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Fuzzy Based Visual Texture Feature for Psoriasis Image Analysis

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***Abstract*—**This paper proposes a rotational invariant texture feature based on the roughness property of the image for psoriasis image analysis. In this work, we have applied this feature for image classification and segmentation. The fuzzy concept is employed to overcome the imprecision of roughness. Since the psoriasis lesion is modeled by a rough surface, the feature is extended for calculating the Psoriasis Area Severity Index value. For classification and segmentation, the Nearest Neighbor algorithm is applied. We have obtained promising results for identifying affected lesions by using the roughness index and severity level estimation.

***Keywords*—**Fuzzy texture feature, psoriasis, roughness feature, skin disease.

I. Introduction

PSORIASIS is a very common long-term skin disease which causes pain and irritation. The complex interplay involving genetics, the environment, skin barrier disruptions and immune dysfunction are factors that are suspected to cause psoriasis. Psoriasis increases the risk of cancer, cardiovascular disease and other disorders like ulcerative colitis. It is an incurable but treatable disease appearing as a reddish lesion that creates itching.

The Journal of American Medical Association reported that psoriasis increases a person's chances of having a heart attack. Of the 3686 psoriasis patients studied, 116 had incidents of cancer. Further, younger patients with psoriasis tended to have the greatest risk of cancer. Psoriasis comes in various forms and exhibits varying levels of severity. As the degree of severity increases, the skin becomes thicker, with silver-white rough scales. Periodical treatment is essential for psoriatic patients to help control the disease.

Areas affected by psoriasis can be estimated through segmentation techniques. The objective of the paper is to propose a fuzzy based roughness feature and use the proposed feature to estimate and classify the severity level of psoriasis.

In [1], the authors used roughness as a feature of scaliness for scoring the Psoriasis Area Severity Index (PASI). To determine the degree of roughness, the authors used a polynomial surface fitting to estimate surface deviations. In [2], a method has been proposed to determine the body surface area (BSA) and lesion area. The vertical deviation of the lesion surface was measured to estimate the roughness of the surface [3]. Features such as skin color and texture (derived from GLCM) are used to detect psoriasis [19] with the help of feed forward neural networks. A color image segmentation approach was proposed in [4], using color fractal dimension as the local feature.

Several methods have been used for texture characterization based on the feature of roughness. Parameters for roughness are divided into four categories namely: amplitude, functional, hybrid and spatial parameters [12]. Roughness can be characterized using various statistical variables including average roughness, root mean square roughness, minimum area valley depth, maximum area peak height etc. [8]. Fractal dimension is the most widely used parameter for defining roughness. Mandelbrot [16] introduced the fractal concept for measuring roughness. Fractal function has also been used for natural scene analysis [20]. Liang Chen et al. [10] used the Normalized Fractional Brownian motion model (NFB) for liver image segmentation to classify ultrasonic liver images and ultrasound images of breast lesions [8]. The directional roughness and weighted roughness feature were proposed by [9]. Arrault et al. [5] used wavelet transform for computing the roughness value. The wavelet based rotationally invariant roughness feature was proposed by [11] for image classification and segmentation. Manik Varma et al. [17] derived local fractal features for classifying texture images with different illuminations. Zhang Jian et al. [28] proposed a method to extract the average texture cycle to describe surface roughness. Sebastien Deguy et al. [24] proposed a method using the multiscale fractional Brownian motion texture model and a parameter 'intermittency' to describe a degree of the presence of textural information. In [21], the authors used the gradient factor of the image to estimate roughness levels. Marcelo L Alves et al. [18] used Haralick descriptors to describe image texture and performed classification. Yong Xia et al. [27] proposed a set of multifractal descriptors and multifractal estimation algorithms to characterize the local scaling properties of textures. Chaudhuri et al. [6] employed a technique based on fractal dimensions and multi fractal concepts and performed image segmentation and recognition.

