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OPTIMIZED ARTIFICIAL NEURAL NETWORK CLASSIFIER FOR THE PREDICTION OF RAINFALL

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ABSTRACT

The estimation of rainfall is one of the most difficult tasks of weather forecasting. Precise and prompt forecasts of precipitation can be very useful in advance in taking effective safety measures concerning: ongoing building projects, transport, agricultural tasks, flight and flood situations etc. Heavy forecasts for rainfall are a big concern for the meteorological department, since they are closely related to human life and economy. For countries such as India, which rely largely on agriculture in their economy, rainfall prediction accuracy is very critical. The mathematical methods are not good for predicting rainfalls due to the complex nature of the atmosphere. The nonlinearity of precipitation data is a stronger technique to the Artificial Neural Network. The aim of this research is to optimise ANN's weights in the rainfall classification using the weather data collection. The Gradient Boosting Machine (GBM) is used to minimise the error function in the classification for this study. Different classifiers, like ANN, RF and NB, are used various performance metrics like precision, TPR, FPR, precision, miss rate, and specificity to compare the performance of the proposed Optimized ANN classifiers.

KEYWORDS: Rainfall Prediction, Machine Learning classification, Artificial Neural Network,Artificial Bee Colony Optimization, Gradient Boosting Machine.

1. INTRODUCTION

The forecast of rainfall remains a serious problem and has drawn government, businesses, risk management and the scientific community's attention. Rainfall is a climate factor affecting a range of human activities, including farming, construction, energy generation, forestry and tourism [1]. In this way, it is important to forecast rainfall since this variable has the highest relationship to adverse natural events, such as landslides, floods, mass movements and avalanches. For years, these events influenced society[2]. Thus, a proper rainfall forecast method allows the prevention and mitigation of these natural phenomena to be taken[3]. These forecasts also promote the monitoring of activities, including agriculture, construction, tourism, transportation and health. The meteorological forecasts will aid decision-making against the potential occurrence of natural disasters in the case of agencies responsible for disaster prevention.

Precise rainfall forecasts is one of the key issues in hydrological science, since premature warnings of extreme weather would avoid natural disaster casualties and damage if predicted in a timely and accurate way. For researchers from different fields such as the mining of weather data[4], environmental machine learning[5], operational hydrology[6] and statistical projection[7], the prediction of exact rainfall is one of the major challenges in developing a predictive framework. One common concern is how to evaluate the past and use the future forecast for these issues. The criteria to predict precipitation, except for a short time, are extremely complex and subtle. A variety of sub-processes typically consist of physical processes in rainfall. Often it is not possible to forecast rainfall correctly by a single global model.

2. RELATED WORKS

Pham, Binh Thai, et al [8] The main objective of this study is to build and compare several advanced Artificial Intelligent (AI) models, namely the Adaptive Network based Fuzzy Inference Method Optimized for the Prediction of HoaBinh Regular Rainfall in the province of Vietnam, with the use of Particle Swarm Optimization (PSOANFIS), Artificial Neural Network (ANN) and Support Vector Machine (SVM). For this purpose we obtained and used the input parameter and daily rainfalls as the output parameter in the models for meteorological variable parameters such as maximum temperature, minimum temperature, wind speed, relative humidity and solar radiation.

Yaseen, Zaher Mundher, et al [9] In this study two weather stations in the arid and half-arid zone of Iraq are expected to evaporate. Four separate ML models were developed and designed using different input combinations of meteorological variables for predicting evaporation: classification and regression tree (CART), cascade correlation neural network (CCNNs), gene expression programming (GEP) and support vector machine (SVM). The findings show that sunlight, wind velocity, relative humidity, rain and minimum mean and maximum temperatures are the best predictions.

