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COMPUTER-AIDED PSORIASIS DISEASE CLASSIFICATION AND SEVERITY DETECTION

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Abstract: Psoriasis is a chronic, inflammatory and autoimmune skin disease with red and scaly plaques. Statistics show that about 125 million people of total world population are suffering from psoriasis disease. Dermatologists generally follow visual inspection and sense of touch which requires skilled training and experience to determine severity of psoriasis disease. This subjective assessment suffers from inter- and intra-observer variability found in dermatologists' examinations which makes the subjective assessment inefficient, unreliable and a time-consuming process. This work attempts to design a computer-aided diagnosis (CADx) system in machine learning paradigm for psoriasis disease classification into healthy and diseased. Further, as the stage and grade of psoriasis severity is clinically relevant and important for dermatologists to provide medication, a new CADx system has been designed for psoriasis severity detection.

Keywords:Psoriasis,Computer Aided Diagnosis

I. Introduction

Psoriasis is a chronic, inflammatory and autoimmune skin disease with red and scaly plaques [1]. Generally, psoriasis appears on scalp, elbows, knees, and lower back but it may spread further to all parts of body [1]. Up to 30% of patients develop a specific form of inflammatory arthritis termed psoriatic arthritis that may lead to joint damage [2]. There is no permanent cure for this disease, but it can be controlled by prolonged and attentive treatment. There are various types of psoriasis which shows distinct characteristics namely plaque, guttate, inverse, pustular, and erythrodermic. Plaque psoriasis is the most common form, almost 80% of all psoriasis cases [3]. Thus, this study is focused on plaque psoriasis. An example of plaque psoriasis lesions on several regions of the human body is shown in Fig. 1.

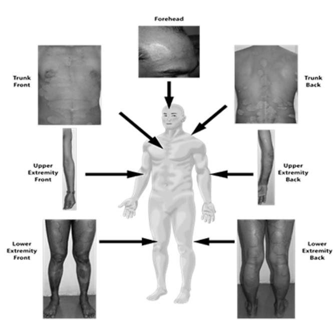

Fig. 1 Examples of plaque psoriasis disease on several body regions (psoriasis images: Courtesy of Psoriasis Clinic and Research Centre, Psoriatreat, Pune, Maharashtra, India; center body image: Courtesy of Global Biomedical Technologies, Inc., Roseville, CA, USA).

Statistics show that 125 million people of total world population are suffering from psoriasis disease [4], [5]. The effect of psoriasis is global, but its prevalence differs depending on the geographical regions. Psoriasis is more commonly found in colder temperate regions than in the tropics [2]. China and Japan are less affected by psoriasis than Europe, while the Andean region of South America is not affected at all. The prevalence of psoriasis in Europe, USA, Malaysia, and India is about 0.6% to 6.5% [2], 3.15% [2], 3% [6], and 1.02% [7], respectively. Though psoriasis can appear at any age, it mostly occurs before the age of 40 years and most of the cases are found within 20–30 years age group [8].

Besides affecting the skin, psoriasis affects the quality of life due to its discomforting social appearance. Several studies have reported that psoriasis patients experienced anguish, stress, embarrassment, stigmatized, fear of worsening disease and enormous disruption in their daily lives [9], [10]. A survey on 6194 psoriasis patients done by National Psoriasis Foundation reported that 79% of them had a negative impact on their lives, 40% felt frustrated with the ineffectiveness of their current therapies and 32% reported that treatment was not aggressive enough [11]. Further, difficulties in workplace, socialization with family members and friends, exclusion from public facilities and getting a job were few other problems reported in this survey. Approximately 60 percent of psoriasis patients missed an average of 26 days of work a year due to their illness [12]. Psoriasis patients may have reduced level of earning livelihood and employment [2]. This results in increased risk of suicidal attempts (about 30%) making psoriasis an equally dangerous disease at par with depression, heart disease and diabetes [13], [14]. Thus,psoriasis has become a major concern to health care organizations and the society.