Keramidas et al. [13] proposed a fuzzy binary pattern and proved its robustness against noise. Chiranjeevi et al. [7] applied a fuzzy membership transformation to the co-occurrence matrix for detecting moving objects. For texture classification, Rocio A.Lizarranga-Morales [22] proposed a fuzzy rule based system. E. M. Srinivasan et al. [25] proposed a fuzzy local texture pattern [FLTP] and authenticated its

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robust performance. A new classifier was proposed by extracting fuzzy rules from texture segmented regions [15]. Volodymyr Mosorov and Lukasz Tomczak [26] proposed a defect detection method for an automatic visual inspection system using texture information and fuzzy c-means clustering. In [14], the authors proposed a fuzzy texture descriptor which combines both fuzzy and neighbourhood difference and applied it to texture classification. Savvas A. Chatzichristofis et al. [23] derived a fuzzy color and texture histogram which combines color, texture and the fuzzy system and used the feature for content based image retrieval.

A. Motivation and Justification of the Proposed Work

Traditional methods, while using color features like luminance and hue have failed to assess the areas affected. The reason is that skin color varies from patient to patients. Psoriasis can be viewed in terms of micro structural changes in the skin. There is a difference in roughness between normal skin and skin affected by psoriasis. Hence it is expected that the accuracy of the estimation of severity will be improved by using roughness as a feature to identify the affected lesions. Roughness is an imprecise and vague property which can be precisely estimated by using a fuzzy based approach. Since the severity of the disease can be controlled, it is also desirable to identify the level of severity so as to facilitate further treatment. The Psoriasis Area and Severity Index (PASI) is recognized as a standard process that helps in severity assessment. The aim of this paper is to propose a new fuzzy based roughness feature extraction method to estimate the severity level of psoriasis. To the best of our knowledge, we believed that such a fuzzy based roughness feature extraction technique has neither been previously proposed nor used for psoriasis image analysis.

B. Outline of the Proposed Work

Psoriasis severity level estimation using the proposed approach is done in two phases as shown in Fig. 1. The two phases are (i) Classification and (ii) Severity Level Estimation through Segmentation. The process of classification is implemented through training and testing phases. In the training phase, the system is trained with features of normal images and psoriasis affected images. In the testing phase, the testing image feature is compared with the trained normal and abnormal (psoriasis) image features derived using similarity measures, and then classified accordingly. If the image is classified as a psoriasis affected skin image, it will be subject to the segmentation process. In the segmentation phase, the psoriasis lesion is segmented and its severity level estimated.

This paper is organized as follows: Section II explains the feature extraction method. Skin image analysis using the proposed method is discussed in Section III. The experimental results and discussion are presented in Section IV. Section V concludes the work.

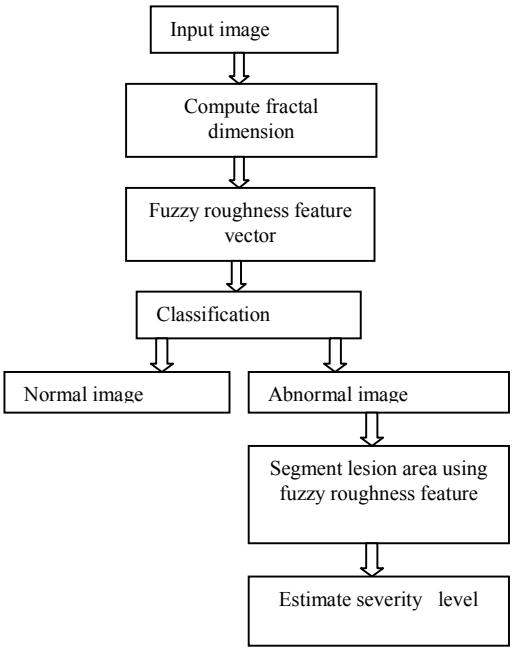


Fig. 1 Flow diagram of Psoriasis Severity level estimation using the proposed approach

II. Methodology

A. Feature Extraction

Features play a significant role in image processing. The transformation of an image into its feature set is called feature extraction and it is a challenging task to extract an effective feature set for image processing. A surface is a feature that physically separates the object from its surrounding medium. The surface consists of three components including roughness, waviness and form which are determined based on the wavelength of the surface profile. Of the three components, roughness not only provides more information about the surface but can also be calculated easily using spatial distribution of pixels. Hence, we have considered in this paper, roughness as a feature for image classification and psoriasis analysis.

