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Computer-aided diagnosis psoriasis lesion and other skin lesions using skin texture features and combination

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ABSTRACT

Psoriasis is one of the weakening and persisting incendiary skin lesions. Frequently confused as a casual skin thickness, it is evaluated that approximately 125 million people overall endures because of this disease. The case is exacerbated when there is no known cure in the status norm. The common classification of psoriasis has been considered as unexpectedly separated, scaly and erythematous plaque at patient's skin. This lesion could follow anyplace on the human body. Diagnosis of psoriasis requires an experienced specialist in the field of dermatology because of the presence of other skin diseases similar to a large extent which lead to majority cases of an error in diagnosis. The purpose of this study is to establish a diagnosis system of psoriasis lesion to ease the role of the physician in diagnosis by providing better and more reliable results, to support the expert's decision to diagnose the lesion, especially doctors with little experience. In this paper, the researcher is interested in the diagnosis psoriasis lesion by using texture features and combination. Aggregate 220 image samples (70 healthy, 50 other skin lesions and 100 diseased) of psoriasis patients are used in our database. Machine learning approaches like Artificial Neural Network (ANN) classifier and Support Vector Machin (SVM) are used to obtain optimized performance. The proposed Computer-Aided Diagnosis (CADx) system shows optimal performance of 90.9% accuracy, 86.9% sensitivity and 87.7% specificity for texture feature combine RGB-Local Binary Pattren, Color Coocurrance Matrix and Gabor filter algorithms. CADx system became a tool for physicians and therefore it is important to have accurate and reliable CADx system. The presented texture features powerful in psoriasis disease classification. The experiments for all the aforementioned feature combination models using a combination of color and texture provide accurate results than using the single feature.

Keywords: classification; texture features; combination; color-texture feature; Psoriasis lesion disease; color images;

1. INTRODUCTION

Psoriasis is a constant skin disease influencing around 125 million individuals overall [1]. The predominance of psoriasis in various topographical areas, for example, Europe, USA, Malaysia and India are around 0.6% to 6.5% [2], 3.15% [2], 3% [3] and 1.02% [4], respectively. It can impact the patients' personal satisfaction because of its humiliating physical appearance [5]. This outcomes in expanded danger of thinking about suicide (~ 30%) which makes it a similarly hazardous sickness at standard with misery, coronary illness and diabetes [6]. Psoriasis shows up in an assortment of structures, specifically plaque, guttate, inverse, pustular, and erythrodermic. In 80% of the cases, plaque is observed to be the most widely recognized types of psoriasis [7] and in this manner the work displayed in this paper is engaged in five sorts of psoriasis lesion. Dermatologists by and large take after visual examination and the feeling of touch to anticipate the seriousness which requires talented preparation for better determination and investigation. Still the subjective appraisal is wasteful, unreliable and a difficult procedure. Subsequently, a Computer-Aided Diagnosis (CADx) system could be valuable in clinical applications. Throughout the years, researchers created a considerably lot of CADx systems for the diagnosis of different skin lesions pictures. The model diagnosis psoriasis lesion vs. other similar skin diseases psoriasis lesion, the model must be with high accuracy because wrong diagnosis is dangerous for patient's life. The proposed support system with more features depending on the texture features will give higher accuracy. These features are interactive for distinguishing between psoriasis lesion vs. other skin lesions.