To assess the severity of psoriasis of any patient, dermatologists generally follow visual inspection and sense of touch. Then by combining the subjective reports

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of patient and dermatologist, the severity of psoriasis disease is anticipated and the effect of earlier treatment on patient is determined. This kind of subjective assessment suffers from following limitations:

(i) It requires skilled training and experience to assess the psoriasis severity of any patient.

(ii) It suffers from inter-observer variability issue. Two dermatologists can have two different views on severity for the same patient, which makes the subjective assessment inefficient and unreliable.

(iii) It also suffers from intra-observer variability issue. Same dermatologists can have two different views on severity for the same patient at different times, which again makes the subjective assessment inefficient and unreliable.

(iv) It is tedious, time consuming and unreliable process.

Therefore, it is highly needed and helpful for dermatologist to have a diagnostic system which could provide quantitative and objective evaluation of the psoriatic lesion. It would be beneficial for assessment of severity of psoriasis and evaluation of treatment as well. With this aim, to facilitate accurate, fast and reliable computer-aided diagnosis (CADx) system for psoriasis, this paperpresents contributions in psoriasis disease classification and severity detection stages in development of a CADx system of psoriasis.

II. Computer Aided Psoriasis Disease Classification System

The preparation of database was done by manually segmenting the healthy skin (normal) and psoriatic lesion (abnormal skin) from the images of each patient. Thus 270 samples of normal skin and 270 samples of abnormal skin are acquired from the images of 30 patients. There were few samples which are fuzzy in nature, *i.e.*, considered as an abnormal sample but actually they belong to normal sample and vice-versa.

Fig.2 shows the flow diagram of a general CADx system. A CADx system consists of two components as shown by the dotted line. The left side reflects the offline system for training while the right side reflects the online system for testing. First step is feature extraction. Here, various features are extracted which are suitable for characterizing an image. The next step is feature selection. As high dimensional data may contain irrelevant and redundant information which in-turn reduce the performance of system and increase the time complexity. Hence, dominant features are selected to reduce the dimensionality of the extracted feature set and to select only unique and highly discriminating features. The above two steps, feature extraction and feature selection, are performed in offline as well as online system. Subsequently, the dominant feature set and a-priori physician classified labels (ground truth) are used as inputs to the offline classifier to determine the machine learning parameters. This machine learning parameters from the offline system and dominant features of test images in online system are used to determine the class label of the test images using online classifier weather it belongs to diseased class or healthy class.

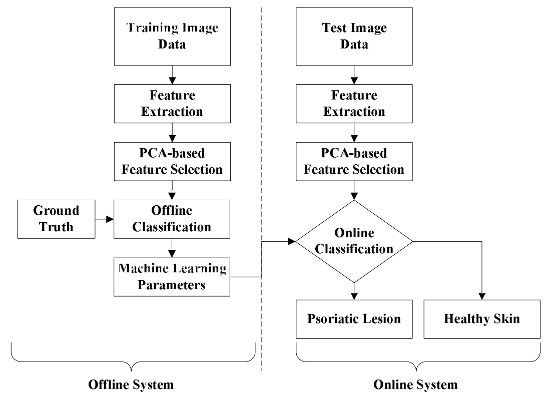


Fig. 2 Flow diagram of the proposed CADx system in binary class scenario.

A .Feature Extraction

Our feature extraction process is motivated by mimicking the dermatologist paradigm. A dermatologist is mainly interested in discriminating a psoriatic lesion and healthy skin by examining the texture and color appearances in psoriasis lesions. Thus, utilizing this framework, our feature population is divided into two categories: texture and color. Since texture of psoriatic lesion due to roughness and scales is dissimilar than healthy skin, it may be significant feature to distinguish psoriatic lesion and healthy skin. Texture features are extracted from gray scale image, thus RGB image is converted to gray scale image using weighted sum of R, G and B components. We have extracted an exhaustive 687 texture features derived using nine different texture feature extraction techniques. Further, since there is a great variability between colors of psoriatic lesion and healthy skin, color features are considered. We have extracted a total of 172 color features utilizing 14 color spaces. In total, our CADx system computes comprehensive feature set of 859 features.

