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Early Prediction of Rainfall in Coastal Region using Optimized Advanced ANN

Rakesh Kumar Godi

Agriculture is major resource for Indian economy and rainfall prediction plays a vital role for proper agriculture. It is very complex to predict the rainfall and due to globalization, the uncertainty is more to get rainfall at the expected monsoon.The current figuring approach is observed to be extremely powerful in creating models which causes for people to adjust the circumstance. In this paper, rainfall expectation for Karnataka state is done with Artificial Neural Network (ANN). Another techniquecalled Teaching Learning Based advancement [16] (mTLBO) is utilized to prepare the loads of the ANN produced for result expectation. Later examination is carried with established back Propagation learning approach and mTLBO (a variation of traditional TLBO). The outcomes result of ANN-mTLBO over ANN-BP [38] on given datasets. The main aim of our work will be helpful in estimating the drought conditions in Karnataka from the forecasts.

I. INTRODUCTION

A. Artificial Neural Networks

ANNs are numerical models with an exceedingly between associated structure like the structure of the human cerebrum and sensory systems. ANN forms dependably work in parallel, which separates them from customary computational strategies. ANNs comprise of numerous layers including an info layer, a yield layer and at least one concealed layers - as delineated in fig 3.1 Each layer comprises of various hubs which are between associated by sets of connection loads. The information hubs get data that is handled through a non-direct exchange capacity to deliver yields to hubs in the following layer. Preparing process utilizes a directed learning calculation that looks at the model yield to the required yield and afterward changes the heaviness of the associations in a retrogressive manner. The procedure can be condensed in scientific shape as pursues.

$$net_j = \sum_{i=0}^{N} W_{ij} X_i \qquad 3.1$$

Where$X_o$is bias i.e (X_o = 1) and $W_{oj}$is bias weight. Here N is given number of input nodes. Later hidden node input (netj) is converted through the non-linear transfer function to deliver a hidden node yield, Yj. The changed function is a sigmoid function and is communicated as pursues:

$$Y_j = f(net_j) = \frac{1}{1+e^{-net_j}} \qquad 3.2$$

Also, the output esteems between the hidden

layer and the output layer are characterized by

$$net_k = \sum_{j=0}^{M} W_{jk} Y_j;\ Z_k = f(net_k) = \frac{1}{1+e^{-net_k}} \qquad 3.3$$

Where W_{jk} = the connection weight from the j^{th} hidden node to the k^{th} output node,
Z_k = the value of the k-th output node and M = the number of hidden nodes;

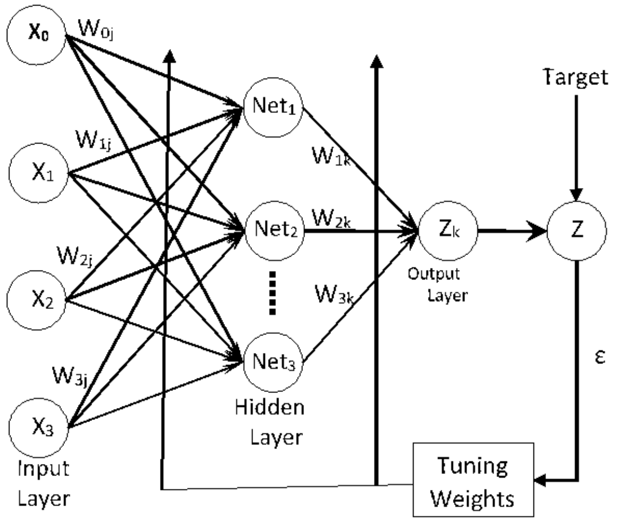

Figure 3. 1 The structure of ANN

The Back-Propagation(BP) algorithm is developed using an optimization method called gradient decent method. The principles of BP are that it computes the gradient of a loss function with respect to all the weights in the network. Later the gradient is inputted to optimization method which tries to minimize the loss function by further adjusting the weights. The major constraint lies with BP algorithm is that, it demands that the activation function used by ANN be differentiable. It is also further analyzed that the hill climbing strategy of gradient decent is guaranteed to work only if there is one minimum. However, we may have conditions where there is a possibility of having many local minima and maxima. The guarantee of the convergence to the global optimal value depends on the starting point of the search.

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* Correspondence Author
Rakesh Kumar Godi* Department of Information Technology, CVR College of Engineering, Hyderabad, India.

If the ANN weights are randomly initialized in between the local maxima and local minima, then the BP algorithm will lead then to the local minima value. In this situation evolutionary computation techniques are found to be suitable candidates. Hence a reliable technique known as teaching learning-based optimization [18] (TLBO) is implemented in this work. The following section presents the basics of the TLBO and its adaptation for developing ANN-TLBO rainfall prediction model.

