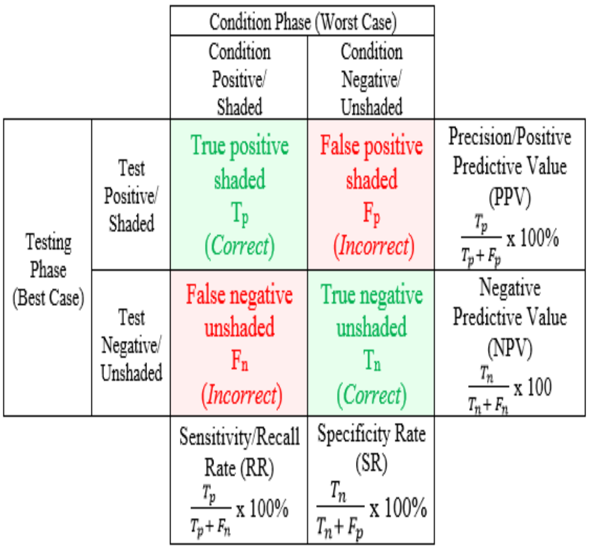
A. CONFUSION MATRIX AND PERFORMANCE MEASURES

The error matrix is another name for the confusion matrix [17,18,19,20,21,22,23,24,25]. It's a matrix that describes the efficacy of a segmentation model on a test data set with knowing true values. This matrix summarises the number of examples properly and erroneously predicted by the classifier and aids in predicting the different performance measures, such as accuracy, sensitivity, and so on, of the segmentation system illustrated in table 4 and Figure 13.

The performance of a segmentation system is the ability of the system to correctly predict the test data to its actual class. Accuracy is the performance measure that is used for the assessment of the goodness of a segmentation system. Accuracy for the four-class segmentation system is defined in terms of class accuracy and overall accuracy. The confusion matrix formula and table has been shown in Figure 12.

- ❖ **Class accuracy:** It is the ratio of correctly Segmented cases of class to the total number of cases in that class concerning ground truth.

❖ **Overall accuracy**: It is the overall correctness of the segmentation system. It is the ratio of correctly Segmented cases (diagonal elements) from each class to the total number of cases.



		Condition Phase (Worst Case)		
		Condition Positive/ Shaded	Condition Negative/ Unshaded	
Testing Phase (Best Case)	Test Positive/ Shaded	True positive shaded T_p (Correct)	False positive shaded F_p (Incorrect)	Precision/Positive Predictive Value (PPV) $\frac{T_p}{T_p+F_p}$ x 100%
	Test Negative/ Unshaded	False negative unshaded F_n (Incorrect)	True negative unshaded T_n (Correct)	Negative Predictive Value (NPV) $\frac{T_n}{T_n+F_n}$ x 100
		Sensitivity/Recall Rate (RR) $\frac{T_p}{T_p+F_n}$ x 100%	Specificity Rate (SR) $\frac{T_n}{T_n+F_p}$ x 100%	

Fig 12: basic confusion matrix with formula

The confusion matrix for the two-class segmentation system is shown in table 3. Here the entries are True Negative (TN), False Positive (FP), True Positive (TP), and False Negative (FN). Where TP is the number of skin disease correctly Segmented as the disease in question; FP is the number of skin disease without disease wrongly Segmented as a disease in question; FN is the number of skin disease wrongly Segmented as without the disease; TN is the number of skin disease correctly Segmented as without disease.

Table 3: Confusion matrix for a MS-ROI segmentation system

	Actual - Skin diseases	***Actual - Not a Skin diseases***	***Total***
Predicted - Skin diseases	TP=890	FP=4	894
Predicted - Not a skin diseases	FN=8	TN=694	702
Total	898	698	1596

Accuracy is expressed by the overall rate of correctly and wrongly Segmented classes
and can be defined as:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} * 100\% \quad (1)$$

$$Accuracy = \frac{890 + 697}{890 + 8 + 4 + 694} * 100\%$$

$$= \frac{1584}{1596} * 100\%$$

$$= 0.992481 * 100\% = 99.2481\%$$

However, for the unbalanced set, accuracy may not be a good criterion for evaluating a segmentation system. The other measures of a diagnostic test are specificity, sensitivity, positive predictive value, and negative predictive value. These are defined as:

Specificity is also called the true negative rate. It measures the proportion of actual negatives cases that are correctly identified.

$$Specificity = \frac{TN}{TN + FP} * 100\% \quad (2)$$
$$= \frac{694}{694 + 4} * 100\%$$
$$= 0.994269 * 100\%$$
$$= 99.42\%$$

Sensitivity is also called true positive rate or recall. It measures the proportion of actual positives cases that are correctly identified.

$$Sensitivity = \frac{TP}{TP + FN} * 100\% \quad (3)$$
$$= \frac{890}{890 + 8} * 100\%$$
$$= 0.99109 * 100\% = 99.10\%$$

Positive predictive value (PPV) is also called precision. It measures the proportion of correctly Segmented positive cases among all cases which are predicted positively by the segmentation system in the test set.

$$Positive\ predictive\ value = \frac{TP}{TP + FP} * 100\% \quad (4)$$
$$= \frac{890}{890 + 4} * 100\% = 0.9955 * 100\%$$
$$= 99.55\%$$

Negative predictive value (NPV) is the proportion of correctly Segmented negative cases which are predicted negatively by the segmentation system in the test set.

$$Negative\ predictive\ value = \frac{TN}{TN + FN} * 100\% \quad (5)$$
$$= \frac{694}{694 + 8} * 100\%$$
$$= 0.9886 * 100\%$$
$$= 98.86\%$$

Table 4: Individual Algorithm Performance Metrics

		ACCURACY (%)	SPECIFICITY (%)	SENSITIVITY (%)	PPV (%)	NPV (%)
Methodology Based on	MS-ROI	99.2	99.4	99.1	99.5	98.86
	Regions (S-ROI)	98.5	98.9	94.3	92.3	91.8
	Thresholding	98.1	96.8	93.5	90.5	89.0
	Edge Detection	89.6	97.6	93.1	88.9	87.6
	K-Means	93.6	95.6	94.6	89.8	87.6
	Clustering	94.8	98.6	94.9	91.5	90.5

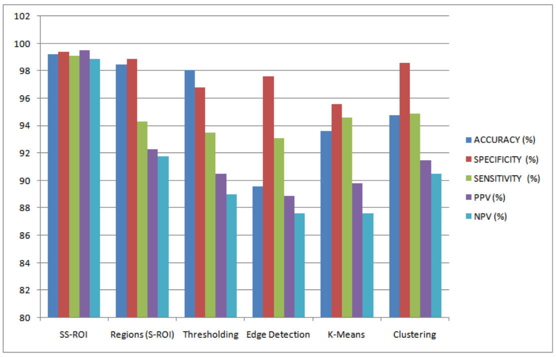


Fig 13: Individual Algorithm Performance Metrics

V. CONCLUSION

In this Research, the goal is to create and implement different new techniques for ESD segmentation. In this regard, first, the preprocessing techniques have applied to the images to remove different artifacts and sharpening the image using filtering or other techniques. The next step, which is the important part of this article, is to present different segmentation algorithms such as MS-ROI, K-Means, Edges, Regions (S-ROI), Orthodox Segmentation, Watershed, Neural Networks. For the evaluation of the segmentation methods, we compare our experimental results with the performance matrixes. The results also prove that the MS-ROI has the highest accuracy comparing with other methods. The segmented results have been applied to different deep learning methods and find the best one in the future..

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