Macabiog, Rose Ellen N., and Jennifer C. Dela Cruz [10] based on various historical weather criteria, intended to suggest a method of forecasting the frequency and non-occurrence of precipitation in La Trinidad, Benguets. To create prediction models for the weather data collection, five algorithms have been used: the fine decision tree, the linear discriminant, the K-Nearest neighbours, Gaussian vector support machines, and Neural network. A bad model choice can't boost predictions any longer.

Foresti, Loris, et al [11] The dynamic nonlinear addiction of growth and decay to input predictors are used in artificial neural networks (ANNs) to understand the geographical location, the mesoscale motion, the height and time of day for freezing stages. The ANN effectively reproduces the average long-term growth and decay patterns, enabling the analysis of their climatology for all forecasting combinations. Due to the poor intrinsic predictability of growth and decline it is more difficult to prediction in real time but considerably improved when persistence, growth and decay, as well as precipitation intensity are applied to the predictors in the immediate past.

Basha, CmakZeelan, et al [12] Seasonal rainfall, such as Linear and Non-Linear, is predicted by two common models. ARIMA Model is the first model. Precipitation can be predicted through ANN like Back Propagation NN, Cascade NN or Layer Recurrent Network. Artificial NNs are similar to Biological Networks.

Quinn, Brandan, and Eman Abdelfattah [13] Presented the method by analysing five classification algorithms and data from common weather data sets more precisely, rainfall. A non-conclusive dataset of weather data from Delhi, India and an Australian meteorical dataset have been trained and analysed in two datasets.

Grace, R. Kingsy, and B. Suganya [14] Proposed a Multiple Linear Regression (MLR) prediction model for an Indian dataset. The data inputs include many weather parameters and are used to more reliably forecast precipitation. The mean square error (MSE), precision, correlation are the parameters for validating the proposed model.

Ahmed, Kamal, et al [15] Multi-Model Ensembles (MMEs) are also used to reduce GCM simulation/projection uncertainties. The goal of this study was to evaluate the performance of MMEs, which are built using machine learning (MLs) algorithms and classify the optimal number of CMMs to be integrated into an MME, based on their performance. ML-Algorithms in this trial were developed: Artificial neural network (ANN), K-Nearest Neighbor (KNN), SVM and Relevance Vector Machine (RVM); precipitation (P), maximum (T_{max}) and minimum(T_{min}) temperature in Pakistan by 36 coupled model intercomparison step 5 GCMs. In the analysis, ML algorithms have been used.

Moon, Seung-Hyun, et al [16] Suggested a framework for an efficient Early Warning System (EWS) with machine learning techniques for very short-term heavy rainfall. In 3 hours, the EWS generates an alert signal when the heavy rain warning criterion is predicted to be reached. The authors designed a selective method of discretization that transforms continuous input variables into nominal variables. Selective discretization and principal component analysis used to pre-process the meteorological data generated from automated weather stations.

Janarthanan, R., et al [17] proposed rainfall preparation using the meteorological department of the nation's expert system model-based fuzzy logic system, for the challenging operational duties required. Fuzzy logic provides many benefits compared to conventional logic. In narrow words, fuzzy logic is a logical structure that is an extension of multivalued logic. Two different kinds of characteristics of Fuzzy logic are: The expert fuzzy scheme includes rules relating to the linguistic variable in the input variable to the output variable of the fuzzy membership. The IF-THEN declarations of the fuzzy production rule relate each of the input variables for defining the output. The input and output variable is related to predict logic operators such as the AND operator.

3. OPTIMIZED ARTIFICIAL NEURAL NETWORK CLASSIFIER

3.1 Proposed Artificial Neural Network Classifier

In the ANN model, when a signal with either a positive or a negative potential occurs neurons cause inhabitation and excitation.When the z+1 signal is obtained, a neuron is excited, while the -1 input inhibits the previous neuronal state with the same potential.Signals are transmitted as a pulse between M totally connected neurons.A neuron m_j state is expressed by its potential at time s, and each m_j neuron has a non-negative integer $L_j(s)$ state. It is said that if $L_j(s) > 0$ is an excited neuron m_j, but if $L_j(s) = 0$, it is in idle mode. If the n_i neuron (i.e., $L_j(s) > 0$) is excited, it randomly transmits a pulse signals at the rate c_j to another m_k with the probabilities of being excited