B. Feature Selection

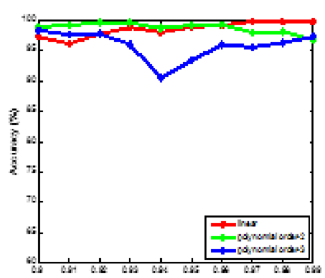
Due to extensive feature space of 859 features (172 color and 687 texture), there is a need for machine learning framework to be able to select the dominant features. It avoids the redundant and noisy features (less dominant features) and thus reduces the dimensionality of the feature space. This results in an optimal feature selection leading to reliable, stable and higher performance. One such tool for feature selection is Principal Component Analysis (PCA).

C. Classification

Support Vector Machine (SVM) is a state-of–the-art technique of classification [82]. It has good generalization properties and performs well on nonlinear data. The goal is to find maximum margin hyper-plane which maximizes the distance between data points of two classes.The maximum margin hyper-plane is determined by constructing two parallel hyper-planes, one on each side of the optimal separating hyper-plane. The points lying on the boundaries of hyper-plane are called support vectors, and the middle of the margin is termed as optimal separating hyper-plane. Non-linear classification can be performed using kernel functions. Here, linear and polynomial kernel of order two and three are used.

D. Results

Experiment presented in this section is about evaluation of performance of classification system and selection of best SVM kernel function for changing PCA-based cutoffs. Here, N=540 images considered which consists of equal number of psoriatic lesion and healthy patient images, *i.e.*, 270. All 859 texture and color features are fed to the CADx system and PCA-based paradigm is adopted for optimal feature selection. Using cross-validation protocol, five performance measures, *i.e.,* sensitivity (SE), specificity (SP), positive predictive value (PPV), accuracy (ACC) and area under the receiver operating characteristic (ROC) curve, *i.e.,* AUC are computed. It is observed that polynomial kernel of order 2 behaved uniformly over all the possible cutoffs as depicted in Fig. 3(a). So, this kernel which shows highest accuracy is selected for SVM classification proposed in this work. Similarly, the feature space is verified for all cutoffs in Fig. 3(b) and found that the number of features in feature space exponentially increases with respect to cutoffs. Table 1 shows all the classification performance measures such as sensitivity, specificity, positive predictive value, accuracy and area under the ROC curve for best selected kernel for all possible cutoffs. From Table 1, it is easily observed that the highest accuracy of 99.77% and overall best performance is obtained at cutoff 0.93. The corresponding ROC curve for cutoff 0.93 is presented in Fig. 4 whose area under curve represents the quality of classifier, *i.e.* AUC 1.0.



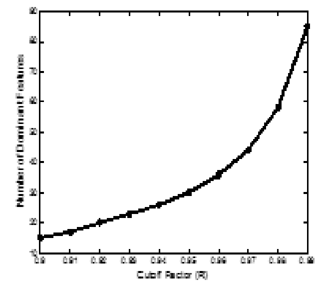


Fig. 3 (a) Accuracy as a function of PCA-based cutoff for K=10, N=540 and T=20 for three different kernel functions. (b) Number of dominant features vs. PCA-based cutoff for K=10, N=540 and T=20 for selected polynomial kernel of order 2.

Table 1 Classification performance parameters at different cutoffs (R) for K=10, N=540 and T=20.

Cutoff	SE	SP	PPV	ACC	AUC
0.90	98.54	99.35	99.37	98.94	0.99
0.91	99.20	99.06	99.10	99.13	0.99
0.92	99.63	99.93	99.93	99.76	1.00
0.93	100.00	99.54	99.55	99.77	1.00
0.94	98.52	98.78	98.81	98.65	0.99
0.95	99.65	98.91	98.95	99.28	0.99
0.96	99.41	99.35	99.38	99.38	0.99
0.97	98.67	97.04	97.18	97.85	0.98
0.98	98.22	97.83	97.94	98.03	0.98
0.99	97.31	96.54	96.66	96.93	0.97

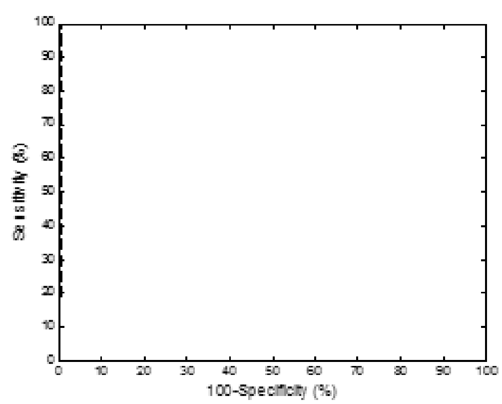


Fig. 4 ROC curve at 0.93 cutoff factor for K=10, N=540 and T=20 using polynomial order two kernel function.

