Environment Change Prediction to Adapt Climate-Smart Agriculture

Aditya Gaikwad[1], Tejashree Jadhav[2], Prajwal Patil[3], Prof. Nidhi R. Sharma[4]
Department of Computer Engineering
[1,2,3,4] Mumbai University

Abstract- *This year the increased climate unpredictability is challenging to agriculturalists. It will assume to influence on yield and livestock productivity. So new methods are essential to farmers with modernized and important statistics so as to ease them in the decision-making practice, and to make them more aware of global climate pattern. The main objective of this project is to develop a web application that predicts the environmental changes and to help farmers in get used to climate-smart Agriculture methods using a neural network-based algorithm for forecasting the temperature. The Neural Networks package supports different types of training or learning algorithms. One such algorithm is Back Propagation Neural Network (BPN). Back propagation Algorithm which will increase the revenue and yield of farmers. This paper is aiming to find Climate-Smart, Decision-Making to problems of climate change, such as global food insecurity, to predicting and justifying the impact of dangerous weather events on global agriculture and also, we can predict the Climate Change around the world using Data Analytics. This paper presents an enhanced automated prediction technique based on Asp.net language for actual weather data analysing and forecasting system*

Keywords- Temperature prediction, decision making process, neural network, Back propagation algorithm.

I. INTRODUCTION

Weather refer to the state of air on earth at a particular place and time. Weather is a dynamic and non-linear phenomenon. There is a necessity to apply statistical post-processing techniques on modeled forecast fields to improve the prediction quality.

India is an agricultural country so weather prediction plays a very essential role. If we can predict that what will be the climate change in future then we can work according to those values the weather calculations should be accurate and more precise. Weather forecasts are made by gathering quantitative data about the present state of the air. The nature of the climate implies the need of massive computational power required to solve the equations that refer to the weather conditions. This is resulted from inadequate understanding of climate change process which mean that forecasts are not accurate.

Weather is a continuous, data-intensive, multidimensional, dynamic and disordered process and these properties make weather prediction a big challenge. Generally, two methods are used for weather predicting

(a) The empirical approach and
(b) The dynamical approach.

The first approach is based on the occurrence of analogy and is often referred by meteorologists as analogy predicting. This approach is useful for forecasting local-scale weather if recorded data are overflowing. The second approach is based on equations and forward replications of the atmosphere and is often referred to as computer modeling. The dynamical approach is only useful for modeling large-scale weather phenomena and may not estimates short-term weather efficiently. Most weather prediction systems use a combination of practical and dynamical techniques. Artificial Neural Network (ARTIFICIAL NEURAL NETWORK) provides a method for solving many types of nonlinear problems that are difficult to be solved by traditional techniques. Most weather-related processes often exhibit temporal and three-dimensional variability. They are suffered by issues of nonlinearity of physical processes, conflicting three-dimensional and time-based scale and uncertainty in parameter estimates.

II. THE NEURAL NETWORK MODEL

A neural network is a controlling data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks be like the human brain in the following two ways:

- A neural network obtains knowledge through learning.
- A neural network's knowledge is stored within interneuron connection strong point known as synaptic weights. Traditional linear models are simply insufficient when it comes to demonstrating data that contains

nonlinear characteristics. In this paper, one model of neural network is selected among the main network designs used in engineering. The basis of the model is neuron structure as shown in Fig. 1. These neurons act like parallel processing units. A non-natural neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of organic neurons and their unique process of knowledge.

III. PROPOSED APPROACH

The aim is to gather dataset consisting weather constraints like temperature, humidity, dew point, atmospheric pressure, sea level, wind speed etc. and perform all compulsory data pre-processing tasks. We have controlled the data using min-max regulation to scale the dataset into the range of 0 to 1.Dataset is gathered from a well-known website 'www.weatherunderground.com' this normalized data is passed to the Back Propagation Neural Network to train the neural network .Thus the neural network is accomplished by updating all the weights and preconceptions as per the obtained errors in each repetition .Now pass the testing dataset as the network is trained the proposed Back Propagation Neural Network model with the established structure can perform good prediction with smallest error. Like this all the neural network estimate algorithms works in weather forecasting. To improve the execution speed and accuracy of Back Broadcast Neural Network we are going to take n number of neural networks of different development and train them and then obtain the values from each network. Now the Back Propagation Neural Network predicts with least error and at high speed than before.