B. Roughness Feature Extraction

A small irregularity present on a surface is called roughness and it is the irregularities that characterize surface texture. Roughness is only a result of abrupt transition located at the edges of the object. The degree of roughness varies for different images. Based on the degree of roughness, images may be classified as smooth, medium rough, rough. Sample images with different degrees of roughness are shown in Fig. 2. The image with a lower degree of roughness is categorized as a “smooth surface image” while the image with a higher degree of roughness is referred to as a “rough surface image”.

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Fig. 2 Sample images with different degrees of roughness (a) Smooth (b) Medium rough (c) Rough

Fractal geometry is used to characterize the degree of self-similarity in sets called fractals. Due to its complexity, it is impossible to describe these sets using classical geometry. The fractal dimension is a measure which characterizes the complexity of a fractal set. By analyzing how a fractal set fills a space, the fractal dimension can be used as a parameter to check whether or not the texture region belongs to a particular class. Due to properties like space invariance and rotational invariance of the fractal dimension, it can be used for classification and segmentation.

In an image processing context, fractals are rough or fragmented geometric shapes of an object or image. Mandelbrot introduced the fractal concept for measuring surface roughness [14]. The fractal dimension is a parameter that measures the geometric relationship between the roughness space of the object and its underlying metric space. As the fractal concept is useful in many applications including biology, fluid dynamics, road analysis, fabric analysis, skin analysis and others where the structural information is important, different fractal models have been proposed in the past. Fractal dimensions can be used in image segmentation if there exists a difference in roughness between the background and the object of interest.

The Fractional Brownian Model (FBM) is one of the fractal methods described by Mandelbrot [14]. FBM has been used in this work for roughness feature extraction. For a given MxN image I, the intensity difference is defined by the following formula.

$$Id(k) = [\sum_{x=0}^{M-1}\sum_{y=0}^{N-k-1}\frac{|I(x,y)-I(x,y+k)|}{M(N-k)} + \sum_{x=0}^{M-1}\sum_{y=0}^{N-k-1}\frac{|I(x,y)-I(x+k,y)|}{M(N-k)} + \sum_{x=0}^{M-k-1}\sum_{y=0}^{N-k-1}\frac{|I(x,y)-I(x+k,y+k)|}{(M-k)(N-k)} + \sum_{x=0}^{M-k-1}\sum_{y=0}^{N-k-1}\frac{|I(x,M-y)-I(x+k,N-(y+k))|}{(M-k)(N-k)}]/4 \quad (1)$$

where Id(k) is the intensity difference, M indicates row(x) and N indicates column(y) and I(x,y) indicates the intensity value at x and y coordinates. k is the distance unit from (x,y) which can be varied from 1 to the maximum possible scale along x and y directions.

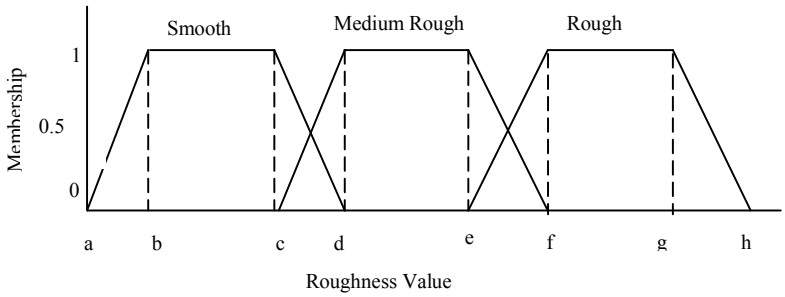


Fig. 3 Fuzzy membership functions for roughness features

C. Fuzzy Based Roughness Feature Extraction

The roughness value calculated using the above method is not an immediate measure that helps to decide whether the image is completely smooth, medium rough or rough. As it is a vague textural property, it is proposed to employ a fuzzy logic in this work for representing imprecision. In most fuzzy based approaches, fuzzy logic has been used for deriving the descriptor in the classification or segmentation phases. We have, in this work, introduced fuzzy logic for the purpose of mapping the feature vector into corresponding feature subclasses. We have derived a mathematically simple trapezoidal-shaped membership function for mapping the roughness value into the fuzzy roughness feature vector. The *fuzzy roughness vector* comprises smooth, rough and medium rough membership values. The graphical representation of the membership function for the roughness feature is illustrated in Fig. 3. The trapezoidal curve is a function of vector x_i, and depends on four scalar parameters. The membership functions for smooth, medium rough and rough are given in (2), (3), and (4) respectively.

