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PATTERN CLASSIFICATION TECHNIQUES FOR THE CLASSIFICATION OF CUTANEOUS MANIFESTATIONS OF SYSTEMIC LUPUS ERYTHEMATOSUS

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ABSTRACT

Systemic Lupus Erythematosus-lupus (SLE-Lupus) is the prototype of multiorgan autoimmune rheumatic disorders with life threatening systemic manifestations and there is no gold standard test for the diagnosis of SLE. Pattern classification techniques are used to classify the images of SLE and their performances are evaluated. A total of images of 400 patients (200 SLE and 200 normal) are collected from various hospitals available in Tamilnadu state of India, for this experimental study. Features are extracted from these images based on color histogram and texture. Two different classifiers are considered in this study, namely, multilayer perceptron and support vector machines. Experimental results show that the multilayer perceptron model provides higher accuracy of 86.25% than other model, support vector machine for SLE identification.

Keywords: Systemic lupus erythematosus (SLE), cutaneous manifestation, Classification, histogram and texture features, multilayer perceptron (MLP), support vector machines (SVM)

INTRODUCTION

Systemic lupus erythematosus (SLE) is a systemic autoimmune disease such that one's own immune system itself affects the body tissues.It affects young women in their 20's to 30's, predominantly affecting in their child bearing age, however it can also occur in children and elderly. Most of the lupus patients have cutaneous manifestations. Lupus skin manifestations are classified into lupus-specific lesions (e.g., malar rash) and non-specific skin lesions (e.g., alopecia) [Gilliam et al., 1982]. Lupus-specific is classified into three major subtypes: systemic or acute cutaneous lupus erythematosus (ACLE), subacute cutaneous lupus erythematosus (SCLE) and chronic cutaneous lupus erythematosus (CCLE) [Font et al., 1990]. Culture, Environment and genetics make variance in incidence and disease severity among various racial and ethnic groups [Mc Cauliffe et al., 2001]. The diversity in the skin lesions ranges from malar rash, discoid lupus to alopecia, oral ulcer, bullous lesions etc. [Laman et al, 1994]

The American College of Rheumatology (ACR) published 11 criteria as a classification tool for identifying the SLE in patients [Tan et al., 1982]. Cutaneous lesions make up to four of the 11 revised ACR criteria of SLE. Lupus-specific skin lesions can be easily diagnosed whereas lupus non-specific skin lesions are associated with failure of multiple organs and hence continuous monitoring of patients is required [Zeevi et al., 2001]. Thus, a rheumatologist should individually evaluate the patients based on the clinical and diagnostic criteria for effective diagnosis and treatment.

Color is an important feature for image analysis and classification. Color histogram technique is widely used to extract the color features of an image [Zhao et al., 2009]. It is used to find out the color bins frequency distribution in an image. Pixels of similar intensity are counted and stored. As color histogram is insensitive to even smaller variations in the image, it is very important for analysis of images [Han et al., 2002]. In addition to color histogram, spatial histogram can also be used for image processing and analysis [Rao et al., 1999]. The various texture descriptors derived using GLCM can be fused and have been tested for different medical image classification problems [Nanni et al., 2001]. Texture features namely, local binary patterns (LBP), speeded up robust feature (SURF), histogram of oriented gradients (HOG), and scale-invariant feature transform (SIFT) are extracted using Gabor filters. The Gray -Level Co-Occurrence Matrix (GLCM) descripttors or second order texture descriptors are extracted by considering the relationship between the two neighbouring pixels [Shrivastava et al., 2015]. The features extracted are classified using different classification techniques such as Neural networks [Saravanan, 2016] and Fuzzy logic [Kowsigan et al., 2017]. A framework for SLE image classification is proposed based on color histogram and GLCM features and it is tested using image datasets. Summarizing, our goal is to achieve an effective and efficient image classification system for assisting the rheumatologist for disease diagnosis by extracting significant features which are more discriminate for classification.