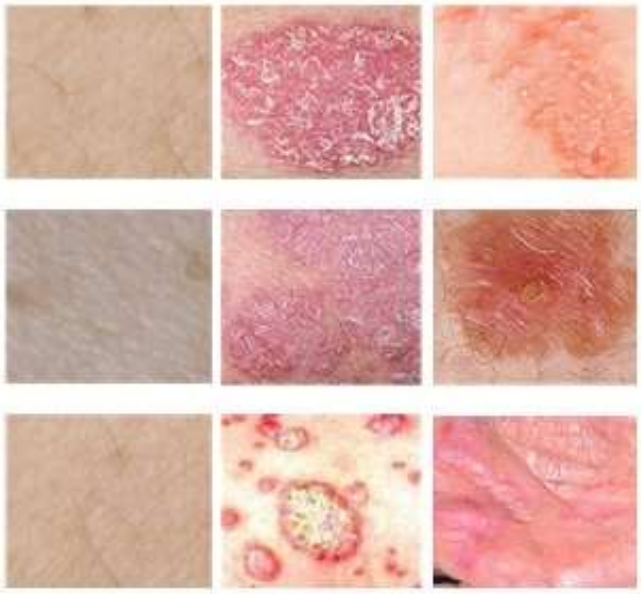
2. RELATED WORK

In diagnosis of skin lesions using image processing the important task is to detect the skin. In addition, the ANN can be effectively used to work with medical images in correct skin lesion diagnosis. Vimal K. Shrivastava et al [4] presented a review on the CADx system for psoriasis lesion severity risk stratification. In the introduced study, the goal is to present the psoriasis CADx a system utilizing distinctive different feature sets. Jason Brand et al [8] presented comparasion of three different methods for skin detection. Researchers utilized simple ratios and color space transforms and numerically efficient approach based on a 3-D RGB probability map. Anal Kumar Mittra et al. [9] Low cost and effective automatic system for recognizing lesion conditions of human skin had proposed by analyzing skin texture images utilizing a set of normalized symmetrical Gray Level Co-occurrence Matrices. Where the color and texture features play important role in diagnosis of skin diseases. 2013, Al Abbadi et al. [10] utilized skin color and texture features to classify skin texture from non skin texture.

3. MATERIALS AND METHODS

3.1 Materials

In this research work, we have gathered colored imageries from the psoriasis section of Ramadi teaching Hospital, Ramadi, Anbar under the supervision of a dermatologist. The images were processed in Joint Photographic Expert Group (JPEG) format with color depth of 24 bits per pixel. For this work, a total of the image includes 220 psoriasis color images that amounted in a total of 120 samples (70 normal and 50 other skin diseases (Eczema, Herpes Zoster, Scarlet Fever, Measles and skin cancer)) and 100 psoriasis lesion cases with 200*200 pixels. Figure 1 shows the samples of the skin.



(a) (b) (c)

Figure. 1 (a) Normal skin. (b) Abnormal skin (Psoriasis lesion). (c) Other skin lesions (Eczema, Herpes Zoster, Scarlet Fever, Measles and skin cancer)

3.2 Methods

3.2.1 The proposed framework

Computer-Aided Diagnosis (CADp) framework is proposed by utilizing color and texture features and their combinations. There is an aggregate of 220 image samples in our database. Machine learning approaches like ANN and SVM classifiers are used to obtain optimized performance and comparisons between results. Combinations of features are powerful in psoriasis lesion classification, when combined, the machine learning model performs the best.

The model is automated, reliable and accurate. We have formed sets of feature combinations of features for accurate classification. Our CADp uses the machine learning paradigm based on ANN and SVM classifieers as shown in Figure 2.

