Rainfall Prediction Using Mixture Neural Network: A Study

Abstract:

A novel rainfall prediction method has been proposed. In the present work rainfall prediction in southern part of west Bengal (India) has been conducted. A two-step method has been employed. Greedy forward selection algorithm is used to reduce the feature set and to find the most promising features for rainfall prediction.first, in the training phase the data is clustered by applying k-means algorithm, then for each cluster a separate neural network (NN) is trained. The proposed two step prediction model (hybrid neural network or HNN) has been compared with MLP-FFN classifier in terms of several statistical performance mwmeasuring metrics. The data for experimental purpose is collected by dumdum meteorological station (west Bengal, indial) over the period feom1989 to 1995.the experimental result have suggested a reasonable improvement over traditional method in predicting rainfall. The proposed HNN model outperformed the compared models by achieving 84.26% accuracy without feature selection and 89.54% accuracy with feature selection.

Keywords- rainfall prediction, neural network, backpropagation, scaled conjugate descent-means

Introduction

Rainfall prediction is considered to be one of the important weather forecasting related research since rainfall heavily affects our nature and surroundings. Natural phenomenon such as flood, draught, weather indicators such as relative humidity, etc.are highly affected by rainfall.thus, robust and accurate methods of predicting rainfall are in interest. Several successful attempts have been made to predict quantitative rainfall [1].rainfall prediction can broadly be classified into two categories. One is by analyzing the different physical laws that governs rainfall in a particular region.though, the approach sound fair enough, it has been found that the number of such constraints that governs rainfall is both spatial and temporal.thus, the prediction involves too much mathematical. Calculation and hence is not computationally feasible. The second approach involves expert system to be involved and discovering hidden patterns of how different features that affects rainfall are actually related with physical rainfall [2]. The later approach has been found to be more suitable. The modern advancement in research of artificial neural networks (ANNs or NNs) has proved that the expert systems based on NNs are exceptionally accurate and robust in solving real life problems [3-15, 28].an well trained ANN can efficiently predict the class label of an unknown sample [16]. rainfall prediction model based on several ANN based architectures have been proposed [17] to predict rainfall in india.models based on ARIMA(1,1,1),MLP-FFN,legendre polynomial equation (LPE) and functional-link artificial neural network (FLANN) have been compared .the FLANN based model has been found to be more suitable and accurate. another ANN based rainfall prediction has been reported where four years hourly data has been used to predict rainfall one to three hour ahead in Delhi. India. The prediction model was based on meteorological parameters such as wet bulb temperature, air pressure, relative humidity and cloudiness. The authors have found that wet bulb temperature could be the deciding factor in prediction of rainfall [18].

Consequently, various aspects regarding weather can be prediction and studied using ANN, where a learning algorithm can be employed to train the network. The learning algorithm tries to find out the optimal set of weights for the neural connections of the ANN. thus, the training phase can be thought of as an optimization problem where an error function is usually minimized. However it has been revealed that the standard algorithms may be unable to approximate the exact pattern of the data if it is reasonably complex [29].thus, achieving expected accuracy is challenging.

Motivated by this, in the current work a hybrid neural network (HNN) model has been proposed to predict rainfall based on several features such as temperature, relative humidity, vapour content and atmospheric pressure. The data has been collected by dumdum meteorological (west Bengal, India) station over the period from 1989 to 1995.a two-step method has been employed in the training phase. First-K means clustering algorithm (with k=2) has been applied on the data. Next, for each cluster (using back-propagation) to build the prediction model. the proposed model has been compared with multilayer Perceptron feed-forward network(trained with scaled conjugate gradient descent algorithm)(or simply MLP-FFN)in terms of accuracy, precision, recall and F-measure.the experimental results have established the superiority of the proposed model over the well-known MLP-FFN.

Background Theory

In the current study a two-step HNN model has been proposed. The first step involves clustering of data, next for each cluster of data a separate NN has been employed solely to recognize the pattern of that cluster only. As in the current study our motivation is to classify data members into two classes, data are clustered into two clusters in the first step.

