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Intelligent Decision Support System for Parkinson Diseases Using Softcomputing

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ABSTRACT: *Artificial neural networks (ANNs), computer paradigms that can learn, excel in pattern recognition tasks such as disease diagnosis. Classification systems can help in increasing accuracy and reliability of diagnoses and minimizing possible errors, as well as making the diagnoses more time efficient. Such applications include the study of neuro-degenerative disorders such as Alzheimer's disease, generation of patient specific conductivity maps for EEG source localization, determination of cortical thickness and substructure volumes in schizophrenia, and partial-volume correction for low-resolution image modalities such as positron emission tomography. Parkinson's disease (PD- A neurological disorder) is the second most common neurodegenerative disease only surpassed by Alzheimer's disease (AD).This area is having lack of medical interpretation techniques and resources; used for diagnosis of PD. This situation leads us towards the need to develop a Decision Support System (D S S) for PD. T h i s paper proposes method based on ANNs and Statistical techniques to aid the specialists in the most accurate diagnosis of PD. Data recorded during 195 examinations carried out on 31 patients; is used to verify the capacity of the proposed binary classifier system.This paper discusses the techniques used to diagnose in general. From exhaustive and care full experimentation, it is concluded that MLP NN Classifier ensures true estimation of the complex decision boundaries, remarkable discriminating ability and out performs other architectures.*

Keywords: *MLP Neural Network, RBF, statistical classifiers, DSS, Parkinson diagnosis.*

I. INTRODUCTION

Studies from WHO (world health organization) and Olmsted County (Mayo Clinic) [1], have computed the life time risk of developing Parkinson's disease to 2% for men and 1.3% for women. The greater incidence in men is repeatedly confirmed. PD is a progressive neuro logical disorder characterized by tremor, rigidity and slowness of movements. It is associated with progressive neuronal loss in the substantia nigra and other brain structures. Non-motor features, such as dementia and dysautonomia, occur frequently, especially in advanced stages of the disease. Diagnosis depends on the presence of two or more cardinal motor features such as rest tremor, bradykinesia, or rigidity [2]. Functional neuro imaging holds the promise of improved diagnosis and allows assessment in early disease. Two studies draw attention to the difficulties in the diagnosis of the disease in the early stages [3]. Having so many factors to analyse to diagnose PD, specialist normally makes decisions by evaluating the current test results of their patients. Moreover, the previous decisions made on other patients with a similar condition are also done by them. These are complex procedures, especially when the number of factors that the specialist has to evaluate is high (high quantity and variety of these data). For these reasons, PD diagnosis involves experience and highly skilled specialists.

In recent times, neural networks have been employed as a widely used method for designing Decision Support System (DSS) for disease diagnosis. There has been a considerable research going on in developing computer based decision support systems for improving the quality of health care. Two problems are the most common in the field of automatic diagnosis: the selection of necessary parameter set for right diagnosis and forming of steady and powerful algorithm which doesn't require long time to run. The use of classifier systems in medical diagnosis is increasing gradually. Recent advances in the field of artificial intelligence have led to the emergence of expert systems and Decision Support Systems (DSS) for medical applications. Moreover, in the last few decades computational tools have been designed to improve the experiences and abilities of doctors and medical specialists in making decisions about their patients. Without doubt the evaluation of data taken from patients and decisions of experts are still the most important factors in diagnosis. However, expert systems and different Artificial Intelligence (AI) techniques for classification have the potential of good supportive tools for expert. Classification systems can help in increasing accuracy and reliability of diagnoses and minimizing possible errors, as well as making the diagnoses more time efficient [4]. The aim is to build an intelligent and optimal system, using Artificial Neural Networks (ANNs). These two classifiers, which are widely used for pattern recognition, provide a good generalization performance in the diagnosis task. The usage of such classifiers, reinforce and complement the diagnosis of the specialists and their methods in the diagnosis tasks. ANN based models have advantage over other types of decision support systems, as ANN based systems are self-organizing type and have learning capabilities. The paper is organized as follows. First the optimal MLP NN based DSS is designed to diagnose the given Parkinson's data base. Later, the RBF and PCA neural network based DSS are developed for the binary classification task. The exhaustive data partitioning is done with a view to test the proposed NN for their robustness as classifier.