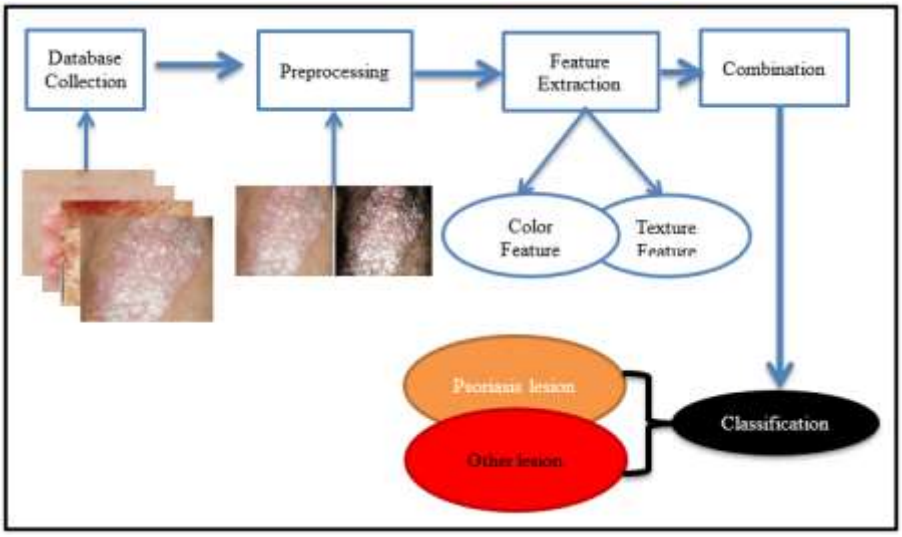


Figure. 2 Proposed system for the psoriasis lesion diagnosis

a) Feature extraction

Feature extraction generally derives features according to the classification guidelines of the current problem. The derived features are called the raw features, and there is the difference between the abnormality segmentation and the diagnosis decision making problems. For the abnormality segmentation task, directly extracted features from images include color and texture. Color features are descriptors of the color information digitized by an imaging modality, and texture features describe regional color intensity changes and color correlation. In this stage, extracting characteristic of the initial set of measured data and building derived values (features) is intended to be a useful and non-redundant, the purpose is to facilitate the learning and dissemination of the subsequent steps leading to a better explanation. The feature extraction in the field of image processing is useful in classification and recognition of images [11, 12]. The main objective of the model is to compare the color and texture features in the classification of psoriasis disease vs. other skin diseases framework. Figure 3 shows the feature extraction stage.

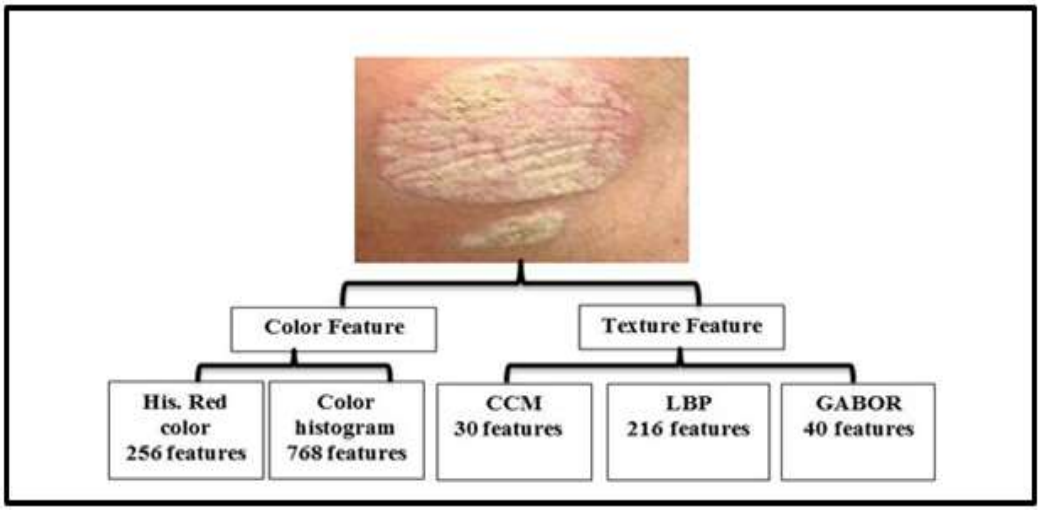


Figure. 3 Feature extraction with different algorithm

We have made fourteen sets of feature and their combinations of five color and texture sets of features, i.e., (1) RED COLOR + THREE COLOR (FC1); (2) CCM + GABOR (FC2); (3) LBP + GABOR (FC3); (4) CCM + LBP + GABOR (FC4); (5) CCM + LBP (FC5); (6) THREE COLOR + CCM (FC6); (7) THREE COLOR + CCM + GABOR (FC7); (8) THREE COLOR + CCM + LBP + GABOR (FC8) and (9) RED COLOR + THREE COLOR + CCM + LBP + GABOR (FC9). We have performed nine experiments for all the afore-mentioned feature combination models using a combination of color and texture would provide accurate results than using the single feature.

a) Texture features

The purpose of a texture feature is to describe a textured zone with, at least, one numerical value. In an ideal scheme, two different textures will have two different values for one given feature. Unfortunately, this rarely happens because usually the discriminating power of each texture feature has been strongly dependent on the kind of treated textures. In a research, four principal texture feature families are identified: statistical methods, geometric methods, model-based methods and, finally, frequency-based methods [13]. There exist different approaches to extract and represent textures. They can be classified into space-based, frequency-based models, and texture signatures. Some popular techniques like wavelet transform, co-occurrence matrix, and Gabor filters are applied to express texture features for image [14]. Major goals of texture research in computer vision are to understand, model and process texture [15]. In this paper, Gabor filter, Color Co-occurrence Matrix (CCM) and Local Binary Pattern (LBP) are used to extract the texture feature of psoriasis lesions images**.** CCM and LBP methods achieved high accuracy to classify psoriasis lesions. Texture analysis has been an active area of research in pattern recognition. A variety of techniques have been used for measuring textural similarity.

b) Conversion to grayscale

The color image of the psoriasis lesion is converted into a grayscale image by behavior hue and saturation. Equation. 1 is used to convert RGB values to grayscale values by forming a weighted sum of R, G and B component, see Figure 4.