$$\mu_Smooth(x_i) = \begin{cases} 0 & if\ x_i \le a \\ \frac{(x_i-a)}{(b-a)} & if\ a \le x_i \le b \\ 1 & if\ b \le x_i \le c \\ \frac{(d-x_i)}{(d-c)} & if\ c \le x_i \le d \\ 0 & if\ d \le x_i \end{cases} \quad (2)$$

$$\mu_Medium_Rough(x_i) = \begin{cases} 0 & if\ x_i \le c \\ \frac{(x_i-c)}{(d-c)} & if\ c \le x_i \le d \\ 1 & if\ d \le x_i \le e \\ \frac{(f-x_i)}{(f-e)} & if\ e \le x_i \le f \\ 0 & if\ f \le x_i \end{cases} \quad (3)$$

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$$\mu_{Rough(x_i)} = \begin{cases} 0 & if\ x_i \le e \\ \frac{(x_i - e)}{(f - e)} & if\ e < x_i < f \\ 1 & if\ f \le x_i \le g \\ \frac{(h - x_i)}{(h - g)} & if\ g \le x_i \le h \\ 0 & if\ x_i \ge h \end{cases} \quad (4)$$

The parameters a, b, c, d, e, f, g and h are estimated from the given input image roughness values as shown below. Firstly, the ranges of the medium rough membership curve are estimated. Thereafter, the ranges of the other membership curves are estimated with reference to the range of the medium rough membership.

$$\alpha = abs(Max_fd - Min_fd) \quad (5)$$

$$\beta = \alpha / 5 \quad (6)$$

$$a = 0;\ and\ b = Min_fd;\ c = Min_fd + \beta \quad (7)$$

$$d = c + \beta\ ;\ e = d + \beta;\ f = e + \beta\ ; \quad (8)$$

$$g = e + \beta;\ h = g + \beta; \quad (9)$$

where Max_fd and Min_fd represent the maximum and minimum fractal dimension values respectively. If the image is smooth, then the smooth membership values will be high and the medium rough and rough membership value will be low. Thus, the membership value of each class will be contributing based on the surface property. Table I shows sample normal and psoriasis affected skin images and their respective fractal dimension values and fuzzy membership values.

TABLE I
ROUGHNESS VALUES AND FUZZY MEMBERSHIP VALUES FOR SAMPLE IMAGES

Image	Roughness Value	Fuzzy Membership to Smooth	Fuzzy Membership to Medium Rough	Fuzzy Membership to Rough
	21.52	0.1378	0.8622	0
	27.99	0	1	0
	21.98	0.1122	0.8878	0
	25.82	0	1	0
	8.21	0.8772	0.1228	0
	7.65	0.9083	0.0917	0
	57.20	0	0.1556	0.8444

III. SKIN IMAGE ANALYSIS

A. Skin Classification

The process of skin analysis is carried out using classification and segmentation. For both processes, we applied the widely used Nearest Neighbour (NN) algorithm which finds the closest samples in training set to a testing sample. The algorithm used for classification is as follows:

- During the training, the fractal dimension is computed for samples of normal images and psoriasis affected skin images. This fractal dimension is then converted into a fuzzy roughness feature and stored as a training feature vector. This training process helps the system to differentiate between psoriasis affected skin images and normal images.
- In the testing phase, every image that is to be classified is converted into a fuzzy feature vector. This feature will act as a testing feature. For each test image, the closest training images are found by computing the Euclidean distance between the training image feature vector and the testing image feature vector. The Euclidean distance measure is defined as

$$D_e(S,M) = \sum_{i=1}^{n} \sqrt{S_i^{\,2} - M_i^{\,2}} \quad (10)$$

where S and M are the testing image feature vector and training image feature vector and n refers to the total number of bins. In our experiment, the value of n ranges from 1 to 3 which corresponds to the roughness value distribution for smooth, medium rough and rough. The computed distance value D_e indicates the probability that two images come from the same class or from different classes. The lower the value, the higher the probability that the two images are from the same class. The higher the value, the higher the probability that the two images are from different classes.