II. CLINICAL DATA SET

Oxford Parkinson's Disease Detection database [5] contains 197samples. All samples have 23 attributes that are name, MDVP: Fo (Hz) - Average vocal fundamental frequency, MDVP: Fhi (Hz) - Maximum vocal fundamental frequency, MDVP: Flo (Hz) - Minimum vocal fundamental frequency. MDVP: Jitter (%), MDVP: Jitter (Abs), MDVP: RAP, MDVP: PPQ, Jitter: DDP–Several measures of variation in fundamental Frequency, MDVP: Shimmer, MDVP: Shimmer (dB), Shimmer: APQ3, Shimmer: APQ5, MDVP: APQ, Shimmer: DDA - Several measures of variation in amplitude, NHR, HNR - Two measures of ratio of noise to tonal components in the voice, status - Health status of the subject (one) - Parkinson's, (zero) – healthy. RPDE, D2-Two nonlinear dynamical complexity measures, DFA - Signal fractal scaling exponentspread1, spread2, PPE - Three nonlinear measures of fundamental frequency variation. This dataset is composed of a range of biomedical voice measurements from 31 people, 23 with Parkinson's disease (PD). There are around six recordings per patient, each column in the table is a particular voice measure, and each row corresponds one of 195 voice recordings from these individuals. The main aim of the data is to discriminate healthy people from those with PD. The database used for this study is a benchmark data available at machine learning database http:/www.ics.uci.edu/pub/m1-repos.

III. ANN CLASSIFIERS

The performances of three different networks in classification of Parkinson's data sets are compared in this article. Those include Multilayer Perceptron (MLP), Radial-Basis Functions (RBF) and Principal Component Analysis (PCA). A brief description of them follows.

III.1 MLP networks

MLPs are feed-forward neural networks trained with the standard back-propagation algorithm. It is shown that a network having a single layer of threshold units could classify a set of points perfectly if they were linearly separable [6]. It is shown that for a set of N data points, a two-layer network of threshold units with $N-1$ units in the hidden layer could exactly separate an arbitrary dichotomy. Since it is very likely that one ends up in a "bad" local minimum, the network should be trained a couple of times (typically at least five times), starting from different initial weights.

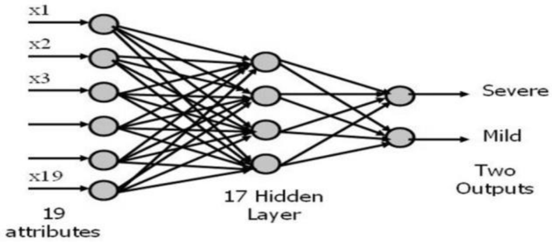

Fig.1. Multi-Layer Perceptron NN

As it has been pointed out in earlier discussion, a MLP NN shown above in fig.1 is chosen as a DSS. In order to design a proper architecture of the MLP NN model; a computer simulation experiment is designed where the number of hidden neurons is varied gradually from 1 to 20. It is found that the performance of the selected model is optimal for 17 neurons in the hidden layer with regard to the MSE, NMSE, correlation coefficients, area under the ROC curve, and percent classification accuracy for the testing data set. When we attempted to increase the number above 17 in the hidden layer, the performance of the DSS was not seen to improve.

Table 1: Optimal Parameters for MLP NN DSS

S.No.	Parameter	Hidden Layer#1	Output Layer
1	Processing Elements	17	2
2	Transfer Function	Lin Tanh	Soft-max
3	Learning rule	Momentum	Delta Bar Delta

III. 2 RBF networks

Radial-basis functions (RBF) were first introduced in the solution of the real multivariate interpolation problem [7]. The construction of a RBF network as shown in fig. 2, in its most basic form, involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to its environment.