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$

Where R, G, B are red, green and blue components of the input color image, respectively.

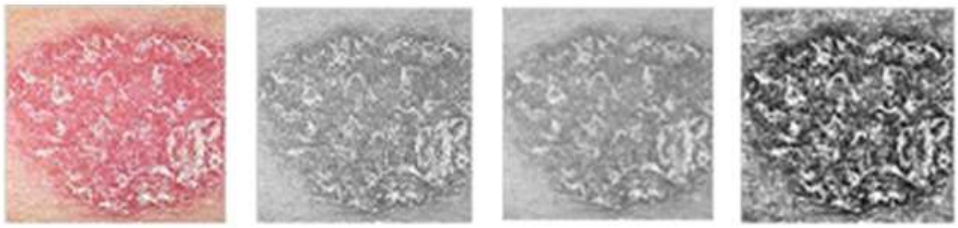


Figure. 4 (a) Color image. (b) Grayscale image. (c) Median filter. (d) Adaptive histogram equalization filter

c) Gabor filter feature

Gabor filters are often used in texture analysis to provide features for texture classification and segmentation [16, 17]. The Gabor filter takes the form of a 2D Gaussian modulated complex sinusoidal grating in the spatial domain [16]. Gabor filters have long been used in the analysis of texture in images [18-20]. Briefly, given a Gaussian distribution function $exp\left(-\frac{(x'^2+\gamma'y'^2)}{2\sigma^2}\right)$, called the envelope, with standard deviation and spatial aspect ratio, and a complex sinusoidal $exp(i(2\pi x'/\lambda+\psi))$, called the carrier, with spatial frequency $1/\lambda$ and phase shift, the Gabor filter is defined by:

$$g(x,y;\gamma,\sigma,\lambda,\psi) = \exp y(-\frac{x'^2+\gamma^2y'^2}{2\sigma^2}\exp y(iy(2\pi\frac{x'}{\lambda}+\psi)) \quad (2)$$

Where $x' = x\ \cos\theta + y\ \sin\theta$ and $y' = x\sin\theta + y\cos\theta$, is the rotation angle. The response of the Gabor filter is obtained by computing the convolution of the filter to the image.

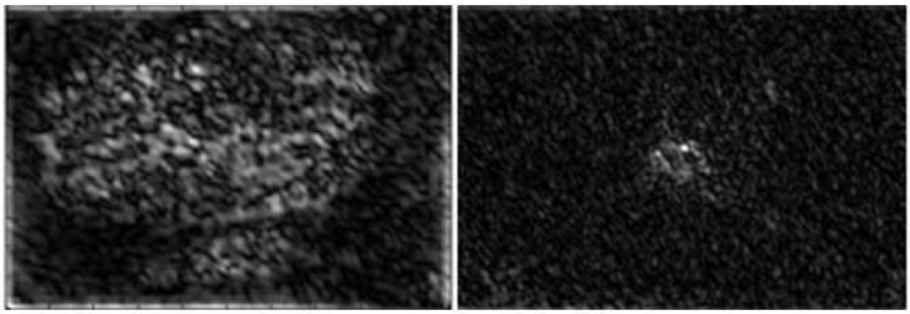
$$r_{x,y} = \iint_{\Omega} I(\mu, \eta) g(x - \mu, y - \eta) d\mu d\eta \quad (3)$$

Where Ω is the set of image points. The response has both real and complex parts that we denote here by $Re(r_{x,y})$ and $Img(r_{x,y})$. The Gabor energy $E_{x,y}$ is defined as the magnitude of the Gabor filter response [18].

$$E^2_{x,y} = Re(r_{x,y})^2 + Img(r_{x,y})^2 \quad (4)$$

In this paper, we use the square of the Gabor energy because it is better in accentuating the differences between scaling in psoriasis lesion and other skin diseases than the more commonly used Gabor energy. The response is highest when the image intensity frequency is close to the Gabor filter. For smooth other skin diseases and normal skin the image intensity is relatively homogeneous and is not sensitive to Gabor filters. For rougher scaly skin, the change of intensity is relatively high. Further, the choice of the standard deviation of the Gaussian envelope depends on the spatial frequency 1/λ, σ= 0.56λ. It is based on the assumption that each texture contains its highest energy in a narrow frequency as given in [21].