3.1. *Teaching-Learning Based Optimization*

This techniquedepends on the influence of teacher on end user that is learners in a class. TLBO is population-based algorithm that utilizes population of solutions to obtain general solution. TLBO is categorized into 2 parts: "Teacher Phase" and "Learner Phase". In "Teacher Phase",teacher will train the learners and in "Learner Phase",there will bediscussion among learners.

3.2.1. Teacher Phase

The good student is imitated as a teacher. The teacher endeavors to share information between students, which will thusly build the learning dimension of the whole class and help students to show signs of improvement result. Subsequently, a teacher updates the mean learning estimation of the class as indicated by his ability for example state the teacher T_1 will endeavor to move mean M_1 towards their very own dimension as per his or her ability, accordingly overhauling the student's level to another mean M_2. Teacher T_1 will put outrageous exertion into showing the students, however students will acquire learning as indicated by the excellence in educating conveyed by a teacher and the nature of students in the class. The nature of the students is made a decision from the mean estimation of the populace. Teacher T_1 place exertion in to expand the excellence of the students from M_1 to M_2, at which arrange the students require another teacher, of unrivaled quality than themselves, for example the new teacher is T_2 for this situation. Let M_i be the mean and T_i be the teacher at any cycle I. T_i will attempt to move mean M_i towards its own dimension, so now the new mean will be T_i picked as M_new.The arrangement is refreshed by the distinction between the current and the new mean given

$$Difference\_mean_i = r_i(M_{new} - T_F M_i) \qquad 3.4$$

where T_F is an instructing factor that chooses the estimation of intend to be changed, and r_i is a random number in the range [0, 1]. The estimation of T_F can be either 1 or 2, which is again a heuristic advance and chose randomly with equivalent likelihood as

$$T_F = round[1 + rand(0,1) * (2-1)] \qquad 3.5$$

This difference modifies the existing solution according to the following expression

$$X_{new,i} = X_{old,i} + Difference\_mean_i \qquad 3.6$$

3.2.2. Learner Phase

Learners Phase increment their insight by two distinct methods: one through contribution from the educator and the other through communication among themselves. A learner cooperates haphazardly with different learners with the assistance of introductions, gather talks and so forth. A learner gets something new if the other learner has more information considered to the person in question. Learner adjustment is communicated as given in following algorithm.

Algorithm Learner Modification:

$For i = 1: P_n$

Randomly choose two learners X_i and X_j, where $i \neq j$

$If f(X_i) < f(X_j) X_{new,i} = X_{old,i} + r_i(X_i - X_j)$

$Else X_{new,i} = X_{old,i} + r_i(X_j - X_i)$

$EndIf$

$EndFor$

Accept X_{new} if it gives a better function value

Different adjustments of Teaching Learning Based Optimization (TLBO) calculation have been improved the situation advancement of calculation. In this paper we have utilized a variation of TLBO known as mTLBO [81] for simulation reason. In this adjustment of TLBO just the Learner period of essential TLBO is altered. The Teacher stage stays same as in TLBO. Through the comprehensive investigation of TLBO idea more the student is prepared better will be the arrangement. In a legacy teaching-learning condition the students yield is reliant on the collaboration among students and the class room conveyance by teachers. To additionally enhance the learning capacity of understudies an additional preparation through the instructional exercise makes a difference. A student collaborates with different students with the assistance of gathering discourses, introductions, formal correspondences, and so on and in the meantime the individual in question can examine all the more intimately with the teacher who is increasingly learned individual in an instructional exercise class. Presently the New Learner alteration is named as instead of its relating condition of fundamental TLBO is given as

$$Xnew_{(i)}^{g} = \begin{cases} X_{(i)}^{g} + rand \times \left(X_{(i)}^{g} - X_{(r)}^{g}\right) + 0.5 * (1 + rand) * (X_{Teacher}^{g} - X_{(i)}^{g}) \; if \;\; f\left(X_{(i)}^{g}\right) < f(X_{(r)}^{g}) \\ X_{(i)}^{g} + rand \times \left(X_{(r)}^{g} - X_{(i)}^{g}\right) + 0.5 * (1 + rand) * (X_{Teacher}^{g} - X_{(i)}^{g}) \qquad otherwise \end{cases}$$

3.8

The given third term in the above equation (3.8) signifies the close interface between a teacher and learner parallel to tutorial concept.

