Department of Applied Mathematics

Soft Computing Techniques in Diagnosis of Some Regular Skin Disorders

Summary of a Thesis

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by

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1 Importance

This is the era of soft computing and cognitive computing is one of the branch getting lots of importance. In cognitive technique a computerised model is created which simulates the working of human thoughts. Soft computing techniques includes many machine learning algorithms, which provides systems the ability to automatically learn. Today the most challenging research has been done in the field of medical science and Artificial Intelligence which plays a very crucial role in medical diagnosis.

The present thesis deals with the diagnosis of the most common dermatological diseases namely Bacterial Infections, Fungal Infections, Eczema and Scabies. These diseases are very common in developing countries. In India also, there are plenty of rural areas which are highly populated, people are not much educated and are not able to keep hygiene which lead to above mentioned skin disorders. Unfortunately in the rural areas hardly specialised doctor - dermatologist is available. So, people are generally treated by the general practitioners and paramedical staff at primary health centres, community health centres and referral hospitals. Also many of the above mentioned diseases have very similar features. So to make proper diagnosis and treat the patients accordingly is very challenging job for non-dermatologist. Generally the patients are treated by administering antibacterial, antifungal and steroidal preparations locally. Such treatment is perilous to the patient. There is certainly a need for proper diagnosis of such common skin disorders. Using the techniques of soft computing we can create an Artificial Intelligence in the computer system which help us in making the diagnosis of such diseases. Such computer aided artificial intelligence not only help the general practitioners and paramedical staff at various hospitals but it can serve the dermatologist also in making diagnosis. Dermatologists use the diagnosis given by the system as second opinion and feel more confident. Sometimes it also prevents undergoing further medical investigations in laboratories and decrease the cost of the treatment.

We use soft computing tools such as Artificial Neural Networks, Support Vector Machines and Extreme Learning Machines in making the diagnosis of the above mentioned four diseases. Unfortunately very less research work is carried out in this direction whereas which is most important.

The following methodologies have been used to deal with the problem. The problem is of diagnosis of the above mentioned four diseases but mathematically it falls under the category of classification. The entire process has been carried out in two phases.

1. Data Acquisition
2. Methodologies for Classification

2 Data Acquisition

Patients information, who are suffering from the common skin disorders viz., Bacterial skin Infection, Fungal skin Infection, Eczema or Scabies were collected from the Skin and V. D. Department, The H M Patel Centre for Medical Care and Education (Shree Krishna Hospital), Karamsad, Gujarat, India.

Initially, a research proposal (according to the Human Research Ethics Committee (HREC) format of The H M Patel Centre for Medical Care and Education) to get the permission to collect data from Skin and V. D. department is prepared. The research proposal was presented in front of the HREC committee. The research proposal got accepted in the second meeting of HREC committee after incorporating all the changes suggested by the committee according to their terms and conditions. Then, a proforma was prepared for the data collection of the above mentioned skin diseases. Dr. Rita Vora, Head of the Department of Skin and V. D., given her valuable guidance to prepare the proforma. Data was collected during OPD through one-on-one interviews with the patients. Patient's consent was taken before beginning the interview. 11 features were non-clinical features and the rest were clinical features in the proforma out of the 47 features. The information regarding non-clinical features were topped off by me in the wake of meeting the patients and the clinical features were ivestigate by the dermatologists of the department. Data was collected for a total of 470 patients. Out of these, 139 patients had Bacterial skin infections, 146 had Fungal skin infections, 98 had Eczema and 87 had Scabies.

3 Methodologies for Classification

The main problem addressed by this study is the classification (diagnosis) of the above mentioned diseases. This requires the use of different soft computing techniques. Components of soft computing includes machine learning techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Extreme Learning Machine (ELM) etc. Basic problem of soft computing techniques is to train the network which gives minimum training error between actual output and network output. So, basically research work is carried out using various optimization techniques which minimize the network training error and perform well on unseen testing data.
For verification of the soft computing techniques, two datasets are used. Dataset-I includes the above mentioned four common skin diseases and Dataset-II is the benchmark dataset available in [4].

The following methodologies (soft computing techniques)have been applied in classification of the above mentioned skin diseases.