MATERIALS AND METHODS

Data set and preprocessing: Patients who satisfied ACR classification criteria for SLE are chosen and their respective images are collected from various hospitals in Tamilnadu. A sample of 200 SLE images and 200 normal images are taken into this experimental study. A total of 400 image samples are taken to classify the images into SLE (affected) and Non-SLE (normal). Samples of cutaneous manifestations of SLE images are shown in figure 1. The first step in analyzing the image is pre-processing. Here the unwanted distortions in the image are removed in order to improve the efficiency of our framework. A nonlinear digital filtering technique called Median filter is applied to remove the noise. The median filter simply replaces each and every pixel by the median of all neighborhood pixels and is given in equation (1).

$$y[m,n] = median\{x[i,j],(i,j) \in w\} \quad (1)$$

Where **w** represents neighborhood pixels, [m, n] represents the center location of the image.

Fig. 1: cutaneous manifestation of SLE patients

Methodology: The objective of the paper is to extract the histogram and texture features from various images in HSV color space and to compare and analyze the performance of the two classifiers MLP and SVM for the extracted features of images. The proposed work architecture to classify the images is illustrated in figure 2. The proposed cutaneous SLE images classification framework consists of three stages: (i) Pre-processing using median filtering technique to remove the noise from the image. (ii) Feature extraction process which is used to extract the histogram-based features and texture-based features in the HSV color space for the images (iii) classifiers, MLP and SVM are used to classify the images into SLE and Non-SLE. The performance of the two classifiers is evaluated using performance measures such as accuracy, sensitivity and specificity along with receiver operating characteristic curve (ROC) by means of area under the ROC curve (AUC).

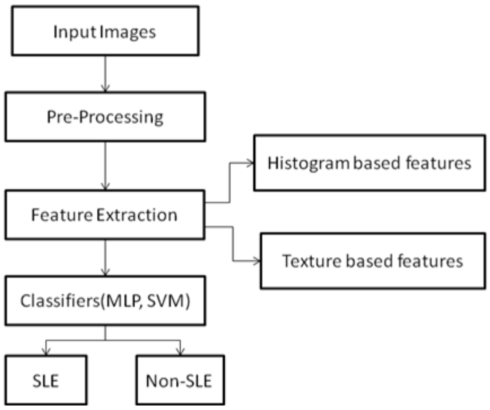


Fig. 2: Proposed work architecture to classify the images.

Feature Extraction: Feature extraction is the process of extracting a set of informative features from the image which is important for analysis and classification. In the proposed work, histogram-based features and the texture features are used to define the feature descriptors. A total of 39 features for HSV color space are extracted from the cutaneous SLE images and provided as an input to the classifiers. These 39 features consist of 3x13 features (5 Histogram features and 8 texture features) for each channel of a color space. The features extracted from HSV are shown in Table 1.

Table 1: Features extracted for classification of images

Histogram based features	Texture features
Mean Variance Skewness Kurtosis Energy	Autocorrelation Contrast Cluster Prominence Dissimilarity Energy Entropy Sum average Sum variance

Histogram based features: Color features provide highly informative regions for image analysis and understanding. The characteristics of the histogram are closely related to the characteristics of the image such as brightness and contrast within a region of histogram distribution of the image is computed. The first order statistical texture features are extracted from SLE images for each channel of HSV. The features of mean, variance, skewness, kurtosis, and energy are calculated based on the probability distribution of the histogram intensity levels. For each channel of HSV color space, these 5 features are extracted.

Texture based features: Texture is a very important characteristic for analyzing the images. The second order statistical texture features are extracted using Gray-Level Co-occurrence Matrix (GLCM) method. The GLCM function extracts the texture features by calculating the spatial relationship with the pair of pixels with specific values, creating a co-occurance matrix. From this matrix, the statistical texture measures are extracted. In order to extract the color texture features, the color images are decomposed into three channels obtaining three different images. The texture features are extracted for each channel of HSV color space. 8 features namely, contrast, autocorrelation, dissimilarity, cluster prominence, energy, entropy, sum average and sum variance are evaluated.

Classification Techniques: Classifiers, Multilayer Perceptron and Support Vector Machine are used to classify the images using the features extracted from it.