B. Skin Segmentation

After classification, normal images need no further process such as segmentation. However, the classified psoriasis-affected images will be subject to segmentation. The affected lesion is segmented, using the proposed approach by means of two methods: (i) supervised segmentation and (ii) unsupervised segmentation.

1) Supervised Segmentation

In this method, the following steps are complied with to segment psoriasis lesions from normal skin.

Training Phase

1. From the training input image, crop samples of size w x w from the normal skin region and from psoriasis lesions. Let them be S_N and S_P.
2. Compute the roughness value for both samples using (1). Let $R(S_N)$be the roughness value for the normal skin region and $R(S_P)$ be the roughness value for the psoriasis affected skin region. Find the fuzzy roughness feature vector by using (2)-(4). Let $FR(S_N)$ and $FR(S_P)$ be the

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fuzzy roughness feature vector of the normal skin region and psoriasis affected skin regions respectively.

Segmentation Phase

3. Take a w x w size sample (S_T) from the test image and calculate the roughness value $R(S_T)$ using (1) and convert it into a fuzzy roughness feature vector $FR(S_T)$ using (2)-(4).
4. Check for the similarity of $FR(S_T)$ with $FR(S_N)$ and $FR(S_P)$ using the fuzzy membership distance measure which is explained in the following section.
5. If $FR(S_T)$ is closer to $FR(S_N)$, then mark the pixel as a normal skin area pixel. Otherwise mark it as a psoriasis lesion pixel.
6. Repeat steps 3 to 5 for the entire test image by scanning from left to right and top to bottom using the sliding window method.
7. The final segmented output will contain a separate psoriasis affected region and a normal skin region.

2) Fuzzy Membership Distance Measure:

To compare the fuzzy roughness feature vectors, Euclidean distance measure is used. The procedure for comparing two fuzzy roughness feature vectors is given below:

1. Let S_T be the testing sample, S_N be the normal skin region sample and S_P be the abnormal (psoriasis lesion) skin region sample.
2. Let $FR(S_T)\{_{Normal,\ Medium\ Rough,\ Rough}\}$ be the fuzzy roughness feature vector for testing sample and $FR(S_N)\{_{Normal,\ Medium\ Rough,\ Rough}\}$ and $FR(S_P)\{_{Normal,\ Medium\ Rough,\ Rough}\}$ be the feature vectors of normal skin and psoriasis affected skin samples.
3. Find the Euclidean distance between $FR(S_T)\{_{Normal}\}$ and $FR(S_N)\{_{Normal}\}$, $FR(S_P)\{_{Normal}\}$
4. Find the Euclidean distance between $FR(S_T)\{_{Medium\ Rough}\}$ and $FR(S_N)\{_{Medium\ Rough}\}$, $FR(S_P)\{_{Medium\ Rough}\}$
5. Find the Euclidean distance between $FR(S_T)\{_{Rough}\}$ and $FR(S_N)\{_{Rough}\}$, $FR(S_P)\{_{Rough}\}$
6. Find the closest sample S_N or S_P to testing sample S_T by considering minimum distance between the testing sample (S_T) and S_N or S_P.
7. Based on closeness, the pixel is marked as a psoriasis lesion pixel or a normal pixel.

3) Unsupervised Segmentation

In this method, there is no need to take samples from the training image. Rather, an unsupervised mechanism is used to perform segmentation. The procedure is explained below:

1. Take a w X w size block from the testing image.
2. Compute the roughness value for using fractal dimension formula $R(S_T)$ using (1) and convert it into a fuzzy roughness feature vector $FR(S_T)$.
3. If $\max(FR(S_T)\{_{Smooth,\ Medium\ Rough,\ Rough}\})$ is $_{Smooth}$ then the pixel is segmented as a normal skin pixel. Otherwise, the pixel is segmented as a psoriasis lesion pixel.
4. Repeat steps 1 to 3 for the entire test image by scanning from left to right and top to bottom, using the sliding window method.