(I) Artificial Neural Network for Classification

An artificial neural network minimize the training error using various optimization method. It can work for linearly separable as well as for linearly non separable data. Here multilayered network is created to classify the skin disorders using one hidden layer as well as using two hidden layers. Back propagation algorithm is used to updates weights of the network in order to minimize network error. The error is minimize using Levenberg Marquardt(LM) optimization technique, whose convergence rate is better compare to most common steepest descent technique.

To evaluate the performance of the classifier, the Dataset-I is randomly divided into 80%-20% and 70%-30% training-testing data partitions. The classification accuracy is obtained using various accuracy measures taking one and two hidden layers. For two hidden layered network, 20 and 10 hidden nodes are used in 1^{st} and 2^{nd} layer respectively. A very good classification accuracies, 96.23% and 97.17% for 70%-30% and 80%-20% training - testing data partitions respectively are achieved by normal accuracy measure. The Dataset-I is imbalanced therefore along with the normal accuracy measure, another good statistical measure of accuracy for imbalance data namely F-score is used to find the classification accuracy. For the same data partitioned 94.23% and 95.70% accuracies are achieved using F-score accuracy measure.

(II) Support Vector Machine with Positive Definite Kernels

Second soft computing technique used to diagnose above mentioned common skin diseases is Support Vector Machine(SVM). SVM is the very good soft computing technique for non linear data. High dimensional data can also be classified with less computational effort due to kernel trick. It is the combination of machine learning theory, optimization algorithms from operation research and kernel functions from functional analysis. It is also known as large margin classifier. Due to soft margin concept, SVM can control the effect of noisy data up to certain extent.

SVM is basically developed for binary classification problem. But, here it is used for four classes. Kernel has a major role in classification accuracy. In this work, classification is carried out with various positive definite kernels. LIBSVM 3.20 is used as a tool to obtain classification accuracies using various kernels [76]. Linear kernel, polynomial kernel and Radial Basis kernel functions are inbuilt kernel functions in LIBSVM. Apart from this we have also used t-student and Inverse multiqadratic kernel function. For each kernel parameters are set using grid search method and validation is done using 10 fold validation method. Classification accuracy is calculated using normal accuracy measures as well as using other performance measures viz., F-score and G-score. Results exhibits that 95.39%, 90.78% and 93.80% classification accuracies are achieved using the normal accuracy measure, F-score measure and G-score measure respectively. These accuracies are obtained for RBF kernel and polynomial kernel. The accuracies remain same for both kernels. These accuracies are achieved for 70%-30% training-testing data partitioned of Dataset-I.

(III) Support Vector Machine with Novel Indefinite Kernel

Measuring similarities among training samples is the fundamental step of classification. Kernels measure similarity between samples and provide classification of data. Though positive definiteness is the traditional requirement of SVM, in many applications indefinite kernels yield better classification accuracy.

This study develops a novel indefinite kernel which is a modified Gaussian kernel. This kernel is used in diagnosis of some regular skin disorders discussed in Dataset-I and Erythemato-Squamous Disease (ESD) discussed in Dataset-II. Similar analysis has been carried out by considering various types of non Euclidean distances in Radial Basis kernel Function and non standard inner products in Polynomial kernel. Positive definite/indefinite property of the various kernels are analyzed.

The modified Gaussian kernel and some other kernels are indefinite. Unlike Mercer's kernels, indefinite kernels are defined in an inner product space endowed with a Hilbert topology called kreĭn space, which is a pseudo Euclidian space [95]. In this space inner product may not be positive definite. So, norm is not induced by inner product. Since, the kernels are indefinite, instead of minimizing the error, the emphasize is on stabilizing the process.

The results exhibits good classification accuracies by these kernels. The classification accuracy obtained by the novel kernel function which is indefinite is 91.50% and 98.63% for the Dataset-I and Dataset-II respectively. This classification accuracy is better than that obtained by traditional Mercer's kernels.

(IV) Probabilistic Approach in Feature Selection

In many datasets, number of features are very high which increase the dimensionality of the dataset. Also, some features are not correlated to any class and increase noise. If we use such datasets for classification, the classifier may face the problem of over fitting and good generalisation may not be obtained. So, it is necessary to remove these types of features from the dataset before applying any classification technique. It will reduce the dimensionality of the dataset and hence help in achieving good generalized classification accuracy. Statistical analysis reveal high correlation among some features which can be exploited to reduce the dimensionality of the dataset. There are three methods for feature selection: Filter method, Wrapper method and Embedded method.

