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Comparison of performance of ANN to classify the type of Erythemato-Squamous Disease

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***Abstract*— Neural network architectures are configured to perform optimally based on the various dataset. In this paper, various NN architectures are built with different parameters. Here the dataset used is the benchmark dataset of erythemato-squamous diseases. The differential diagnosis of erythemato-squamous diseases is a difficult problem in dermatology. Artificial Neural Network (ANN) classifies the given samples when trained and nearly 98% classification accuracy is achieved. Generalized Feed Forward Neural Network (FFNN) can solve the multivariable classification problem of determination of skin disease. The performance of MLPNN, RBFNN, Modular NN, SOFM and Recurrent ANN are also studied to determine the type of Erythemato-Squamous Disease, which all share the clinical features of erythema and scaling, with very little differences. The diseases are classified into six classes, namely psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris.**

***Keywords*—** *classification, MLP NN, FFNN, RBF, erythemato-squamous disease*

I. INTRODUCTION (*Heading 1*)

A neural network performs pattern recognition by first undergoing a training session, during which the network is repeatedly presented a set of input patterns along with the category to which each particular pattern belongs. Later, a new pattern is presented to the network that has not been seen before, but which belongs to the same population of patterns used to train the network. The network is able to identify the class of that particular pattern because of the information it has extracted from the training data. Pattern recognition performed by a neural network is statistical in nature, with the patterns being represented by points in a multidimensional decision space. The decision space is divided into regions, each one of which is associated with a class. The training process determines the decision boundaries. The construction of theses boundaries is made statistical by the inherent variability that exists within and between classes.

The use of neural networks in signal processing is becoming increasingly widespread, with applications in pattern recognition. Research on the rapidly expanding use of neural networks to identify, detect and classify patterns is still in its infancy. Thus, there has been ample scope for employing neural networks in the above-mentioned tasks. In the proposed research work, the bench mark erythemato-squamous diseases data from UCI Machine learning repository has been used.

In dermatology, the differential diagnosis of erythemato-squamous diseases is a genuine problem. They all share the clinical features of erythema and scaling, with very little differences. The diseases in this group are psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis, and pityriasis rubra pilaris. Usually a biopsy is necessary for the accurate diagnosis but unfortunately these diseases share many histopathological features as well. Another difficulty for the differential diagnosis is that a disease may show the features of another disease at the beginning stage and may have the characteristic features at the following stages. Patients are first evaluated clinically with 12 features. Afterwards, skin samples are taken for the evaluation of 22 histopathological features. The values of the histopathological features are determined by an analysis of the samples under a microscope. ANN can solve the multivariable classification problem of determination of skin disease. ANN approach is studied to determine the type of Erythemato-Squamous Disease. FFNN classifies the given samples when trained and overall 98% classification accuracy is achieved on testing. Except for pityriasis rosea class, all other classes exhibit 100% classification accuracy. Consistently, the pityriasis rosea class has 88.235% classification accuracy, which is reasonably good. There are techniques such as decision tree classifier, fuzzy weighted preprocessing and genetic programming methods [1,2,3] used and the classification accuracy is reported as 86.18, 97.57 and 96.64% respectively.

Classes	Features		
	Clinical	Histopathalogical	
A - psoriasis	fl: erythema	f12; melanin incontinence	f23; pongiform pustule
B - seboreic dermatitis	f2: scaling	f13; eosinophils in the infiltrate	f24; munro microabcess
C - lichen planus	f3: denite borders	f14; PNL infiltrate	f25; focal hypergranulosis
D - pityriasis rosea	f4: itching	f15; fibrosis of the papillary dermis	f26; disappearance of the granular layer
E - chronic dermatitis	f5: koebner phenomenon	f16; exocytosis	f27; vacuolization and damage of basal layer
F - pityriasis rubra pilaris	f6: polygonal papules	f17; acanthosis	f28; spongiosis
	f7;follicular papules	f18; hyperkeratosis	f29; saw-tooth appearance of retes
	f8;oral mucosal involvement	f19; parakeratosis	f30: follicular horn plug
	f10: scalp involvement	f20; clubbing of the rete ridges	f31: perifollicular parakeratosis
	f11: family history	f21; elongation of the rete ridges	f32: inflammatory mononuclear infiltrate
	f34: age	f22; thinning of the suprapapillary epidermis	f33: band-like infiltrate

In classification, the input data is assumed to be multi-class, and the purpose is to separate it into appropriate classes as accurately as possible. Different input data may be generated by different mechanisms and that the goal is to separate the data as well as possible into correct classes. The desired response is a set of arbitrary labels (a different integer is normally assigned to each one of the classes), so every element of a class will share the same label. Class assignments are mutually exclusive, so a classifier needs a nonlinear mechanism such as an all-or-nothing switch.

