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Application of Artificial Neural Network to Predict Squall-Thunderstorms Using RAWIND Data

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Abstract - Severe thunderstorm is a mesoscale weather phenomenon which occurs seasonally. It affects people in a devastating manner. It happens in many subtropical places of the world. Different scientific researches are going on to the forcasting of this severe weather feature in advance to reduce damages. Nowadays, machine learning techniques are applied in meteorological field. The present study is performed by the application of artificial neural network Multilayer Perceptron (MLP) model to predict seasonal severe thunderstorms associated with squall occurring in Kolkata, India. It is trained and tested with rawindsonde data recorded in the early morning at 00:00UTC (06:00 Local Time). In this paper, it has been found how much correct prediction of the 'occurrence'/ 'no occurrence' of severe storms can be done using vertical wind shears at different geo-potential heights of the atmosphere having the nowcasting time of around 12 hours. Multilayer Perceptron is found to yield very promising result. The result indicates that forecasting can be done correctly above 98% both for 'squall-storm days' and 'no storm days'.

Index Terms- Back Propagation, Machine Learning, Multilayer Perceptron, Rawind, Severe Thunderstorm, Squall, Wind-shear.

1 INTRODUCTION

Severe thunderstorm is an extreme atmospheric feature which is associated with squall, thunder, lightning, and sometimes with hail, [1]. Squall is a sudden and sharp increase in the wind speed over a short time interval. The strong wind which has the speed of at least 45 kilometers per hour with the duration of minimum 1 second is termed as squall. Such high wind usually occurs in a region of strong mid-level height falls or mid-level tropospheric cooling, which forces strong localized upward motions at the leading edge of the region of cooling, and then enhances local downward motions just in its wake, [2].Thunderstorms occur in different subtropical places of the world seasonally, [3]. People are affected due to the devastating features of squall-storms, [4]. Correct prediction of severe thunderstorm is necessary to make the people alert from the catastrophy caused by this event. Accurate prediction of such severe weather feature is very difficult task due to the dynamic nature of atmosphere, [5]. Generally, various surface as well as upper air weather data are required to predict squall-thunderstorms. In this study, only the upper air vertical wind shear is taken into account for the squall-storm prediction. Wilhelmson and Klemp (1978) demonstrated how cyclonic and anticyclonic severe storms may evolve in the presence of environmental wind shear, [6]. Linear theory predicts that an initially axisymmetric updraft interacts with a shear flow in a way that produces a favorable vertical pressure gradient, [7] to produce severe thunderstorms.

In the present paper, our intention is to observe how much correct prediction of thunderstorms can be done using only one type of weather feature such as vertical wind shear having 10 to 12 hours lead time. Here the predictor wind

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shear is considered at four different heights (such as 900hpa, 700hpa, 500hpa and 200 hpa) of the upper air. Wind speeds at different geopotential heights which were recorded by rawindsonde in Kolkata (22.3°N/88.3°E), India in the morning time at around 06:00 Local Time (00:00UTC) are taken for this analysis. All these data were procured during the period of 18 years from 1990 to 2008 for the months of March-April-May (MAM). These three months are known as pre-monsoon season in north-east India. Most of the thunderstorms generally occur in this season. Prediction of various climatic features with neural network models has received increasing interest, [8]. Neural network as an important branch of artificial intelligence has been applied to space weather forecasting such as forecasting of geomagnetic storm [9] and solar flair [10]. The use of artificial neural network (ANN) has been recognized as a promising way of making prediction on time series data [11].