IV. ARTIFICIAL NEURAL NETWORK APPROACH

An Artificial Neural Network is a statistics processing paradigm that is inspired by the way biological worried systems, such as the brain, process information. The key element of this paradigm is the new structure of the facts processing system. It is composed of a huge number of highly unified processing elements (neurons) working together to solve detailed problems. Artificial NeuralNetwork, like people, learn by example. An Artificial Neural Network is configured for a particular application, such as pattern recognition or data classification, through a learning process. Learning in genetic systems adds adjustments to the synaptic connections that occur between the neurons. The Artificial Neural Network has capability to extract the relationship between the inputs and outputs of a process, without the physics being explicitly provided. Thus, these properties of Artificial Neural Network are well suited to the problem of weather predicting. The main purpose is to develop the most suitable Artificial Neural Network architecture and its associated training technique for weather prediction. This growth will be based on using two different neural network architecture to establish the suitable one for this application. Back Propagation (BPN) feed forward network and radial basis function network which were trained by differential evolution algorithm are the selected architectures in this study. The basic architecture of the both Radial Basis Functions (RBF)neural network and multilayer provender forward neural networks are given. Components of a modern weather predicting system include the following modules: data collection, data assimilation and numerical weather prediction.

A. Data gathering: Observations of atmospheric compression, temperature, wind speediness, airstream direction, stickiness and precipitation are made near the earth's surface by trained spectators, automatic weather stations. The World Atmospheric Association acts to standardize the composition, observing practices and timing of these observations international.

B. Data Assimilation: During the data assimilation process, valid data increased from the observations is used in merging with a mathematical model most recent estimates for the time that observations were made to produce the atmospheric analysis. This is the best evaluation of the current state of the climate. It is a three-dimensional representation of the distribution of temperature, moisture and air. The features considered in this study are bar temperature and reading, sea and mean sea level pressure, dry and wet bulb temperature, due point temperature, vapor pressure, wind speed, humidity, cloudiness, precipitation, air direction, and for prediction of rain. It is easy to implement and produces desirable predicting result by training the given data set.

C. Numerical weather prediction: Numerical Weather Prediction (NWP) uses the power of computers to make anestimate. Composite computer programs, also known as evaluations models, run on super computers and provide predictions on many atmospheric variables such as temperature, pressure, air and rainfall. Anestimate examines how the features predicted by the computer will interact to produce the day's weather.

V. BACK PROPAGATION

Back propagation is a public method of training artificial neural networks how to perform a given mission. It is a administered learning method, and is a simplification of the delta rule. It requires a teacher that knows, or can calculate, the desired output for any input in the physical activity set. It is most useful for feed-forward networks the term is a contraction for "backward propagation of faults". Back propagation requires that the initiation function used by the artificial nodes be differentiable.

For better understanding, the back-propagation education algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Every propagation contains the following steps:

1. Forward propagation of a physical activity pattern's input through the neural network in order to create the propagation's output initiations.

2. Backward propagation of the circulation's output beginnings through the neural network using the working out patterns. Pointed in order to generate the deltas of all output and hidden nodes.

Phase 2: Weight update for every weight-synapse:

1. Multiply its output delta and input activation to get the slope of the weight.

2. Take the weight in the reverse direction of the slope by deducting a ratio of it from the weight. This ratio influences the speed and value of learning; it is called the learning rate. The sign of the gradient of a weight shows where the mistake is increasing; this is why the weight must be updated in the reverse direction.

Repeat phase 1 and 2 until the performance of the network is accomplished. Once the training of the network is done, it will provide the wanted output for any of the input patterns.

The network is first prepared by setting up all its weights to be small casual numbers – let's assume between –1 and +1. Next, the input form is applied and the output designed this is called the forward pass. The calculation gives an output which is completely different to what you want since all the weights are casual. We then analyse the Error of each neuron, which is fundamentally: Target – Definite Output.This error is then used statistically to change the weights in such a way that the error will get smaller. In other words, the Output of each neuron will get nearer to its Target this part is called the opposite pass. The process is repeated again and again until the error is negligible.