C. Psoriasis Severity Level Estimation:

The disease that is psoriasis can be classified into mild, moderate and severe. Two parameters, which are Body Surface Area (BSA) and Psoriasis Area Severity Index (PASI) are commonly used metrics for psoriasis assessment. The PASI metric is used for assessing the severity of the lesions present. Dermatologists take a look at several representative lesions to estimate the severity of the disease. In this work, we have used the roughness value of the affected region to estimate the level of severity. The average roughness value is computed for the segmented lesion area and PASI is scored. The steps are as follows:

1. During the segmentation phase, the average roughness value is calculated for the psoriasis lesion area using the following formula:

$Rough_{avg}$ = Sum of fractal dimension value for all blocks which have been identified as psoriasis lesions / Total number of elements (pixels) in all psoriasis segments

2. Based on the $Rough_{avg}$ value, the severity level is estimated using Table II.

TABLE II
AVERAGE ROUGHNESS RANGE FOR SEVERITY LEVEL ESTIMATION

Average roughness range	PASI roughness description	Severity stage of psoriasis in levels
0-10	Smooth	Normal
11-30	Slightly Rough	Mild stage
31-70	Medium Rough	Moderate stage
71-100	Completely Rough	Severe stage

The roughness value is experimentally computed for well known psoriasis images and the average values are taken. These values may differ, based on the experimental images.

D. Performance Measure

In this section, we present the performance metrics used for evaluating our proposed method for psoriasis skin analysis. The classification accuracy measure is used to evaluate the performance of the classification arrived at using the proposed approach. For evaluating segmentation, we used the common measures which are explained in the following sections.

1) Classification Accuracy

Classification accuracy is computed using (11):

$$\text{Classification accuracy} = \frac{\text{No.of correctly classified images}}{\text{Total no.of images}} \quad (11)$$

2) Segmentation Assessment Measures

In order to assess the performance of the proposed method for segmentation, quantitative measures such as accuracy, error rate, sensitivity and specificity are used. Ground truth images are generated from the input images using expert knowledge which differentiates psoriasis lesion regions from the normal skin regions. The performance of the proposed method is compared with the results derived from the ground truth images. Pixels found in psoriasis lesions and segmented as such, are denoted as true positive (TP). Pixels of psoriasis

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lesions, wrongly segmented as normal skin regions, are defined as false negative (FN). Pixels not shown in lesion regions, and not segmented as lesions, are defined as true negative (TN) classifications. Pixels in normal skin areas, but segmented as lesions are defined as false positive (FP) pixels. Using these parameters, performance measures are computed using the formula given in Table III.

TABLE III
FORMULA FOR COMMON MEASURES

Accuracy	(TN+TP)/(TN+TP+FP+FN)
Error rate	(FP+FN)/(FP+FN+TP+TN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)

IV. EXPERIMENTS AND DISCUSSIONS

In order to evaluate the effectiveness of the proposed approach, we carried out a series of experiments. First of all, we took the roughness feature and analyzed its role in image classification. Then we proved, by means of conducting certain experiments on the texture database, that the roughness feature possesses rotational invariance property by conducting some experiments on texture database. Finally we applied the fuzzy concept to improve the results.

A. Experimental Setup

We conducted a series of experiments to evaluate the performance of our proposed method using a database of skin images. The Skin Image Database has been created with 50 normal skin images and 50 psoriasis skin images. The images are color images in nature. We converted the images into gray scale images and conducted the experiments.

B. Skin Classification

The first experiment was conducted for checking the presence of psoriasis lesion. In training, the fuzzy roughness feature vector is calculated and kept in a feature database. In testing, image features are computed and comparison is made with the training feature set. The image is classified based on the distance measure value. Table IV shows the confusion matrix for skin classification.