Here Machine learning technique has been applied to forecast the 'occurrence'/'no occurrence' of squall-storm. The main features of ANN are its ability to map input data to output data to any degree of non-linearity [11]. Neural Network is a generalization of traditional statistical methods for non-linear regression and classification [12]. These new net topologies and algorithms have achieved a considerable amount of success [13]. Multi layer perceptron (MLP) and K-nn techniques have been applied by Chakrabarty et al., 2012 to predict squall-storms occurring in Kolkata using only two weather variables such as adiabatic lapse rate and moisture difference from surface level to five different geopotential heights of the atmosphere with around 12 hours lead time, resulting 91% accuracy in forecast. In the present work, more than 87% accuracy in the prediction of 'squall-storm' and nearly 100% accuracy in the prediction of 'no squall-storm' have been obtained. Over all, more than 98% accuracy in the prediction of both 'squall-storm' and 'no squall-storm' have been obtained applying MLP. The interesting thing is that using only one type of upper air weather variable such as vertical wind shear as the input data such high level of accurate result has been found. Here, it is observed that wind shear parameters play an important role in forecasting severe thunderstorms. The significance of this work is that very accurate prediction can be done by this network using only the vertical wind shear data with the lead time of around 12 hours.

2 DATA

2.1 Data Collection

All the weather data were collected from India Meteorological Department, Govt. of India during the period of 18 years from 1990 to 2008 for the months of March-April-May. The data were recorded at 00:00 UTC by rawindsonde. The data considered for analysis here are both for the days when squall-storms occurred and for some of the days when squall-storms did not occur. The numbers of 'squall-storm' days are 81 and 'no squall-storm' days are 302. Training dataset and testing dataset for 'squall-storm' days are 41 and 40 respectively. For the 'no squall-storm' days, a set of 40 data points are considered for training and 262 as testing dataset.

2.2 Data Description

Here wind shear at four different geopotential heights of the atmosphere are considered to be as input variables (predictors), represented by x_i's. The predictand is the squall storm, y. A wind shear occurs whenever the wind changes speed with altitude, [14]. The wind shear has been calculated by the difference in wind speed between two consecutive heights of the upper air with respect to the difference between those respective heights (dw/dx). The upper atmosphere altitudes are (i) 900 hpa and 700 hpa (approximately 980 meters to 2500 meters), denoted by (x_1), (ii) 700 hpa and 500 hpa (approximately 2500 meters to 12340 meters), denoted by (x_2), and (iii) 500 hpa and 200 hpa (approximately 12340 meters to 35000 meters), denoted by (x_3). Surface wind data were not considered as they were not available properly. A vertical wind shear characterizes the friction layer because horizontal winds strengthen with altitude, [14]. An unstable friction layer features a weaker vertical wind shear and relatively energetic and gusty surface winds, [14].

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3 METHODOLOGY

A three-layered Multilayer Perceptron (MLP) network has been used in this study. It consists of an input layer, one hidden layer and an output layer. The input layer contains the sensory units of four input nodes where the first 3 nodes correspond to predictor weather variables x_1, x_2, x_3 and the fourth one x_4 is considered as the 'bias' term. The value of the fourth node is assumed as 1, irrespective of 'storm' or 'no storm' days. The input nodes x_1, x_2, and x_3 indicate vertical wind shears at different ranges of heights from 900 hpa to 200 hpa levels of the upper atmosphere. There is one hidden layer having several computation nodes and an output layer having two computation nodes.

3.1 Learning Phase

In the learning phase of the Multilayer Perceptron, the value 1, 0 for nodes 1 and 2 respectively in the output layer would mean that the input is a 'squall storm' data point and 0, 1 for nodes 1 and 2 respectively would mean the observation corresponds to 'no storm' day. Each unit of each layer is connected to each unit of the next layer by the connection weights. A sigmoid function, which is a nonlinear activation function, is widely used as a transfer function. There are two ways of learning the weights of an MLP: Batch mode learning and On-line learning. Here, On-line method of learning the weights is followed.

3.2 Feed Forward Stage

In this stage each node (say *i*) in a layer α is joined to each node (say *j*) in the next layer ($\alpha + 1$), with a connection weight represented by $W_{ij}^{(\alpha)}$. Let X_i be the i-th input node in the input layer. Then the activation unit for the hidden layer is Y_i, which is the output from the nodes of the input layer. Y_i is the total input received for the j-th node in the hidden layer.

$$Y_i = \sum_{i=1}^{n} X_i W_{ij}^{(\alpha)}. \qquad (1)$$

The output from the j-th node of the hidden layer is Y_j . A transfer function is used to obtain this.

$$Y_j = \frac{1}{1+\exp(-Y_i)} \qquad (2)$$

This is valid for every layer.