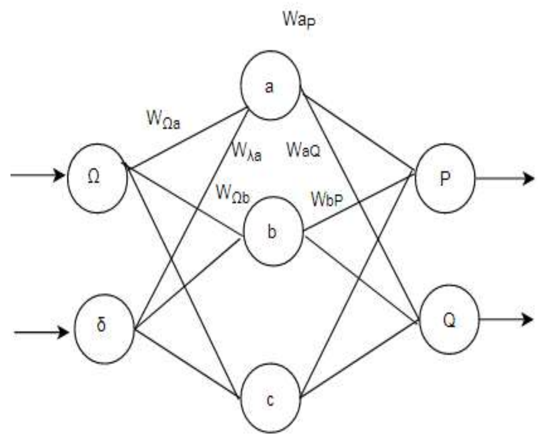


Fig.4 a single connection learning in a BPN

The connection we're interested in is between neuron A (a hidden layer neuron) and neuron B (an output neuron) and has the weight WAB. The diagram also shows another connection, between neuron A and C, but we'll return to that later. The algorithm works like this:

ALGORITHM:

1. First apply the inputs to the network and work on the output (this initial output could be anything, as the initial weights were random numbers.)
2. Now work out the error for neuron B. The error is What you want – What you actually get, in simple words: ErrorB = OutputB (1-OutputB)(TargetB – OutputB) The "Output(1-Output)" term is necessary in the equation because of the Sigmoid Function – if we were only using a threshold neuron it would just be (Target –Output).
3. Change the weight. Let WT AB be the new (trained) weight and WAB be the initial weight. WT

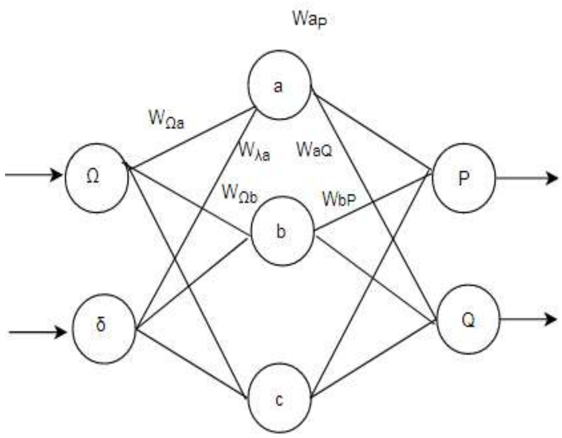
AB = WAB + (ErrorB x OutputA)

Notice that it is the output of the connecting neuron (neuron A) we use (not B). We update all the weights in the output layer in this manner.
4. Calculating the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly (because we don't have a Target), therefore we Back Propagate them from the output layer This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example, if neuron A is connected as shown to B and C then we take the errors from B and C to generate an error forA. ErrorA = Output A (1 - Output A) (ErrorB WAB + ErrorC WAC)

Again, the factor "Output (1 - Output)" is present because of the sigmoid squashing function.

5. Having obtained the Error for the hidden layer neurons now proceed as in stage 3 to change the hidden layer weights. By repeating this method, we can train a network of any number of layers.

This may well have left some doubt in your mind about the operation, so let's clear that up by explicitly showing all the calculations for a full-sized network with 2 inputs, 3 hidden layer neurons and 2 output neurons as shownin figure 3.4. WT represents the new, recalculated, weight, whereas W represents the old weight.



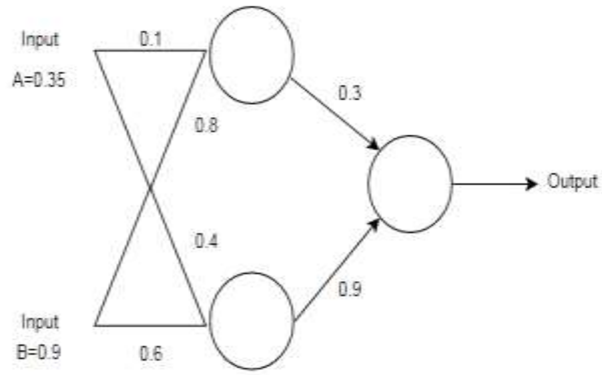
1. Calculate errors of output neurons
δP = outP (1 - outP) (TargetP - outP)
δQ = outQ (1 - outQ) (TargetQ - outQ)

2. Change output layer weights
WTaP = WaP + ηδPouta
WTaQ= WaQ + ηδQouta
WTbP = WbP + ηδPoutb
WTbQ= WbQ + ηδQoutb
WTcP = WcP + ηδPoutc
WTcQ= WcQ + ηδQoutc

3. Calculate (back-propagate) hidden layer errors
δa = outa (1 – outa) (δPWaP + δQ WaQ)
δb = outb (1 – outb) (δP WbP + δQ WbQ)
δc = outc (1 – outc) (δP WcP + δQ WcQ)
4. Change hidden layer weights
WTλa = W λa + ηδainλ
WTΩa = WTΩa + ηδa inΩ
WTλb = W λb + ηδbinλ
WTΩb = WTΩb + ηδb inΩ
WTλc = W λc + ηδcinλ
WTΩc = WTΩc + ηδc inΩ

The constant η (called the learning rate, and nominally equal to one) is put in to speed up or slow down the learning if required.