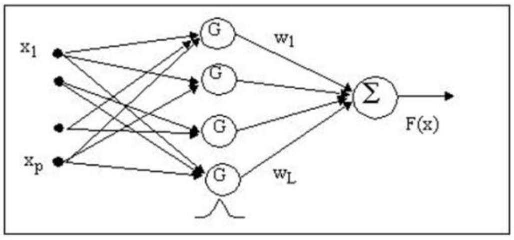

Fig.2. Radial Basis Function

Different initial conditions are tried to make sure that we are really converging to the absolute minimum. Moreover, this also removes biasing in the learning mechanism. Therefore, in order to ensure true learning and proper generalization, the network is run at least three times to gauge performance. The training of RBF constitutes 100 epochs in unsupervised learning mode for setting the centres and width of the Gaussians and at least 1000 epochs in the supervised learning mode to compute the connection weights in the output layer. The supervised learning may terminate earlier if the minimum specified error threshold of 0.01 is reached earlier. An exhaustive experimental study has been carried out to design the optimal parameters of RBF NN as depicted in table 2.

Table 2. Optimal Parameters for RBF NN

S.N.	Optimal Parameters of RBF NN	
1	No. of Clusters	120
2	Transfer Function	Softmax
3	Supervised learning rule	DeltaBarDelta
4	Competitive learning metric	Euclidean
5	Unsupervised learning rule	Conscience-full

III.3 PCA networks

Principal component analysis networks (PCAs) combine unsupervised and supervised learning in the same topology. PCA is a very well-known statistical procedure in which input data of very large dimensionality (D dimensions) is projected onto a smaller-dimensionality space M (M < D), a step that is commonly called feature extraction as shown in fig.3. The linear projection that accomplishes this goal is the PCA. It is an unsupervised linear procedure that finds a set of uncorrelated features, principal components, from the input. A MLP is used to perform the nonlinear classification from these components.

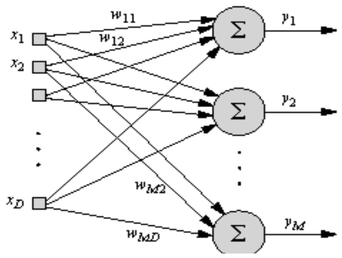

Fig. 3 Principal Component Analysis network

PCA is a data reduction method, which condenses the input data down to a few principal components. As with any data reduction method, there is the possibility of losing important input information. The two most robust learning rules are Oja's and Sanger's implementations of the Hebbian principle. Between the two, Sanger's is preferred for PCA because it naturally orders the PCA components by magnitude.

Table 3 Optimal Parameters for PCA NN DSS

S.No.	**Parameter**	**Hidden Layer#1**	**Output Layer**
1	Processing Elements	17	2
2	Transfer Function	Lin tanh	Soft-max
3	Learning rule	Momentum	Delta Bar Delta

IV. NN PERFORMANCE INDEX

MSE (Mean Square Error):

The formula for the mean squared error is defined by Eq. (1) as follows:

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}\left(d_{ij} - y_{ij}\right)^2}{N.P}$$

Where P = number of output neurons, N = number of exemplars in the dataset, y_{ij} = network output for exemplar i at neuron j, d_{ij}= desired output for exemplar i at neuron j.

V. PERFORMANCE OF NN

The results of three optimal neural networks MLP, RBF and PCA are evaluated on the basis of three parameters classification accuracy, MSE and Area under ROC. Performance of ANN on data set indicating % classification accuracy, MSE and area under ROC. All the three figures below show consistent performance of the neural networks[8].