Scales are an important feature characterized by psoriasis and is an important factor in the diagnosis of psoriasis lesion from other skin diseases similar to them. Thus, we used the Gabor filter, the Gabor texture highlights difference between the rough scaling in psoriasis lesion and smooth scaling in other skin diseases or normal skin shown in Figure 5. Gabor filters are very sufficient for segmenting scaling of normal skin and then extract features of every filter, especially when the color difference between the two is small. Scaling is presented as a rough textured surface in 2-D images that distinguishes it from the more smoothly textured normal skin and other skin diseases. The rough texture of scaling combined with other features provide a good combination of features for diagnosis of psoriasis lesion vs. other skin diseases. Gabor filters are used to analyze the roughness of the scaly texture. A bank of Gabor filters is designed to differentiate different kinds of scaling from normal skin. The filtering results are fused into a gray-scale Gabor texture image, in which rough scaling has a higher intensity value than other skin lesions. The variations in the textures of scaling of psoriasis lesion, normal skin and other skin diseases in different lesions and in different people make the choice of one single Gabor filter unlikely. The algorithm uses a bank of 20 Gabor filters designed to respond well in a variety of skin and scaling texture conditions. ***5*** scales at different frequencies and 4 orientations every 45º degrees are θ=0, π/4, π/2 and 3π/4 are created. The bank of Gabor filters is applied to the image and the results are integrated into a single Gabor texture image using the technique given in [21]. First, the square of the Gabor energy image is filtered using a hyperbolic tangent to narrow the range. Second, the Gabor texture image is obtained by summing the smoothed output over all of the rotation angles and frequencies of the Gabor filters. Finally, we calculated mean and standard derivation for every filter at one orientation. The results of the 40 features of image are saved in a matrix to enter to NN and SVM classifiers. An example of a Gabor feature image is shown in Figure 5. Scaling has a high Gabor filter response while the normal skin and other lesions have a markedly lower Gabor filter response. The summation in the final step preserves the differences between the higher response from scaling and the lower response from normal skin and other skin diseases. However, the scaling presented as a rough textured surface in 2-D images that distinguishes it from the more smoothly textured normal skin and other diseases than psoriasis lesions. The rough texture feature of scaling is combined with other features (texture or color) to provide a good combination of features to diagnose psoriasis lesions.



(a) (b)

Figure. 5 (a) Gabor feature for psoriasis image. (b) Gabor feature for other skin diseases image.

d) Classification phase based on NN and SVM

Machine learning involves adaptive mechanisms that enable computers to learn from experience, learn by example and learn by analogy simulated human's brain. One of the main methods of machine learning is an Artificial Neural Network [22]. Classification is an important stage in identifying psoriasis lesion vs. other skin diseases. In classification, classifier is used for object recognition and classification. The classifiers recognize the object and classify based on the extracted features of an image given as an input. The objective of the step is to classify psoriasis lesion and other skin diseases. After preprocessing, features are extracted as feature vector and stored, there comes the diagnosis step. In our work, ANN is used to distinguish psoriasis lesion and other skin diseases along with SVM. The performance of ANN relies on the network architecture. Algorithm 1 describes the steps of a ANN.

Algorithm. 1: NN Classification
Input: A vector of combination texture features. ***Output: Total accuracy from the NN.*** ***Goal: Classification into psoriasis lesion or not.***
Step1: Loading of feature matrix. ***Step2:*** Creating a feed-forward neural network with one hidden layer, 60 neurons, the input layer of the neural network is identified by characteristics of the inputs. We have 286 feature vector. Therefore, the number of neurons in the input layer is 286, and output layer neurons are determined by the number of classes, we have two classes (psoriasis lesion vs. other skin diseases) therefore the number of neurons in output layer is two. ***Step3:*** Divide the available data into training, validation and test data. ***Step4****:* Determine the important parameter, learning rate equal to 0.00001, epochs equal to 10000, maximum number of iterations, training times infinity, data division function (divide rand), transfer function of ith layer hyperbolic tangent sigmoid transfer function is used 'tansig', the linear activation function is selected for output layer 'purelin', performance function, default = 'mse 'and training function is backpropagation function, weight and bias are generated randomly. ***Step5:*** Train the network by train data and target matrix, target matrix is a matrix with two rows and two columns, each row consists of a vector of zero values except a 1 in element i, where i is the class they are to perform. ***Step6:*** Simulate the neural network by taking the initialized net and a network input matrix (train data), return the indices to the large output as a class predict. ***Step7:*** Evaluate the model using the validation set by computing the network performance**.** ***Step8:*** Simulate the neural network by taking the training net, validation data and test data, return the indices to the large output as class predict. ***Step9:*** Assess this final model using the test set by computing the network performance**.**

