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Extreme Learning Machine for the Classification of Rainfall and Thunderstorm

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Abstract: Forecasting rainfall and thunderstorm is one of the important requirements for planning and management of many applications, including, agriculture, flood and traffic. Considering the relevance and importance of the study, this research study aims at classification of rainfall and thunderstorm. There are various classifiers available but not limited to, Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbourhood classier (KNN), Adaboost, etc. Recently Dr. G.B. Huang suggested and proposed an efficient classifier based on single layer feedforward Neural Network called as Extreme Learning Machine (ELM) which is extremely powerful to be an Universal classifier. Hence, this study focuses on the classification of rainfall and thunderstorm. The results of the classification using ELM show a classification accuracy of 87.69% which is much better when compared to the results of other classifiers, namely, SVM and ANN. Hence, ELM can be considered as a good classifier for the classification of rainfall and thunderstorm.

Key words: Rainfall prediction, thunderstorm prediction, extreme learning machine

INTRODUCTION

Weather forecasting is the application of science and technology to predict or classify the weather at a given location. Weather forecasts are made by collecting data about the weather parameters at a given place and applying mathematical models to that data. Rainfall and thunderstorm forecasts are essential for many fields such as agriculture, flood, traffic etc. It helps better planning and management in many applications. Despite the growth of science and technology, rainfall and thunderstorm prediction is still a challenging problem.

The ANN (Sharma and Manoria, 2006; French *et al*., 1992) based approach is used by several researchers to forecast rainfall successfully. Similar research includes but not limited to thunderstorm forecasting by Ali *et al*. (2011), Chen and Takagi (1993) study using meteorological satellite images to predict four different rain intensity levels, weather forecasting system by Sharma and Manoria (2006) to forecast rain, thunderstorm, sunshine and dry, daily rainfall simulation to identify the weather types (Cheng *et al*., 2010).

Extreme Learning Machines (ELMs) proposed by Huang *et al*. (2006) are universal approximators and can be used for classification. The ELM out performs other machine learning techniques like Neural Network and Support Vector Machines. Hence, by considering the relevance of the prediction of rainfall and thunderstorm and by considering the advantages of ELM, the aim and objective of this study focuses on the classification of rainfall and thunderstorm using extreme learning machines (ELMs).

MATERIALS AND METHODS

Traditional neural networks take initial weights randomly and optimize those values using some iterative methods and hence these methods will lead to local optima and will be slow. Extreme learning machines proposed recently by Huang *et al*. (2004, 2006) makes use of single hidden layer feedforward networks (SLFNs) in which inputs weights (i.e., the weights of the connection between input layer and hidden layer) are assigned or chosen randomly and the output weights (i.e., the weights of the connection between hidden layer and output layer) are calculated using Moore-Penrose (MP) pseudoinverse.

Suppose there are N known observations:

$$([x_j^1, x_j^2, x_j^3, \ldots x_j^P], [t_j^1, t_j^2, \ldots, t_j^Q]),\ j = 1,2,3, \ldots, N$$

where, P is the number of input variables, Q is the number of output variables. Then a SLFN can be constructed as shown in Fig. 1.

Then the output of k-th output neuron for j-th observation will be:

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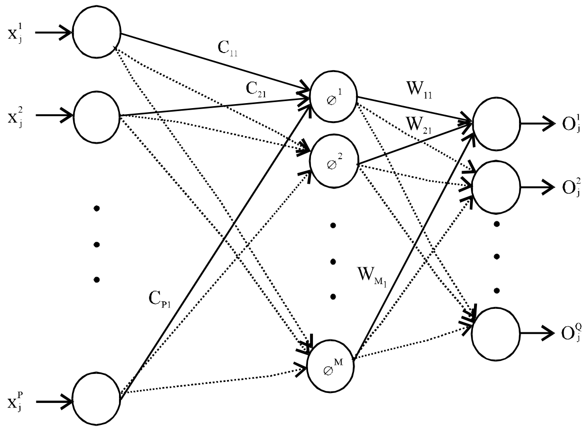

Fig. 1: Single Layer Feedforward Network (SLFN) with P input neurons, M hidden neurons and Q output neurons

$$O_j^k = \sum_{s=1}^{M} w_{sk} \times \varnothing_s \left(\left(\sum_{r=1}^{P} c_{rs} \times x_j^r \right) + b_s \right)$$