3.3 Connection weights

Connection weights (W 's) are initialized to small random values in the range (-0.5 to 0.5). A threshold value is also assumed. The weight values are modified during back propagation of the learning of the model until the error is minimized. The modified weights are used to validate the testing datasets. The back propagation method basically used gradient descent technique for changing the weights. It is used to reduce the possibility of getting stuck in local optimal points or saddle points of the network.

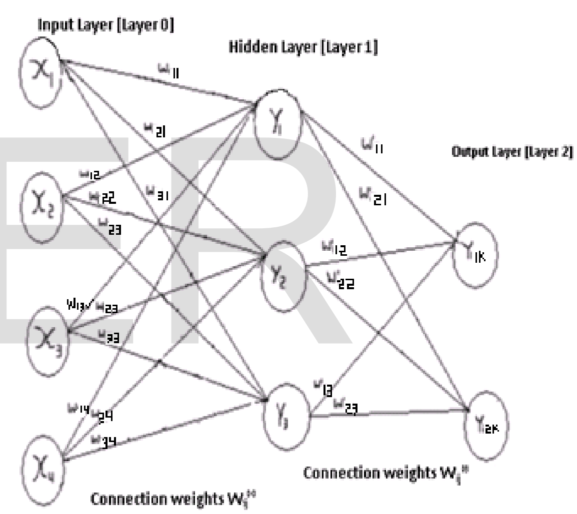

Fig. 1. 3 layered MLP with architecture 4-3-2

3.4 Error

The error function is the mean square error, which is expressed by,

$$E = \frac{\sum_{j=1}^{2} (o_j - e_j)^2}{2} \qquad (3)$$

The expected output (e_j) for every point in the training set is known. For a particular observation, the actual output value for the j-th node in the output layer is o_j. This error is to be minimized during the training phase by the back propagation. Iteration is continued until the error is minimized around 0.005 to 0.001.

3.5 Back Propagation of Error

In the present case, back propagation rule is applied on the set of training patterns pair. This rule basically uses gradient descent technique for changing the weights. It is not necessary to have all the training data set at one time, nor the training data set to be a finite set. The objective is to determine the weight update for each presentation of an input-output pattern pair. Since given data may be used several times during training, let us use the index *m* to indicate the presentation step for the training pair at step *m*. For training a multilayer feedforward neural network, we use the following estimate of the gradient descent along the error surface to determine the increment in the weight connecting the units *j* and *i*:

$$\Delta w_{ij}(m) = -\eta \frac{\partial E\,(m)}{\partial W_{ij}} \tag{4}$$

where $\eta = 0.01$ is the learning rate parameter.

3.6 Updation of weights

The weight update is given by,

$$W_{ij}(m+1) = W_{ij}(m) + \Delta w_{ij}(m) \tag{5}$$

The modified weights are used in test dataset to validate the outputs.

Sometimes, even when the number of iteration becomes a large number or if the classification on test set be unsatisfactory, the error may not be reduced. In such cases, the architecture of MLP is to be changed by changing the number of nodes in the hidden layer. So several 3 layered MLPs are to be studied. Three layer MLP consists of input layer, one hidden layer, and output layer. The number of nodes in hidden layer is varied from 2 to 7 to get a good classification. The different 3-layered architectures of MLPs which were used in this study are 4-2-2, 4-3-2, 4-4-2, 4-5-2, 4-6-2, and 4-7-2.

4 RESULT

The results are shown in table 1.