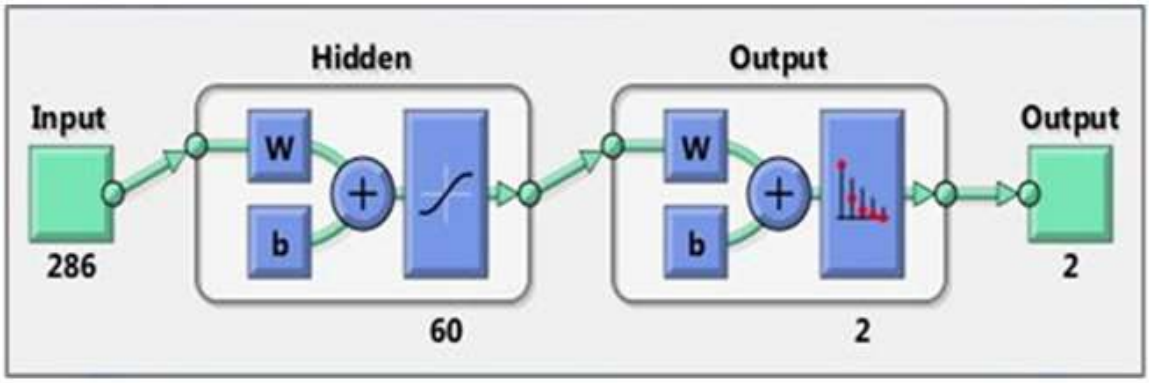


Figure. 6 Structure of neural network for psoriasis lesion vs. other skin diseases

Figure 6 shows the network structure with one input layer, one hidden layer and two output layer. It is the 286×60×2 network structure. The input vector is 286. The output vector is two. This research uses the above ANN architecture, feed-forward backpropagation learning algorithm to generate, train and test the neural network for psoriasis lesion diagnosis. MATLAB software with its neural network toolbox is used. Data sets are portioned into three subsets, training set, validation set and testing set. The network gives high accuracy when train is equal to 90.1%, validation equal to 81.8 and test equal to 83.0% with a simple training time equal to (1 second) at 39 epochs with best validation performance is 0.2962 at epoch 33 as shown in Figure 7.

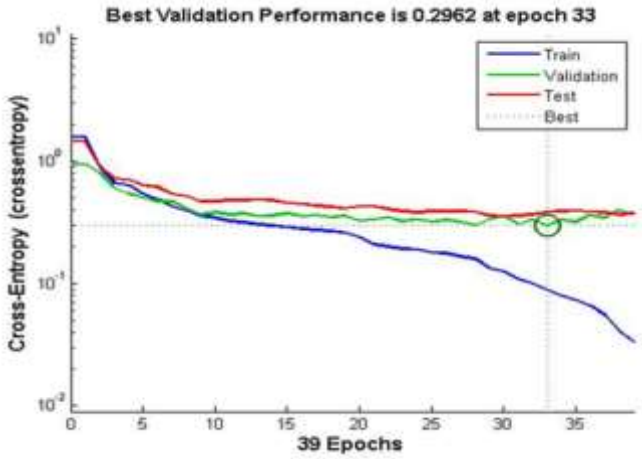


Figure. 7 Neural network training, validation and testing performance

Table 1 refers to all the classification results when testing the program by using texture features, a color feature separately and combine features at training, validation and testing phases. The proposed model achieved high success rates during the classification stage and determined the type of disease if the psoriasis lesion vs. other skin diseases, when testing the program by using texture features combination (CCM+LBP+GABOR) at the training, validate and test phases give higher accuracy of 90.9% classification results in case of NN.