- With a probability $q^+(j,k)$, it can enter neuron n_j as an excitation signal.
- The probability of $q^-(j,k)$ hits neuron n_j as a signal of inhibition.
- The d(j) probability for the start of Neural Network

Mathematically,

$$d(j) + \sum_{k=1}^{M} [q^{+}(j,k) + q^{-}(j,k)] = 1, \forall j \qquad (1)$$

$$b^{+}(j,k) = c_j q^{+}(j,k) \geq 0 \qquad (2)$$

Likewise,

$$b^{-}(j,k) = c_j q^{-}(j,k) \geq 0 \qquad (3)$$

Combining,

$$c_j = (1 - d(j))^{-1} \sum_{k=1}^{M} [b^{+}(j,k) + b^{-}(j,k)] \qquad (4)$$

The rate of transmission among neurons in the equation (4), can be describedas $c_j = \sum_{k=1}^{M}[b^{+}(j,k) + b^{-}(j,k)]$. The "b" matrices are used for evaluating neuron weight updates and always have positive values, because the signal rate and probabilities are the outcome.The proposed model connects M neurons to each other to exchange information that can be positive or negative based on signals. If the signal arrives at the neuron (j), the signal is positive, then the Poisson rate $\Lambda(j)$ and the Poisson rate $\theta(j)$ is indicated in the negative signal. The output activation function is therefore defined for each node (j) as:

$$p(j) = \frac{\theta^{+}(j)}{c(j) + \theta^{-}(j)'} \qquad (5)$$

Where

$$\theta^{+}(j) = \sum_{k=1}^{m} p(k)c(k)q^{+}(j,k) + \theta(j) \qquad (6)$$

And

$$\theta^{-}(j) = \sum_{k=1}^{m} p(k)c(k)q^{-}(j,k) + \theta(j) \qquad (7)$$

3.2 Gradient Descent Algorithm

We used an iterative optimization algorithm called gradient descent (GD) to obtain the minimum level of a function. It was generally accepted among researchers as a common training algorithm. Basically, the cost function of GD is minimised. The error feature can be defined as:

$$F_q = \frac{1}{1} \sum_{j=1}^{m} \alpha_j \left(p_j^q - z_j^q\right)^2, \alpha_j \geq 0, \qquad (8)$$

In cases where $\alpha \in (0,1)$ refers to a neuron j output state, p_j^q is a real differential function, and the predicted output value is given by z_j^q. In accordance with equation (8), let us look into the relation between two neurons z and y, where weighting $b^{+}(z,y)$ is modified to $b^{-}(z,y)$, in order to define the local minima and lower the error cost functions values.

$$b_{z,y}^{+s} = b_{z,y}^{+(s-1)} - \beta \sum_{j=1}^{m} \alpha_j \left(p_j^q - z_j^q\right) \left[\frac{\tau p_j}{\tau b_{z,y}^{+s}}\right]^{s-1} \qquad (9)$$

And, similarly,

$$b_{z,y}^{-s} = b_{z,y}^{-(s-1)} - -\tau \sum_{j=1}^{m} \alpha_j \left(p_j^q - z_j^q\right) \left[\frac{\tau p_j}{\tau b_{z,y}^{-s}}\right]^{s-1} \qquad (10)$$

GD is utilized to train the proposed ANN model. Neurons are modified to measured weights and biases as the algorithm measures the error.