3.2. *Experimental Set Up and Simulations*

The exploratory model process comprises of following five successive advances:

1. Proper determination of the information and the yield information for the directed BP/TLBO learning.
2. Going for standardization of the info and the yield information.
3. Training period of the standardized information utilizing BP/TLBO learning.
4. Than testing the integrity of attack of the model.
5. Comparing the anticipated yield with the ideal yield

The precision of ANN model depends on selection of the inputs and cleanliness of the input values. The selection of inputs varies for short-range and long-range prediction. The short-range prediction involves many parameters and its very complex to form a structure, however long-range prediction which is usually termed as monthly, quarterly even yearly prediction is slightly relaxed towards selection of input parameters but heavily dependent on the quality of the rainfall model selection. The primary focus of this work is on selection of a model for long-range prediction to improve the model accuracy in addition to quantity of rainfall at different months, emphasize has been given to two significant input parameters which specifies the atmospheric rotation pattern such as ENSO and EQUINOO. The same input parameters are taken in both ANN-BP and ANN-*m*TLBO model for fair comparison. The inputs to the developed model are consisting of four values namely the month, corresponding rainfall of the month, corresponding ENSO value of the month and corresponding EQUINOO value of the month.

3.2.3. *Data Description*

The data utilized in the model comprises of month perception of precipitation and other two parameters ENSO and EQUINOO. El Nin˜o– Northern is fundamental wellsprings of bury yearly inconstancy in climate and atmosphere around the globe [13]. Endeavors were made to estimate hydrologic factors, similar to precipitation, stream, and so forth., utilizing ENSO data everywhere throughout the world [14][15][11]. IOD mode is essentially a strange condition of air-ocean communication over westernand eastern piece of tropical Indian Ocean, who adjusts the air course. The data from 1959 through 1990 are utilized for preparing reason for the approval reason data from 1990 to 2002 are utilized and data from 2002 to 2010 are utilized for testing the model. At first the data is normalized in the scope of - 1 to 1. The factors are rescaled utilizing normalized systems and esteem is changed in accordance with convey it to a scope of - 1 to 1.

3.2.4. *Designing the Model*

The proposed model uses input layer, one hidden and one output layer. Here single hidden layer is opted to construct a simple ANN. The number of inputs for the prototype is four, each represents the values of lag12(previous year rainfall per month) and Month (here month takes the values 1 to 12 fromDecember to January respectively), monthly lag4 values ENSO and lag4 values of EQUINOO for the corresponding month rainfall. The description of input data is given below.

i. Month number
ii. Monthly rainfall of the chosen month.
iii. Four previous monthly values of ENSO indices
iv. Four previous monthly values of EQUINOO indices

P_v(Predicted Value) = (Month (n), month rainfall (r), ($ENSO_{r-1}$, $ENSO_{r-2}$, $ENSO_{r-3}$, $ENSO_{r-4}$), ($EQUINOO_{r-1}$, $EQUINOO_{r-2}$, $EQUINOO_{r-3}$, $EQUINOO_{r-4}$)

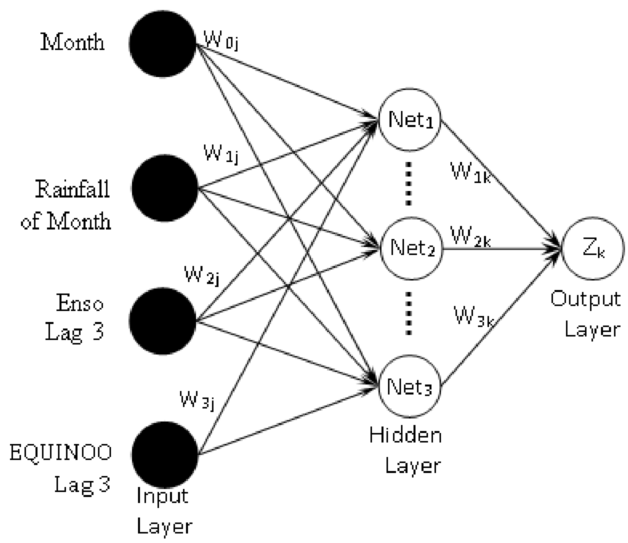

Figure 3. 2 Proposed neural network model

The information informational index is a grid with four segments and lines equivalent to the extent of the training dataset. The normal precipitation of a month is a component of the contributions to the neural system. The model uses just a single output unit which demonstrates the conjecture of month to month precipitation as appeared in figure 3.3 Number of neurons in hidden layer is at first begun with one neuron and dependent on the Root MeanSquare Error of the model the quantity of neurons is developed.