This database contains 34 attributes, 33 of which are linear valued and one of them is nominal. There are six classes based on the symptoms. These classes are as given in Table 1

Table1: The dataset used in the experiments

In the dataset constructed for this domain, the family history feature has the value 1 if any of these diseases has been observed in the family, and 0 otherwise. The age feature simply represents the age of the patient. Every other feature (clinical and histopathological) was given a degree in the range of 0 to 3. Here, 0 indicates that the feature was not present, 3 indicates the largest amount possible, and 1, 2 indicate the relative intermediate values.

II. Performance of ANN Classifier

The important parameter to test the performance is classification accuracy, which is depicted in the confusion matrix.

A. *Confusion Matrix*

A confusion matrix is a simple methodology for displaying the classification results of a network. The confusion matrix is defined by labeling the desired classification on the rows and the predicted classifications on the columns. For each exemplar, a 1 is added to the cell entry defined by (desired classification, predicted classification). the predicted classification should be the same as the desired classification, the ideal situation is to have all the exemplars end up on the diagonal cells of the matrix (the diagonal that connects the upper-left corner to the lower right).

The confusion matrix tallies the results of all exemplars of the last epoch and computes the classification percentages for every output vs. desired combination. It is used to determine the percentage of correctly classified exemplars for each output class.

III. Computer Simulation

Total 366 samples of patients suffering from erythemato-squamous diseases are there in this dataset. These samples are divided in training, testing and cross validation. 60% (219) are used for training, 15% for cross validation CV (55) and 25%(92) for testing. Following NN architectures are exhaustively trained and tested and their performances are analyzed and compared.

A. *Multilayer Perceptron Neural Network (MLPNN)*

MLP based NN model has solid theoretical foundation. MLPs are feedforward Neural Networks trained with the standard backpropagation algorithm [4,5]. They are supervised networks so they require a desired response to be trained.

A meticulous and careful experimental study has been carried out to determine the optimal configuration of MLP NN model. All possible variations such as number of hidden layers, number of PEs (processing elements) in each hidden layer, different transfer functions in the output layer, different supervised learning rules are investigated in simulation. MLP NN model having single hidden layer with 15 PEs gives better performance as compared to other possible models. This model uses lineartanh transfer function and momentum learning rule in output layer. Table 2 depicts the classification accuracy which shows 100% classification for all classes except D class i.e pityriasis rosea. Here one patient is misclassified D as class E and two others as class B. Therefore classification accuracy drops to 82.352%. Performance parameters MSE and MAE of the MLP NN model for various classes for MLP NN architecture 34-15-6 are displayed.

TABLE 2:CLASSIFICATION ACCURACY FOR MLPNN ARCHITECTURE

Performance	pityriasis rubra pilaris	pityriasis rosea	chronic dermatitis	lichen planus	psoriasis	Seboreic Dermatitis
MSE	0.00305	0.05249	0.01237	0.0030	0.00314	0.02841
MAE	0.05437	0.12119	0.05386	0.0488	0.05514	0.10689
Percent Correct	100	82.35	100	100	100	100

B. Radial Basis Function (RBF)

RBF was first introduced in the solution of the real multivariate interpolation problem.[6,7]. The construction of a RBF network, in its most basic form, involves three layers. The input layer is made up of source nodes (sensory units) that connect the network to its environment or inputs. The second layer, the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space. The output layer is linear, supplying the response of the network to the activation pattern (signal) applied to the input layer.