Table. 1 Classification accuracy of psoriasis vs. other skin lesions by using ANN and SVM

Features Type	*ANN Accuracy*	*SVM Accuracy*
RED COLOR HISTOGRAM	76%	72.7%
THREE COLOR HISTOGRAM	78%	76.1%
GLCM	54.5%	55.6%
CCM	87%	77.2%
LBP	59%	73.8%
GABOR	73%	73.8%
FC1	87.7%	76.1%
FC2	84.1%	82.9%
FC3	86.8%	75%
FC4	90.9%	69.3%
FC5	71.1%	78.4%
FC6	62.7%	72.7%
FC7	80.5%	77.2%
FC8	77.7%	80.6%
FC9	88.2%	79.5%

e) Fusion implementation

The fusion process implementation improves system accuracy for diagnosis of psoriasis lesion.

f) Texture features fusion

Figure 8 shows the classification accuracy for every feature separately and combination texture features in Table.1, fusing texture features derived from different methods, the combination texture features have the highest efficiency that improves the classification rate.

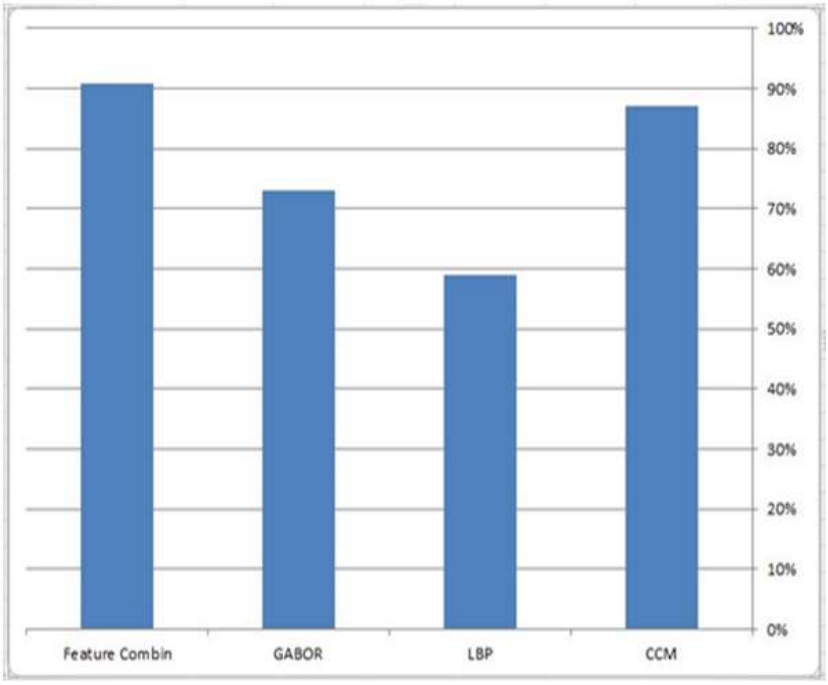


Figure. 8 Improved classification accuracy with feature combination

g) Data analysis

From a dermatologist's point of view, wrong diagnosis of psoriasis lesion is dangerous, harmful and sometimes fatal due to taking high doses of treatment. Also, the re-diagnosis results in high financial losses. From the other hand, if a patient with a psoriasis lesion disease is diagnosed to be healthy or even sick with other skin diseases, the patient may only need to do another future doctor visit for further examination. And that can only add the doctor visit fee. The accuracy of our model depends on two important factors: texture and color features. There are three texture features and two color features that were classified separately and combined in this research. The highest accuracy of 90.9% was achieved from using the combined texture features. Data training set of 110 samples and data testing set with 88 samples were used in the proposed model. Based on an experienced doctor examination, the test samples were characterized and 39 of which were labeled with psoriasis lesion, 27 were labeled as healthy skin and the rest of the 22 samples were diagnosed to have other skin lesions. The goal of this research is to correctly diagnose the non-psoriasis lesion samples, otherwise the patient will be at risk of taking harmful medication for treating non-existed illness. In our proposed model, only 6 samples out of 49 were mistakenly diagnosed to have psoriasis lesion as shown in Figure 9. Those same 6 samples were also diagnosed by another doctor to have a psoriasis lesion. Moreover, the same doctor didn't give a decision to another 4 samples that shouldn't have a psoriasis lesion as shown in Figure 10. He would need a physical patient presence and more information about the patient, such as the family health history. The disease diagnosis can be different from one doctor to another, depending on the doctor experience.