After a few reenactments we find that the model gave genuinely great outcomes seven neurons in the hidden layer. The quantity of info weights the hidden layer weights and the output layer weights are appropriately picked dependent on the development of the hidden layer.The information utilized in the model comprises of month perception of precipitation and other two parameters ENSO and EQUINOO. Endeavors were made to conjecture hydrologic factors, similar to precipitation, stream, and so on., utilizing ENSO data everywhere throughout the world [14][15][11]. IOD mode is essentially an irregular condition of air-ocean cooperation over eastern and western piece of tropical Indian Ocean, which adjusts the environmental course just as the climate design over Indian Ocean and its environment. The information from 1959 through 1990 are utilized for training reason for the approval reason information from 1990 to 2002 are utilized and information from 2002 to 2010 are utilized for testing the model. At first the information is standardized in the scope of - 1 to 1. The factors are rescaled utilizing standardized strategies and esteem is changed in accordance with convey it to a scope of - 1 to 1. For example, if the number of neurons in the hidden layer is five then the number of input weights are twenty and output weights are five and hidden weights are negligible. Hence the total thirty-five number weights are tuned to optimal values separately using (Back Propagation) BP and *m*TLBO algorithm with same set of input data. The error of the network is computed taking the difference of predicted value and target value which is expressed in terms of monthly rain in millimeter. RMSE is opted to measure how best the forecast predictions are to final outcomes given in the data.

3.3. Evaluation of Results

The table below provides the model performance in terms of RMSE.

Table 3. 1Outcome Model results

Data sets	Model	RMSE
Input sample	ANN-BP	3.28
Output Sample	ANN-BP	3.34
Input sample	ANN-*m*TLBO	3.31
Output sample	ANN-*m*TLBO	3.52

The anticipated qualities with the end estimations of togetherArtificial Neural Network-BP and Artificial Neural Network -mTLBO is shown in the beneath figure. The ANN-mTLBO beats ANN-BP as far as anticipated precision which can be found in the underneath figure 3.4. The table 1 indicates RMSE which is selected for theauthentication of the better anticipated exactness of Artificial Neural Network -mTLBO. The whole simulation was done with Back Propagation algorithm and the parameters for m-TLBO were browsed [8]. In the meantime, the TLBO is a crowd-based algorithm a few imitations are taken to average the Root Mean Square Error displayed in the work. It is proof from the outcome's examination that m -TLBO isn't trapped in nearby ideal arrangement dissimilar to BP algorithm. It might be repeated here that BP algorithm has the inadequacy to be get trapped to nearby optima arrangement as it is angle based. While the populace-based methodology of m-TLBO gives the flowchart to look for the proper arrangements district after a few cycle and gives streamlined weights and bias qualities for the picked Artificial Neural Network model.Initially the information is standardized in the scope of - 1 to 1. The factors are rescaled utilizing standardized methods and esteem is acclimated toconvey it to a scope of - 1 to 1.

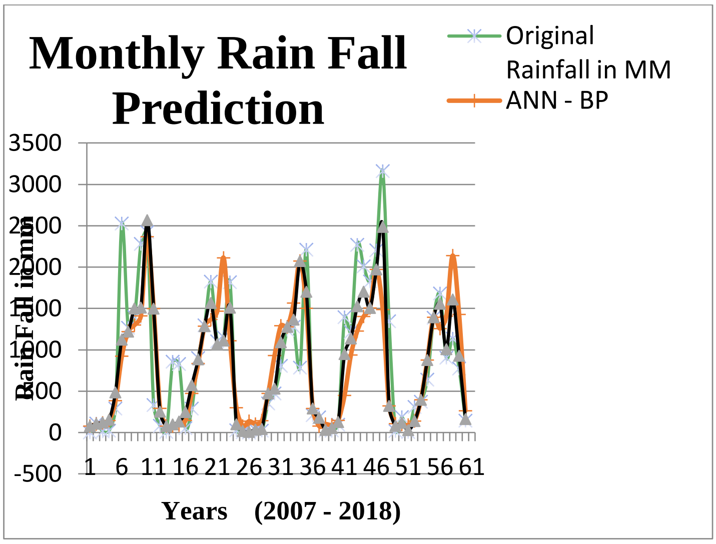

Figure 3. 3. Figure appearing among unique and anticipated precipitation of Coastal Karnataka years (2007-2018)

II. CONCLUSION

The fundamental goal of paper is to anticipate amount of rainfall in Karnataka for utilizing a reasonable Artificial Neural Network demonstrate. Here, reasonable prototype for rainfall identification in Coastal Karnataka is created utilizing both back propagation and TLBO algorithm. An extremely insignificant Artificial Neural Network display chose with forward choice component comprising of one shrouded layer with eight neurons are trained independently utilizing Back Propagation algorithm and a variation of TLBO known as m-TLBO. The outcomes got from simulations uncover the better precision of Artificial Neural Network -mTLBO over Artificial Neural Network -BP. The exhibitions are compared, Root Mean Square Error values and the chart of anticipated and targeted outputs is appeared as examination for the two methodologies.

The discoveries of the prototype created are exceptionally useful to recognize dry spell circumstances in several districts of Karnataka and appropriate advances can be started by the administration associations to conquer the weaknesses. Further investigation can be improvedby accepting a few different parameters as contributions for rainfall forecasts.

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