If the transfer functions in all the hidden neurons are same then $\varnothing_S$ in the above equation can written as $\varnothing$. Now the problem is to have weights in such a way that the error given by the following equation is minimum:

$$E = \frac{1}{N} \sum_{j=1}^{N} \left(t_j^k - o_j^k \right)^2$$

The matrix format for the SLFN can be written as:

$$O = HW$$

Where:

$$W = \begin{bmatrix} W_{11} & \cdots & W_{1Q} \\ \vdots & \cdots & \vdots \\ W_{M1} & \cdots & W_{MQ} \end{bmatrix} \text{of size } (M \times Q)$$

$$O = \begin{bmatrix} t_1^1 & \cdots & t_1^Q \\ \vdots & \cdots & \vdots \\ t_N^1 & \cdots & t_N^Q \end{bmatrix} \text{of size } (N \times Q)$$

and:

$$H = \begin{bmatrix} \varnothing\left(\left(\sum_{r=1}^{p} c_{r1} \times x_1^r\right) + b_1\right) \ldots \varnothing\left(\left(\sum_{r=1}^{p} c_{rM} \times x_1^r\right) + b_M\right) \\ \vdots \qquad \ldots \qquad \vdots \\ \varnothing\left(\left(\sum_{r=1}^{p} c_{r1} \times x_N^r\right) + b_1\right) \ldots \varnothing\left(\left(\sum_{r=1}^{p} c_{rM} \times x_N^r\right) + b_M\right) \end{bmatrix} \text{of}$$
size (N×M)

Now in ELM (Huang *et al*., 2004, 2006), the input weights were randomly generated and the output weights were calculated using $W = H^+ O$.

The MP pseudoinverse, H^+, can be calculated (Huang *et al*., 2004, 2006) using any of the equations: (1) $(H^TH)^{-1}H^T$ (orthogonal projection method), (2) $(H^TH+\lambda I)^{-1}H^T$ (regularized orthogonal projection method), (3) $V\Sigma^+U^T$, where, V and U are unitary matrices and Σ^+ is a diagonal matrix and the values are the inverses of the singular values of H.

Other extended versions of ELM includes but not limited to, evolutionary extreme learning machine (Zhu *et al*., 2005), convex incremental extreme learning machine (Huang and Chen, 2007), online sequential extreme learning machine (Er *et al*., 2012). Two of the interesting applications of ELM include illuminance prediction through Extreme Learning Machines (Ferrari *et al*., 2012) and comparison of short-term rainfall prediction models for real-time flood forecasting (Toth *et al*., 2000).

RESULTS AND DISCUSSION

Inorder to show the performance in terms of classification for Extreme Learning Machine (ELM), a benchmarking dataset, namely, IRIS dataset is chosen. The Iris dataset is a multivariate dataset with 150 samples of iris flowers falling in the categories of setosa, versicolor and virginica (fifty instances for each category). The attributes are sepal length, petal length, sepal width and petal width. The total dataset is divided into two and 120 instances are used for training and 30 instances are used for testing. Table 1 shows the results of Iris data classification. It is clear from the Table 1 that ELM outperforms other methods.

Now, in the following, the classification of rainfall and thunderstorm using ELM is shown.

The meteorological parameters for rainfall and thunderstorm predication includes, temperature, dew point (moisture level in air), humidity, sea level pressure (rainfall and sea level pressure are inversely proportional), visibility, wind speed, cloud cover and wind direction degrees. The dataset is collected from www.wunderground.com for the year 2010 at a particular location with 362 samples. This dataset contains real time observations of the weather for a particular period of time at a particular location. There are mainly three classes: (1) Day without rain and thunderstorm, (2) Days with rain or thunderstorm, (3) Days with rain and thunderstorm. The total dataset divided into two, 297 instances used for training and 65 instances used for testing.

Table 2 shows the results of rainfall and thunderstorm classification using ELM for various numbers of hidden nodes.

Table 1: Comparison of IRIS data classification

Algorithm	Accuracy (%)
Hong and Lee's method (Hong and Lee, 1996)	95.57
Chang and Chen's method (Chang and Chen, 2001)	96.07
Wu and Chen's method (Wu and Chen, 1999)	96.21
Back propagation (5000 epochs) for the present implementation using Neural network	96.33
Castro's method (Castro *et al.*, 1999)	96.60
Hong and Chen's method (Hong and Chen, 1999)	96.67
Chen's and Fang method (Chen and Fang, 2005)	97.33
ELM (present implementation)	98.33

Table 2: Rainfall and thunderstorm classification using ELM for various numbers of hidden nodes

No. of hidden nodes	Training accuracy (%)	Testing accuracy (%)
10	65.32	73.85
50	74.41	75.38
100	77.44	84.62
200	82.83	87.69

Table 3: Comparative results of the classification of rainfall and thunderstorm

Classifier	Accuracy (%)
SVM (sigmoid)	66.85
ANN (MLP, Gradient descent bp, 2000 epochs)	80.07
ANN (MLP, BFGS quasi Newton, 2000 epochs)	81.50
ANN (MLP, LM, 2000 epochs)	83.70
ELM	87.69

As the dataset for rainfall and thunderstorm classification is not used by anybody in the literature for classification purpose, comparison with existing literature study is very difficult and hence not provided. Hence, the comparison of the dataset for various other classifiers for the classification of rainfall and thunderstorm is shown in Table 3.

The results show that the performance of ELM is highly efficient for the classification of rainfall and thunderstorm. The ELM can also be used as a Universal Classifier for classifying any type of dataset.

CONCLUSION

In this study Extreme Learning Machine (ELM) is used to classify rainfall and thunderstorm. The results are compared with SVM and MLP. The result shows ELM is suitable for weather forecasting and can be considered as an alternative to traditional meteorological approaches for classification.

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