A rigorous experimental study has been undertaken to determine optimal performance of RBF NN model. Different learning rules, Transfer functions, cluster centers are varied. RBF NN architecture with tanh transfer function, momentum learning rule and 200 cluster centers gives maximum classification accuracy. It is observed from the Table 3 that except disease pityriasis rosea all diseases are perfectly classified. The classification accuracy, MSE and MAE for RBF NN for different classes are depicted in Table 3.

TABLE 3: PERFORMANCE PARAMETERS OF RBF NN

Performance	pityriasis rubra pilaris	pityriasis rosea	chronic dermatitis	lichen planus	psoriasis	Seboreic Dermatitis
MSE	0.01098	0.05656	0.01595	0.00475	0.01761	0.0554
MAE	0.08448	0.17543	0.0974	0.052	0.11222	0.15273
Percent Correct	100	82.235	100	100	100	100

C. Modular NN

Modular feedforward networks are a special class of MLP. These networks process their input using several parallel MLPs, and then recombine the results. In contrast to the MLP, modular networks do not have full interconnectivity between their layers. Therefore, a smaller number of weights is required for the same size network (i.e. the same number of PEs). This ten 4: ds to accelerate training times and reduce the number of required training exemplars.

Modular NN model performs optimally for single hidden layer with 4 PEs. Table 4 shows the performance parameters for Modular NN. It is noticed that all other diseases except pityriasis rosea are perfectly classified.

TABLE4: PERFORMANCE PARAMETERS OF MODULAR NN

Performance	pityriasis rubra pilaris	pityriasis rosea	chronic dermatitis	lichen planus	psoriasis	Seboreic Dermatitis
MSE	0.00174	0.03327	0.00201	0.00073	0.001234	0.03095
MAE	0.02749	0.08856	0.03163	0.02127	0.03367	0.09591
Percent Correct	100	82.3529	100	100	100	100

D. SVM NN

The Support Vector Machine (SVM) is implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs which fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data, which share complex boundaries.

Table 5 shows the performance parameters for SVM model. It seen that all classes are perfectly classified except class D i.e. pityriasis rosea. Also chronic dermatitis

Performance	**pityriasis rubra pilaris**	**pityriasis rosea**	**chronic dermatitis**	**lichen planus**	**psoriasis**	**Seboreic Dermatitis**
MSE	0.0031	0.08739	0.00203	0.00268	0.01171	0.03993
MAE	0.04229	0.18251	0.04101	0.04523	0.06269	0.11569
Percent Correct	100	82.352	100	100	100	100

disease is fairly classified.

TABLE 5: PERFORMANCE PARAMETERS OF THE SVM NN MODEL

Performance	**pityriasis rubra pilaris**	**pityriasis rosea**	**chronic dermatitis**	**lichen planus**	**psoriasis**	**Seboreic Dermatitis**
MSE	0.09205	0.10528	0.09265	0.06752	0.04936	0.14506
MAE	0.26027	0.2396	0.25962	0.21549	0.18692	0.32561
Percent Correct	100	47.0588	92.3077	100	100	100

E. Recurrent NN

Recurrent networks have feedback connections from neurons in one layer to neurons in a previous layer. Different modifications of such networks have been developed and explored. A typical recurrent network has concepts bound to the nodes whose output values feed back as inputs to the network. So the next state of a network depends not only on the connection weights and the currently presented input signals but also on the previous states of the network. The network leaves a trace of its behavior; the network keeps a memory of its previous states.

There are two models of recurrent network. Fully recurrent networks feed back the hidden layer to itself. Partially recurrent networks start with a fully recurrent net and add a feedforward connection that bypasses the recurrency, effectively treating the recurrent part as a state memory. These recurrent networks can have an infinite memory depth and thus find relationships through time as well as through the instantaneous input space. Most real-world data contains information in its time structure. Recurrent networks are the state of the art in nonlinear time series prediction, system identification, and temporal pattern classification [8].

Hidden layer, number of PE and transfer function variations are attempted. It is seen that optimal performance is achieved for partially recurrent NN with 6 PEs and tanh transfer function in output layer.

Table 6 shows the performance parameters for Recurrent NN. It is observed that except class pityriasis rosea, all classes are perfectly classified.

TABLE 6 : PERFORMANCE PARAMETERS OF THE RECURRENT NN MODEL

F. FFNN (Generalised Feed Forward Neural Network)

Generalized Feedforward is, in essence, the MLP plus additional layer-to-layer forward connections. It has additional computing power over standard MLP.