Multilayer Perceptron: Multilayer perception (MLP) is a technique that is used to map the input information into desirable results. AMLP consists of three layers, input layer, hidden layer and output layer, every single layer is totally linked with the next layer. The architecture of multilayer perceptron is shown in figure 3. Nodes in the hidden and the output layer are processing elements that contains a non-linear activation function. Each unit carries out the weighted number of their inputs and passes into activation level (unipolar sigmoid function) to generate their output. A multilayer perceptron may include multiple intermediate layers [Samundeswari et al., 2017]. In the proposed approach, the MLP architecture contains 39 nodes in the input layer, only one hidden layer of 20 nodes and 2 nodes in the output layer. The approach uses the feed forward topology.

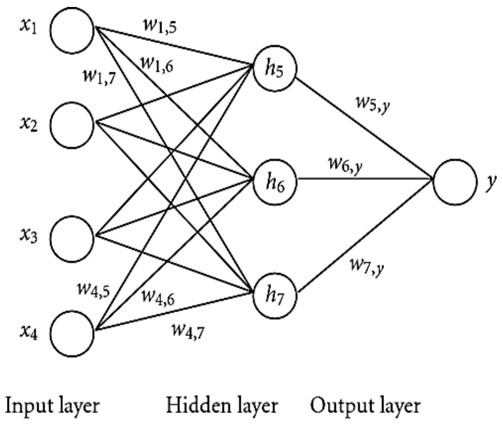


Fig. 3: Architecture of Multilayer percepron

Support Vector Machine: SVM is one of the classification algorithms, shown good performance in different varieties of classification tasks. SVM is used to classify both linear and nonlinear data [Shrikant Burje et al., 2016]. SVM maps the input data to a high dimensional feature space and a maximum margin hyperplane is constructed.

RESULTS AND DISCUSSION

In this work, images of patients are collected for analyzing and evaluating the performance of the classifiers for identifying the lupus. Features are extracted from the images based on color histogram and GLCM in HSV color space. Feature extraction is done using MATLAB software. The classifiers, MLP and SVM (with polynomial kernel) are trained to produce the required output for the given input features. The training and testing are done using 10-fold cross validation. The WEKA tool is used for the classification. The performance indicators, precision, recall, specificity and accuracy are used to evaluate to classify the images into SLE (affected) and Non-SLE (normal) to find the performance given by the said classifiers.

$$Precision = TP / (TP + FP) \tag{2}$$

$$Recall = TP / (TP + FN) \tag{3}$$

$$Specificity = TN / (TN + FP) \tag{4}$$

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \tag{5}$$

Where TP (True Positive) represents the number of SLE images correctly classified, FP (False Positive) represents the number of SLE images that are misclassified, FN (False Negative) represents the number of Non-SLE images that are misclassified, and TN (True Negative) represents the number of Non-SLE images correctly classified.

Performance Evaluation: Table 2 represents the precision and recall values of the classifiers. Figure 4 is graphical representation of Table 2. One can infer from the figure 4 that MLP outperformed over the other classifier SVM (with Polynomial Kernel).

Table 2: Classifiers with Precision and Recall values

CLASSIFIERS	PRECISION		RECALL	
	SLE (%)	NON-SLE (%)	SLE (%)	NON-SLE (%)
MLP	85.7	86.8	87.0	85.5
SVM	81.5	78.2	77.0	82.5

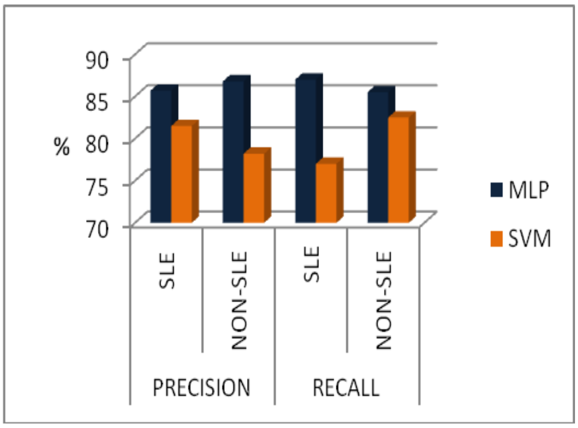


Fig. 4: Classifiers vs. Precision and Recall

The classifiers versus various performance measures (sensitivity, specificity and accuracy) are shown in Table 3. From Table 3, one can observe that again MLP outperforms over SVM in all the performance measures, namely, sensitivity by 10%, specificity by 3% and accuracy by 7.5%

Figure 5 is the graphical representation of Table 3. From figure 5, one can observe that the MLP provides better classification by means of sensitivity, specificity and accuracy values over SVM. A receiver operating characteristic curve (ROC) is a graphical representation of True Positive Rate (TPR) and False Positive Rate (FPR). The area under the curve (AUC) is a measure such that the classifier correctly classifies the patients with and without SLE.