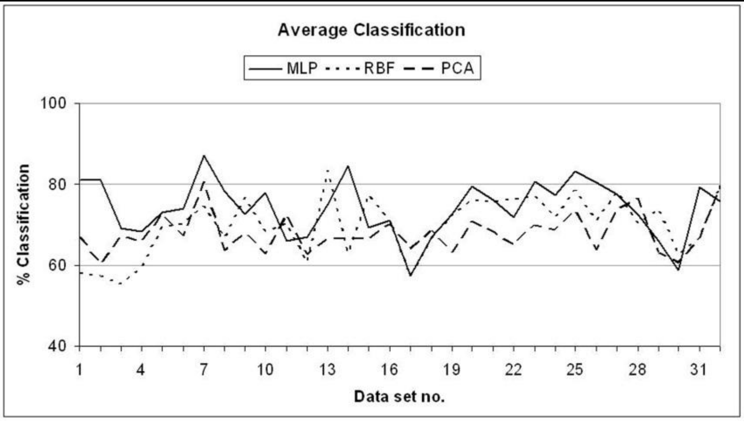

Fig.4 Classification accuracy of NN[s]

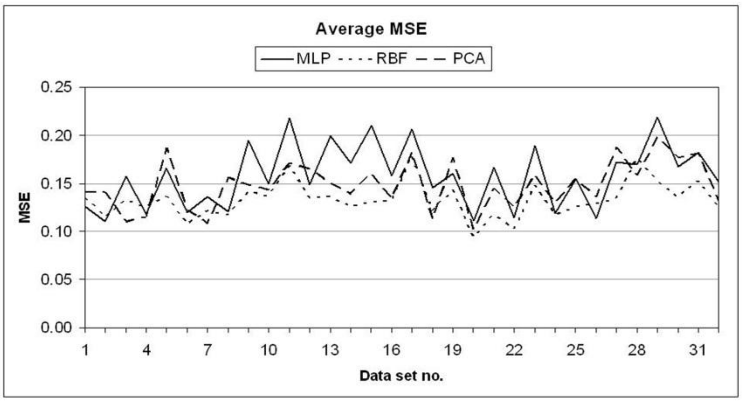

Fig.5.MSE of NN[s]

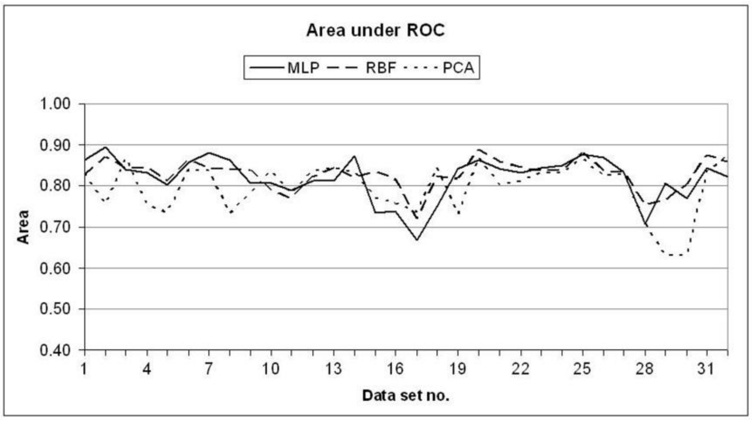

Fig. 6 Area under ROC of NN[s]

Table 4.Best Performance of NN

NN	%Classification Accuracy	MSE	Area	N/P	Time

	SEVERE	**MILD**		**under ROC**	**ratio**	**elapsed/epoch/ exemplar**
MLP	92.30	95.91	0.0484	0.9835	0.247	9.677 e-5
RBF	76.92	93.87	0.0761	0.9592	0.0203	2.365 e-4
PCA	69.23	89.79	0.1044	0.8799	0.417	8.602 e-5

VI. CONCLUSION

The percentage average Classification accuracy of MLP NN is higher as compared to RBF and PCA NNs and it has performed excellent on such complex and insufficient data set. The classification performance of the MLP NN model is not only superior to rule based statistical models but also to other NN models like RBF and PCA. It is observed that the MLP NN based DSS delivers consistently reasonable performance. Though, MSE is not a useful measure in the classification, it is reported for completion of the documentation. Thus, the proposed MLP NN based DSS could be employed as a good decision-making aid by the physicians and it could always be used for meticulous cross-examination and second opinion for reliable diagnosis of the disease.

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