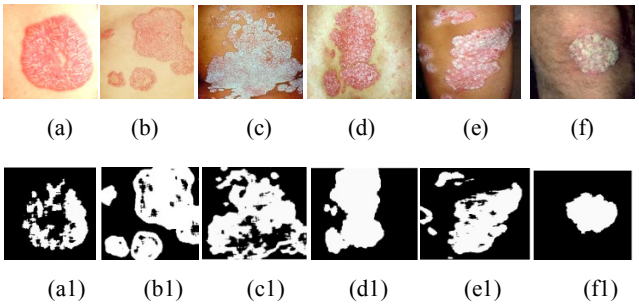
TABLE IV
CONFUSION MATRIX FOR SKIN CLASSIFICATION

Image type (No. of images)	Roughness Feature Approach			Roughness with Fuzzy Approach		
	Classified as normal skin	Classified as psoriasis skin	Accuracy	Classified as normal skin	Classified as psoriasis skin	Accuracy
Normal skin images (50)	48	2	96%	50	0	100%
Psoriasis skin Images (50)	3	47	94%	0	50	100%
Overall accuracy			95%			100%

Classification accuracy using the roughness feature is 95%, whereas we obtained 100% accuracy for the proposed fuzzy based approach. Hence, it is concluded that the proposed method is suitable for image classification, provided there exists a roughness property.

C. Supervised Segmentation of Psoriasis Lesions:

The second experiment was conducted to segment psoriasis lesion areas. We used a set of psoriasis images for analysis. As already discussed, psoriasis analysis is carried out in two phases. The following Fig. 4 contains a set of images with psoriasis [Fig. 4 (a)-(f)] and segmented outputs using the roughness feature are given in Figs. 4 (a1)-(f1). Segmentation outputs using the fuzzy based supervised method are given in Figs. 4 (a2)-(f2). Using the measures given in Table III, the performance of the proposed method (employing supervised algorithm) is evaluated and the results given in Table V.



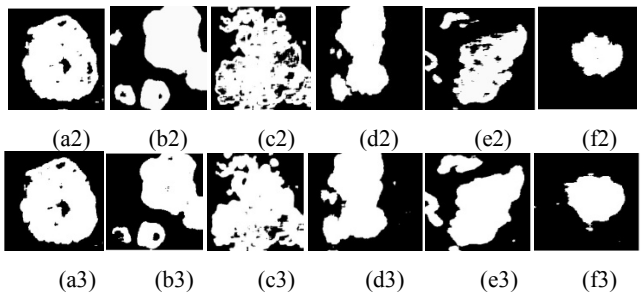


Fig. 4 Segmented Outputs: (a)-(f) Sample psoriasis images used for segmentation; (a1)-(f1) Segmentation output using the roughness feature; (a2)-(f2) Segmentation output using the fuzzy based supervised method; (a3)-(f3) Segmentation output using fuzzy based unsupervised method

D. Unsupervised Segmentation of Psoriasis Lesions

The previous experiment is supervised, since the system needs all the information on normal skin and abnormal lesions. An unsupervised process is required for real- time medical image analysis. In this experiment, we conducted an unsupervised segmentation of psoriasis images and compared it with previous supervised segmentation outputs. Segmentation outputs using the fuzzy based unsupervised method are given in Figs. 4 (a3)-(f3). Using the formula given in Table III, the performance of the proposed method for an unsupervised algorithm is evaluated and the results given in Table VI.

TABLE V
PERFORMANCE OF PROPOSED METHOD USING SUPERVISED ALGORITHM FOR PSORIASIS IMAGE SEGMENTATION

Image	Roughness Feature Approach				Roughness with Fuzzy Approach			
	Accuracy	Error Rate	Sensitivity	Specificity	Accuracy	Error Rate	Sensitivity	Specificity
Image 1	77.17	22.53	49.63	99.59	87.32	12.68	96.70	79.86
Image 2	80.34	19.66	99.23	72.36	88.02	11.98	68.27	94.42
Image 3	75.29	24.71	69.66	82.86	82.59	17.41	92.84	68.82
Image 4	80.48	19.52	75.57	82.82	81.08	18.92	73.15	84.88
Image 5	93.83	6.17	89.06	94.55	94.47	5.53	85.09	95.89
Image 6	75.35	24.65	24.26	83.31	77.79	22.21	18.26	87.07
Image 7	84.65	15.35	69.08	96.31	84.65	15.35	69.08	96.31
Image 8	70.32	29.68	10.78	94.47	70.61	29.39	6.09	96.77
Image 9	91.10	8.90	96.59	88.05	91.71	8.29	90.78	91.34
Image 10	92.24	7.76	97.42	89.71	93.08	6.92	96.65	91.33
Image 11	83.61	16.39	87.65	76.91	83.63	16.97	83.70	81.92
Image 12	86.65	13.35	69.08	96.31	87.94	12.06	62.12	97.53
Image 13	75.93	24.07	45.81	95.03	74.04	25.96	38.56	96.54
Image 14	74.65	25.35	80.29	71.81	75.66	24.34	73.48	76.75
Image 15	74.51	25.49	90.66	69.09	75.09	24.91	85.49	71.59
Average	81.07	18.93	70.32	86.21	85.11	14.89	69.35	87.40