TABLE 1

RESULTS OF 3-LAYERED MLP

Design of the network	Number of accurately classified and % of accurate points for 'squall-storm' days in the test dataset (Number of 'squall-storm' days in test dataset is 40)	Number of accurately classified and % of accurate points for 'no squall-storm' days in the test dataset (Number of 'no squall-storm' days in test dataset is 262)	Total number of accurately classified and % of accurate points in the test dataset. Datasets of both 'squall – storm' and 'no squall-storm' days considered. Total size of test dataset is 302.
MLP (4-2-2)	10, 25%	191, 73%	201, 66.55%
MLP (4-3-2)	35, 87.5%	262, 100%	297, 98.34%
MLP (4-4-2)	23, 57.5%	188,71.75%	211, 69.86%
MLP (4-5-2)	21, 52.5%	153,58.39%	174, 57.61%
MLP (4-6-2)	23, 57.5%	109,41.60%	132,43.7%
MLP (4-7-2)	24, 60%	119,45.42%	143, 47.35%

It is observed that 4-3-2 model of MLP gives the most satisfactory result comparing with the other 5 models of MLP. This 4-3-2 network resulted in 87.5% correct prediction of 'squall days' and 100% correct prediction of 'no squall days'. Total number of accurately classified both the 'squall days' and the 'no squall days' using the said MLP classifier is 98.34%.

Chakrabarty et al., 2013 [1] applied MLP and K-nn methods for the forecasting of severe thunderstorms in Kolkata with 10-14 hours lead time. They used radiosonde data of moisture difference profile and adiabatic lapse rate at five different geopotential heights of the upper atmosphere. MLP classified 82.22% of the 'squall-storm' days and false alarm rate was 37.19%. In the present work, 98.34% correct classification of both 'squall-storm' days and 'no squall-storm' days has been predicted. Here the false alarm rate is 1.66%.It has been found here that 4-3-2 MLP network is a very good classifier which cans nowcast severe thunderstorms using only one upper air parameter, i. e., vertical wind shear at different heights of the atmosphere. It is to be noted that this classifier is the one parameter model which can predict 'squall-storm' and 'no squall-storm' with around 12 hours lead time.

5 Conclusion

A wind shear occurs whenever the wind changes speed with altitude, [14]. The magnitude of this wind shear varies and is influenced by air stability, [14]. Cumulonimbus clouds are developed through the levels of strong vertical wind shear, [15]. Byers and Braham (1949) found that radar echoes of young and growing convective clouds drift with the low level winds, and as their height increases, the direction of their motion changes gradually to that of the high-level winds, [16]. Byers and Battan (1949) computed the vertical windshear by a horizontal displacement R between the level h_b (bottom) and h_a (top) of a titled turret, at two successive times t_1 and t_2 as,
$\delta(\cot\alpha)/\,\delta t = [(R_2\text{-}R1)/(h_b - h_a)]/(t_1 - t_2)$, [17]. In this paper, the difference in wind speeds with respect to the heights (dw/dh) is considered for wind shear calculation. A theoretical treatment of the effect of wind shear upon the cumulus clouds undergoing entrainment while going through shear levels was undertaken by Malkus (1949), [18]. The entrainment is assumed to be the only mechanism by which the rising in-cloud air is accelerated, [15]. Vertical wind shear of the horizontal wind is inimical to the development of shower clouds, squall-lines and large thunderstorms, which show a preference for the jet-stream region where this shear is pronounced, [19]. For this reason, in the present article, the wind speeds of the upper air heights of 500 hpa to 200hpa are considered, as these zones of the upper atmosphere are treated as the jet-stream regions.

Newton (1963), [20] cited that squall-lines and large thunderstorms causing severe weather actually show a preference for the jet-stream region where there is strong shear, [21]. A study of radar observations by Byers and Batton (1949) disclosed that individual cumulus towers are sheared at a much lesser rate than would be expected if they drifted with the wind, [17]. Isolated cumuli are often seen to be torn asunder, when subjected to strong vertical shear, [20].

In this present work the results have been found using the RSRW data. Generally, Radar data may not be available from all the weather stations. So, weather variables may be obtained from RSRW flight.

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