Table 3: Classifiers versus various performance measures

Classifiers	Sensitivity (%)	Specificity (%)	Accuracy value (%)
MLP	87.00	85.50	86.25
SVM	77.00	82.50	79.75

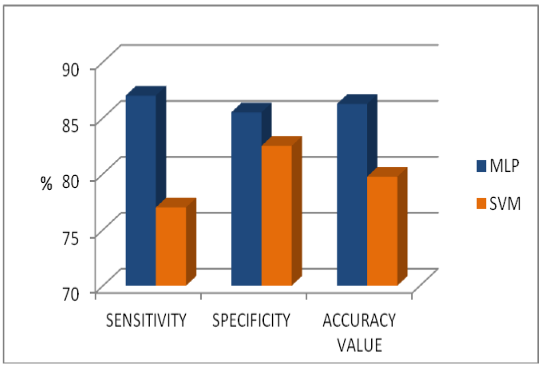
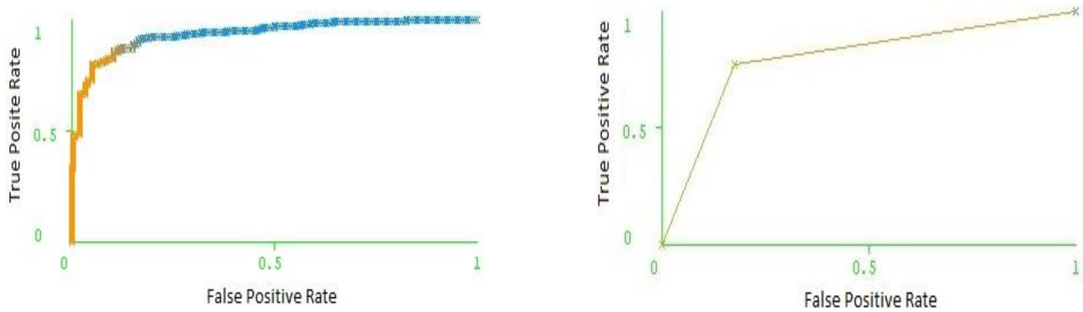


Fig. 5: Performance measures (sensitivity, specificity and accuracy) by various classifiers

The ROC curve of MLP is nearer to the left border of the ROC space compared to the ROC curve of SVM. When the ROC curve is closer to the left border of the ROC space, then the classifier gives good accuracy rate. From the figure 6, one can infer that MLP yields better accuracy rate than SVM.



(a) (b)

Fig. 6: Receiver Operating Characteristics Curve for (a) MLP (b) SVM

Table 4 gives AUC values of MLP and SVM classifiers for the classification of images.

Table 4: AUC of ROC by various classifiers

CLASSIFIERS	SLE
MLP	0.933
SVM	0.798

Table 4 shows that AUC value of MLP is much higher than SVM. It indicates that MLP classifier yields better classification in classifying images into SLE and Non-SLE than SVM classifier.

CONCLUSION

Cutaneous manifestations provide vital information for the rheumatologists to diagnose whether the patient has lupus or not. As lupus increases the morbidity rate, proper diagnosis and management of the disease is very important. Classification of cutaneous manifestation of SLE using machine learning techniques is proposed. This proposed work retrieves color histogram-based features and texture features from the images and classifier algorithms, MLP and SVM are applied for classifying a group of patients into SLE and

Non-SLE. MLP shows better performance than the other classifier SVM, yielding maximum accuracy of 86.25%. If sensitivity, specificity and accuracy are considered together, one can conclude that MLP is the better choice than SVM with polynomial kernel.

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CONFLICTS OF INTERESTS

All authors have none to declare

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