In this study dermatological disorders discussed in Dataset-I and Dataset-II are diagnosed using a novel approach of feature selection. To overcome drawbacks of filter techniques and wrapper techniques we have combined both techniques which we call Filter technique and Partial Forward Search (F_PFS) algorithm. The method works for both balanced and imbalanced datasets as well as for binary and multiclass datasets.
A comparison analysis of F_PFS algorithm with IFSFS method discussed by Xie *et. al.* given in [136] is also discussed.

The results show that the new approach of feature selection i.e. F_PFS algorithm have reduced 26% features from Dataset-I and 39% features from Dataset-II with good classification accuracies of 89.36% and 97.27% for 70%-30% data partitions of the respective Datasets. The accuracy obtained by IFSFS method when applied on Dataset-II for 70%-30% training-testing data partitions is 94.44%.
The classification accuracy remain same for both F_PFS and IFSFS algorithms when the methods are applied on Dataset-I. But, by F_PFS method the dimensionality of the model of highest classification accuracy is less than that of IFSFS method. This shows that the accuracy achieved by newly developed F_PFS algorithm is better. Also, using F_PFS algorithm comparatively less effort is required due to threshold technique used in the algorithm.

(V) Kernel Based Extreme Learning Machine for Classification

The major pitfall of feedforward neural networks is their slow speed due to gradient descent based learning methods. In 2004 Haung *et.al.* have proposed a new learning algorithm called Extreme Learning Machine(ELM) which is a single layer feedforward neural network [53]. ELM is based on empirical risk minimization theory [32]. The advantage of ELM is, the weights need not to be trained hence learning is very fast.

In this method, the rectangular system of linear equations to obtain network weights can be solved using the Moore-Penrose inverse. Therefore there is no requirement to train the network to find weights, instead they can be obtained analytically. This enables the algorithm very fast. The Moore-Penrose inverse gives minimum norm least-squares solution of a linear system [121]. Using ELM the network weights are not only minimum but they are smallest norm that gives unique solution. So, the best generalised solution is obtained.

This work uses ELM with Polynomial kernel, Radial Basis Gaussian kernel and Exponential Chi-square kernel. Comparative study of Extreme Learning Machine with Artificial Neural Network and Support Vector Machine is also carried out. It has been observed that good generalized performance (92.91% classification accuracy) with extremely high speed (0.0324 seconds) is achieved using Exponential Chi-Square kernel in ELM to diagnose skin diseases.

Publications:

The following are the research publications resulted during the present thesis work.

1. **Krupal S Parikh, Trupti Shah, Rahulkrishna Kota, Rita Vora,** *Diagnosing Common Skin Diseases using Soft Computing Techniques*, International Journal of Bio-Science and Bio-Technology, vol. 7, issue 6, pp.275-286, 2015. http://dx. doi.org/10.14257/ijbsbt.2015.7.6.28.
   (Indexed by Scopus)
2. **Krupal S Parikh, Trupti Shah,** *Support Vector Machine- a Large Margin Classifier to Diagnose Skin Illnesses*, Procedia Technology, Elsevier, vol. 23, pp.369-375, 2016.
   doi: 10.1016/j.protcy.2016.03.039.
   (Procedia Technology, Elsevier)
3. **Krupal S Parikh, Trupti Shah,** *Kernel Based Extreme Learning Machine in Identifying Dermatological Disorders*, International Journal of Innovative Science, Engineering & Technology, vol. 3, issue 10, pp.370-375, 2016.
4. **Krupal S Parikh, Trupti Shah,** *Feature Selection Paradigm using Weighted Probabilistic Approach*, International Journal of Advanced Science & Technology, vol. 100, issue 3, pp.1-14, 2017. http://dx.doi.org/10.14257/ijast.2017.100.01.
5. **Krupal S Parikh, Trupti Shah,** *Novel kernel to Diagnose Dermatological Disorders*, Journal of Applied Computer Science & Mathematics, vol. 12, issue 1, pp. 28-33, 2018.
   doi: https://doi.org/10.4316/JACSM.201801004.
   (UGC Approved)

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