III. Computer Aided Psoriasis Severity Detection

The proposed CADx system as shown in Fig. 5 works on the state of art machine learning paradigm in multiclass framework. The multiclass framework has the same spirit as binary class paradigm used in section 2. To implement multiclass problem using SVM, we have adapted "one-against-all" approach [15,16].

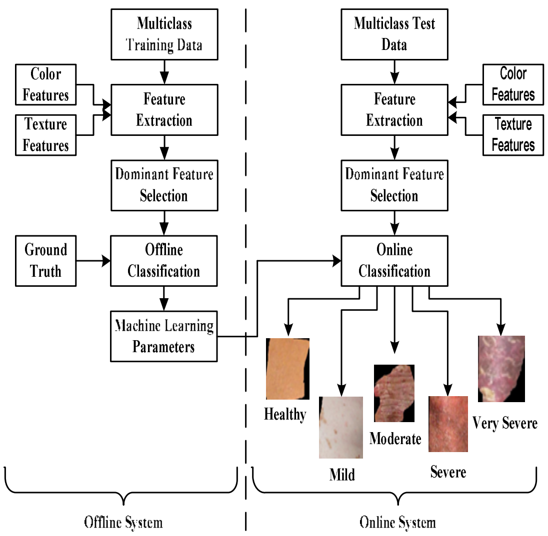


Fig. 5 Architecture of the proposed CADx system in multiclass scenario.

A. Results

In this experiment, the data size of N=848, has been kept fixed. We observed that the polynomial kernel of order two showed the best classification accuracy throughout the cutoffs. As a result, we fixed our analysis on subsequent experiments using this polynomial kernel of order two. The performance parameters are depicted in Table 2 while the ROC curve demonstrating the performance for all five classes is presented in Fig. 6.

Table 2 Classification performance parameters of our CADx System

	SE (%)	SP (%)	PPV (%)	Class-ACC (%)	AUC
Healthy	99.65	99.39	99.28	99.50	1.00
Mild	92.05	99.20	88.97	98.81	0.96
Moderate	98.43	99.10	97.85	98.90	0.99
Severe	97.65	99.39	97.23	99.09	0.99
Very Severe	67.92	99.70	90.54	98.63	0.94

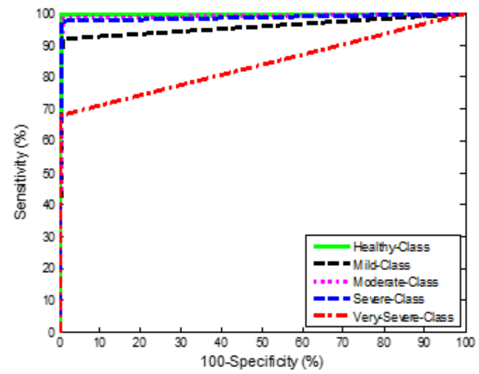


Fig. 6 ROC curves for all five classes.

IV. Conclusions

In this thesis, a CADx system has been proposed for binary classification of psoriasis images into diseased and healthy classes. Further, we have extended this to multiclass scenario, where along with the classification of healthy and diseased images, severity of psoriasis disease has been stratified into five classes, *i.e.*, mild, moderate, severe and very severe. In experiment for disease classification, the proposed system performed significantly giving accuracy of 99.77% at PCA cut-off 0.93. Similar experiments like binary classification have been performed with similar features to design new CADx system for severity deteection. The system showed an accuracy of 98.24% and reliability of 98.05% which is encouraging for a multiclass CADx system and hence the CADx system proposed here to stratify psoriasis severity has been found successful.

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