We have tested more than a hundred images for segmentation. For most images, the fuzzy based approach produces improved results, with the ordinary approach. For a few images, both approaches produce uniform results. However, we have computed the accuracy, error rate, sensitivity and specificity for a few images and the values are tabulated. The fuzzy based approach tries to segment those imprecise psoriasis lesion pixels which are otherwise uncovered by an ordinary approach. From Tables V and VI, it is evident that the fuzzy based roughness feature is the best choice for psoriasis image segmentation. The parameters of the membership functions also play a vital role in improving performance. In the unsupervised approach, we obtained 83.08% accuracy, which is lesser than the accuracy obtained in the supervised method.

TABLE VI
PERFORMANCE OF THE PROPOSED APPROACH USING AN UNSUPERVISED ALGORITHM FOR PSORIASIS IMAGE SEGMENTATION

Image	Accuracy	Error Rate	Sensitivity	Specificity
Image1	84.67	15.33	98.20	74.42
Image2	85.80	14.20	90.67	83.39
Image3	82.68	17.32	89.35	73.72
Image4	79.47	20.53	77.91	80.22
Image5	90.90	9.10	93.65	90.48
Image6	80.28	19.72	93.87	74.73
Image7	93.06	6.94	90.40	93.51
Image8	73.35	26.65	58.26	65.41
Image9	86.16	13.84	99.90	75.84
Image10	89.62	10.38	98.29	85.37
Image11	82.43	17.57	92.14	66.30
Image12	83.34	16.66	98.34	62.25
Image13	80.84	19.16	65.93	87.63
Image14	78.43	21.57	85.80	70.20
Image15	75.18	24.82	89.77	70.28
Average	83.08	16.92	88.17	76.92

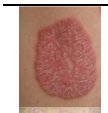
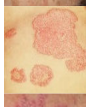
The results obtained in Table VI indicate that the performance of the proposed method is most encouraging.

E. Psoriasis Severity Level Estimation:

In order to score the Psoriasis Area Severity Index, the average roughness value is computed for psoriasis lesion areas. The average roughness value will be higher in severe cases and lower in mild cases. Based on the ranges given in Table II, the severity stage of the disease is estimated. Table VII shows psoriasis affected images with varying degrees of severity.

The assessment has been made by experts in this field, who fully concur with the categorization set forth above. The ranking order obtained from our experiment is very closely connected to the assessment arrived at.

TABLE VII
PSORIASIS IMAGES AND THEIR SEVERITY STAGE

Image	Roughness Index	Severity Stage	Image	Roughness Index	Severity Stage
	6.06	Moderate		66.19	Moderate
	41.59	Moderate		56.91	Moderate
	42.45	Moderate		67.32	Moderate
	50.74	Moderate		77.93	Severe
	23.05	Mild		22.41	Mild

V. CONCLUSION

There are limited methods available for segmentation of psoriasis lesions. To the best of our knowledge, the roughness feature has not been so far for psoriasis image analysis. From Tables IV and V, it is clear that the fuzzy roughness feature is

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a good choice for skin image classification as well as psoriasis image analysis.

The results given in Tables V and VI indicate that the performance of the proposed method is encouraging, even if the skin images are similar in appearance. The use of the fuzzy helps improve accuracy in terms of classification and segmentation. Going forward, this work will be extended to calculate other factors such as erythema and the thickness of psoriasis lesions and will comprehensively cover color images too.

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