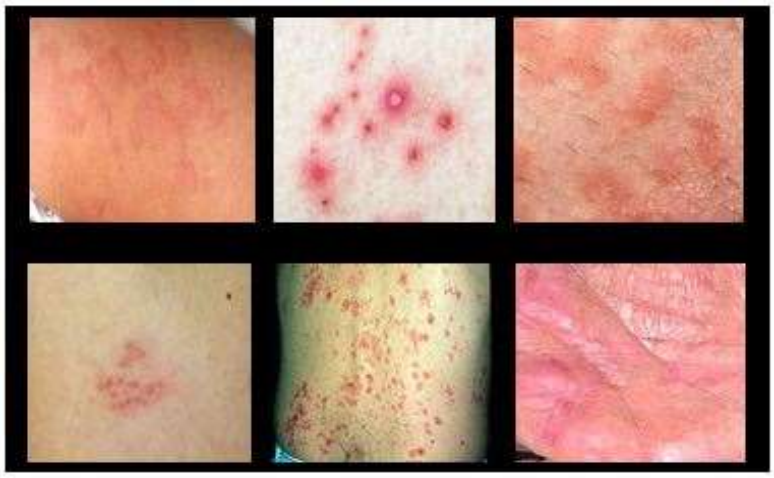


Figure. 9 Six samples have two diagnoses (psoriasis lesion and not psoriasis) by two dermatologists. Our proposed model decision is psoriasis lesion

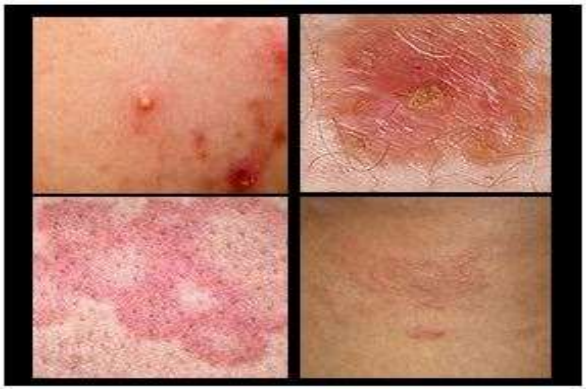


Figure. 10 Four samples the dermatologist and our model diagnosis not psoriasis. The other doctor is unable to make the decision

The main challenge in psoriasis lesion a color feature imaging in in this research is associated with the similarities to other skin diseases in many properties such as the red skin and scaling (white pixels) which makes the diagnosis very hard to rely on the color features only.

h) Performance evaluation measure for psoriasis lesion recognition

When classification is done results may have an error rate, whether to fail to identify a psoriasis lesion vs. other skin lesions.

Table. 2. Show overall performance assessment of the proposed ANN for diagnosis model psoriasis lesion vs. other skin disease.

	Combine texture classification NN	Combine texture classification SVM
Sensitivity	86.9%	75%
Specificity	87.7%	67.1%
PPV	83.3%	46.1%
NPV	82.6%	87.7%
Accuracy	90.9%	69.3%

The system passed all the significant tests ensuring all classification parameters such as sensitivity, specificity and accuracy for all feature set. Further, it shows the dominant strong behavior of texture features. Overall, this research shows encouraging results and confirms the ability to develop a CADx system for diagnosis of psoriasis and its clinical translation.

4. CONCLUSIONS

This paper presented a Computer-Aided Diagnosis system for psoriasis image classification using different feature sets like texture, color and combination. As in today's world, CADx system became a tool for physicians and therefore it is important to have accurate and reliable CADx system. Classification psoriasis lesion vs. other skin diseases similar psoriasis diagnostic system using computer based techniques is more efficient than the conventional biopsy methods. The cost involved as well as the time taken for detection is less in this proposed methodology. These systems will be a great help in diagnosis of lesions for faster, inexpensive, more intuitive and efficient treatment. Support Vector Machines (SVM) have generally produced better results, but it is more difficult to find the optimal parameters which give the best results. For this reason it usually takes longer time to produce a good SVM model than an ANN model, ANN gives higher accuracy than SVM.

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