A. Neural Network Based Classsification

The ANN is one of the most used modeling approaches [19, 20].it achieves accurate classification even with very small dataset. The ANN structure is consists of interconnected computational neurons, which involved in the mathematical mapping through the learning process, which attempt to adjust the weight value. Initially, the training phase is started by a part of the dataset to classify its input along with its class label to create the classification model afterward; the validation phase is performed to confirm the effectiveness of the trained model using another dataset. Finally, the evaluation phase is used to test the classification model accuracy using another set of test data. In general, the artificial neuron uses the input signal (x) and their equivalent weights (w) to form the input (nj). This input is then surpassed to a linear threshold filter till it exceeds the output signal (y) to another neuron. If nj exceeds the threshold of that neuron, the neuron is inspired. the net input (nj)is calculated by the following equation.

Where, n is the number of the input signals, w is the weight and x is the strength of each signal. consequently, the output(y)is computed as follows:

Here, ([image:]) is the bias. the sigmoid and logistic functions can be used as an activation functions. the Perceptron learning rule is employed to attain the optimal weight vector in finite number of iterations[21].for the MLP-FFN experiments, two- layer Perceptron feedforward network can be conducted[22].

B. K-Means Clustering

The clustering problem can be posed as a partitioning problem where a set of ndimensional points needs to be portioned into clusters such that the squared error between the cluster center (mean of cluster)and rest of the cluster members is minimized. Considering a

X(i) to be a set of kn dimensional point where i=1,2,……m, The goal of the k-means algorithm[23]is to minimize the squared error for all k clusters. The squared error for ith cluster can be expressed as;

Where pj is the jth point of ith cluster ,and mi denotes the cluster center of the same. The overall error can be expressed as;

Hybrid Neural Network Model

The hybrid neural network (HNN) model is a two-step method. first the data is v clustered using k-means algorithm. next for each cluster a separate NN is employed and trained to build the model. Figure 1 depicts the HNN model. in the present study k-means algorithmic applied on the training set of data with k=2.next for each cluster one NN is employed. the model enables a particular NN to learn the pattern for a particular class of data points.

Fig 1: The hybrid NN Model

Experimental Methodology

The proposed method has been applied on a dataset obtained from dumdum weather station. the dataset features are described in table 1.the experimental methodology is depicted in figure 2.first ,the greedy forward selection method has been applied to find the most suitable features in predicting rainfall. Since, inappropriate set of features may lead to poorly performing ANNs. Greedy forward selection. the algorithm[25] is extensively used for feature selection. The algorithm first considers each feature as a single set of features and gradually adds new feature based on a greedy improvement strategy.

Table 1:Feature Set Before Feature Selection Operation

Attribute

Explanation

Pressure_min

Minimum Pressure(in mb)

Pressure_max

Maximum Pressure(in mb)

Vapour_min

Minimum vapour quantity

Vapour _max

Maximum vapour quantity

Relative humidity_min

Minimum Relative humidity

Relative humidity_max

Maximum Relative humidity

Temperature_min

Minimum Temperature

Temperature_max

Maximum Temperature

The advantage of the used forward greedy algorithm is that it works with a sparse solution explicitly, which leads to efficient computation. Afterwards, the dataset is clustered using unsupervised k-means algorithm(taking k=2).next the data corresponding to each cluster is fed as input to separate neural networks.

Fig 2: Experiential method flow

During this training phase 80% data of each cluster has been used to train corresponding NNs. Rest (20%) of the data has been used during testing phase. The proposed model has been compared with BPNN and MLP-FFN(trained with scaled conjugate gradient descent algorithm)in terms of the following performance measure metrics [27] such as the accuracy, recall, precision, and F –measure are calculated to assess the proposed system compared to the other system, where:

Where ,tp (true positive), fp(false positive), fn(false negative), tn(true negative) carries usual meaning in the context of confusion matrix.

Expermental Results And Analysis

Table 2 presents categorization of different approaches of rainfall forecasting. the categorization is based on following features: region, training and testing period, type of neural network, number of input , output and hidden layer, activation function, accuracy measure, rainfall predicting variable.

Conclusion

Rainfall takes a vital role in deciding the weather condition and also deciding factor of natural disaster such as floats throughout etc. accrual sectors can avail the benefit of knowing weather condition in advance and take precautionary steps according. This is directly helps in improvement of nationally

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