To illustrate this let's do a worked Example



Expect that the neurons have a sigmoid initiation work an :

1.Perform forward pass on the system
2.Perform Reverse pass(traning)once (target=0.5)
3.Perform Futher Forward pass and remark on the outcome

Results:

Answer:(i)

Input to top neuron = (0.36x0.1) +(0.91x0.8) =0.764. Out = 0.68.

Input to bottom neuron = (0.91x0.6) +(0.36x0.4) = 0.69. Out = 0.6637.

Contribution to conclusive neuron = (0.3x0.68) +(0.9x0.6637) = 0.801.Out = 0.69.

(ii) Yield mistake δ=(t-o) (1-o)o = (0.5-0.69)(1-0.69)0.69 = - 0.04.New weights for output layer

W1T = W1T(δ x input) = 0.3 + (-0.0406x0.68) = 0.272392. W2T = W2T(δ x input) = 0.9 + (-0.0406x0.6637) = 0.87305. Errors for hidden layers:

δ1 = δ x w1 = -0.0406 x 0.272392 x (1-o)o = -2.406x10-3 δ2= δ x w2 = -0.0406 x 0.87305 x (1-o)o = -7.916x10-3 New hidden layer weights:

W3T=0.1 + (-2.406 x 10-3 x 0.35) = 0.09916.
W4T = 0.8 + (-2.406 x 10-3 x 0.9) = 0.7978.
W5T = 0.4 + (-7.916 x 10-3 x 0.35) = 0.3972.
W6T = 0.6 + (-7.916 x 10-3 x 0.9) = 0.5928.

(iii)

Old error was -0.19. New error is -0.18205. Therefore, error has reduced.

VI. CONCLUSION

In this paper, how neural networks are useful in estimating the weather and the functioning of most powerful prediction algorithm called back propagation algorithm. User would get to know the climate of current as well as next few days prediction. A 3dimensional neural network is designed and qualified with the existing dataset and obtained a relationship between the existing non-linear parameters of weather. Now the trained neural network can predict the future temperature with fewer error.

REFERENCES

[1] MohsenHayati, and Zahra Mohebi,"Application of Artificial NeuralNetworks for Temperature Forecasting," World Academy ofScience,Engineering and Technology 28 2007.
[2] Arvind Sharma, Prof. Manish Manoria," A Weather Forecasting System using concept of Soft Computing," pp.12-20 (2006)
[3] Raúl Rojas," The back-propagation algorithm of Neural Networks – A Systematic Introduction, "chapter 7, ISBN 978-3540605058
[4] K.M. Neaupane, S.H. Achet," Use of backpropagation neural network for landslide monitoring," Engineering Geology 74 (2004) 213–226.
[5] http://www.wunderground.com/history/airport/VABB/2010/9/1/CustomHistory.html?dayend=1&monthend=9&yearend=2011&req_city=NA&req_state=NA&req_statename=NA
[6] lail.l. et al." Intelligent weather forecast" Third international conference on machine learning and cybernetics, shanghai, 2004.
[7] Mathur S. et al" A feature based neural network model for weatherforecasting" World academy of science, engineering and technology34,2007.
[8] Isa I.S. et al. "Weather forecasting using photovoltaic system and neural network" Second international conference on computational intelligence, communication systems and networks, 2010.
[9] Baboo S.S. and ShereefI.K." An efficient weather forecasting systemusing artificial neural network" International journal
[10] Gill J. et al "Training back propagation neural networks with genetic algorithm for weather forecasting" IEEE 8th international symposium onintelligent systems and informatics serbia, 2010.
[11] " Data Mining: Concepts and Techniques" by Jiawei Han and MichelineKamber, Morgan Kaufmann, 2001.
[12] http://www.ijettjournal.org/volume-3/issue-1/IJETT-V3I1P204.pdf