Generalized feedforward networks are a generalization of the MLP such that connections can jump over one or more layers. Generalized feedforward networks often solve the problem much more efficiently than MLP [9].

An exhaustive and careful experimental study has been carried out to determine the optimal configuration of FFNN model. Number of hidden layers, number of PEs, transfer functions and learning rules are varied. Optimum performance is obtained for FFNN model having single hidden layer with 6 PEs in hidden layer and transfer function tanh, learning rule step.

The classification accuracy, MSE and MAE for FF NN for different classes are depicted in Table 7.

TABLE 7: PERFORMANCE PARAMETERS OF THE FF NN MODEL

Performance	pityriasis rubra pilaris	pityriasis rosea	chronic dermatitis	lichen planus	psoriasis	Seboreic Dermatitis
MSE	0.00212	0.09121	0.00455	0.00178	0.00169	0.03359
MAE	0.0436	0.15954	0.03551	0.04217	0.03847	0.11876
Percent Correct	100	88.235	100	100	100	100

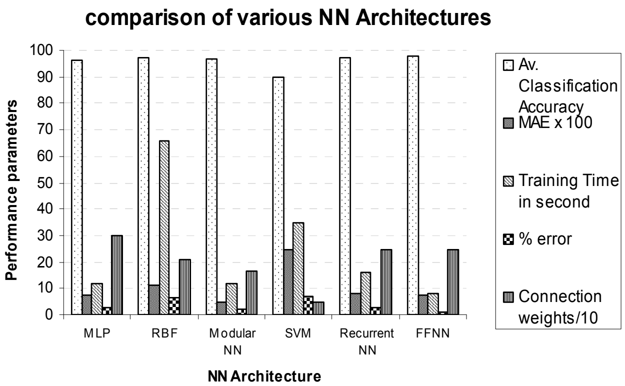
IV. COMPARISON OF NEURAL NETWORK ARCHITECTURES

MLP NN, RBF NN, Modular NN, SVM, Recurrent NN and FFNN are extensively trained. Table 9 portrays the various performance features. It is seen that the performance of FFNN is consistent for training and testing.

TABLE 9: COMPARISON OF VARIOUS NN MODELS

NN Archiecture	Av. Classification Accuracy	MAE	Training Time (sec)	% error	Connection weights
MLP NN (34-15-6)	96.32	0.073	12	2.56	300
RBF (Cluster Centers= 200)	97.55	0.112	66	6.3	210
Modular NN (34-4-6)	97.05	0.049	12	2.32	166
SVM	89.89	0.247	35	7.2	46
Recurrent NN (34-6-6)	97.06	0.081	16	2.6	246
FFNN (34-6-6)	98.04	0.073	8	1.33	246

It is observed from Fig 1 that the FFNN performs the best. It is seen from the graph that the classification accuracy for FFNN is found to be the highest among these NN architectures. It is depicted from the Fig 1that FFNN requires the least training time of 8 seconds. Percentage error and MAE



are also the least for FFNN.

Fig. 1. Comparison of performance of various NN models

V. RESULT

In this paper, performance of various NN architectures is studied. FFNN based classifier is designed optimally for reasonable differential diagnosis of erythemato-squamous diseases. Other NN architectures such as MLP NN, RBF NN, Modular NN, SVM, and Recurrent NN are trained and compared with FFNN. FFNN is found to be the best classifier. A FFNN model gives 100% classification accuracy for the five diseases namely, psoriasis, seboreic dermatitis, lichen planus, chronic dermatitis and pityriasis rubra pilaris. For one class, i.e, pityriasis rosea, consistently 88.235% classification accuracy is achieved. This is because of the fact that for a few patients this disease is often confused with seboreic dermatitis and chronic dermatitis. This is happening because of slightly overlapping of the symptoms among pityriasis rosea, seboreic dermatitis and chronic dermatitis. It is proposed that FFNN architecture with single hidden layer with 6 PEs is efficient and accurate enough to determine and classify the type of Erythemato-Squamous disease. The FFNN model is trained & tested using 10-fold cross validation in order to verify the performance of our classifier which is quite reasonable.

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