3.3 Proposed Optimization based ANN classifier

In this work, the ABC algorithm is used for training the ANN. The ABC algorithm calculates the optimized weights of the ANN. The procedure for finding the optimal weights for the ANN using the ABC algorithm is as follows:

Step 1: Initialize the c_z population of solutions generated randomly by the scout bees by the below given equation:

$$c_{zx} = c_{min}^{x} + rand\ (0,1)(c_{max}^{x} - c_{min}^{x}) \qquad (11)$$

Where c_{zx} is a food source value, varying with the size of the colony, $z = 1, \ldots, PS$, where PS is the colony size (population). A D-dimensional parameter search space is to be optimised for each current solution.

Step 2: Evaluate the current population by default function.

Step 3: Training begins on the Artificial Neural Network (ANN), where each solution is formulated using neurons of the input layer In_m in the regular path, neurons on the hidden layer Hd_j, and the neurons on the output layer Ot_v of a model. The space for the D-dimensional search is calculated using the term:

$$[(In_m \times Hd_j) + (Hd_j \times Ot_v)] \times 2 \qquad (12)$$

During the training process, the food location in the whole population is randomly distributed among the neurons is $c_z = [b_{jl}^{+U0U1} b_{lo}^{+U1U2}, b_{jl}^{-U0U1} b_{lo}^{-U1U2}]$, where $j \in In_m, l \in Hd_j, o \in Oy_v$.

Furthermore,

- b_{jl}^{+U0U1} is a positive potential of mutual weight distribution between neurons j and l of layer 0 and layer 1;
- b_{lo}^{+U1U2} is a positive potential of mutual weight distribution between neurons l and o of layer 1 and layer 2;
- b_{jl}^{-U0U1} is a negative potential of mutual weight distribution between neurons j and l of layer 0 and layer 1; and
- b_{lo}^{-U1U2} is a negative potential of mutual weight distribution between neurons l and o of layer 1 and layer 2.

Step 4: Evaluation of the fitness (fit_a) of a population using objective function:

$$fit_z = \begin{Bmatrix} \dfrac{1}{1 + f(z)} & f(z) \geq 0 \\ 1 + |f(z)| & f(z) < 0 \end{Bmatrix} \qquad (13)$$

Step 5: Calculate the new solution, N_{zx}, as identified by the onlooker bees, and evaluate the fitness of the new source.

$$N_{zx} = c_{zx} + \lambda_{zx}(c_{zx} - c_{dx}) \qquad (14)$$

Where

- D= 1,2,…,PS
- x= 1,2,…, A are randomly chosen indexes; and
- λ_{zx} is used to control the difference between two neighbour food sources, based on their fitness value.

Step 6: Start the greedy selection process.

Step 7: Calculate the probability value q_z of the solution c_z by using equation (15) and normalize it into the interval [0,1]:

$$q_z = \frac{fit_z}{\sum_{m=1}^{PS} fit_z} \qquad (15)$$

Step 8: Onlooker bees find new solution M_{ab} based on the probability Q_{zx}.

Step 9: Calculate the new fitness value fit_z.

Step 10: Re-apply the greedy selection process.

Step 11: Scout bee to abandon food source if profitability of solution is not improved. New random value is generated using Equation (11).

Step 12: Store the best solution and erase the previous value, based on fitness.

Step 13: Repeat Step 4 for a new feasible solution, until maximum iterations or unchanged value of mean square error (MSE) is reached.

4. RESULT AND DISCUSSION

4.1 Dataset Description

The weather dataset is taken from the Kaggle Repository. Table 1 depicts the features involved in the weather rainfall dataset [18].

Table 1: Description of the Dataset

Feature Number	Feature Name
1	meantempm
2	maxtempm
3	mintempm
4	meantempm_1
5	meantempm_2
6	meantempm_3
7	meandewptm_1
8	meandewptm_2
9	meandewptm_3
10	meanpressurem_1
11	meanpressurem_2
12	meanpressurem_3
13	maxhumidity_1
14	maxhumidity_2
15	maxhumidity_3
16	minhumidity_1
17	minhumidity_2
18	minhumidity_3
19	maxtempm_1
20	maxtempm_2
21	maxtempm_3
22	mintempm_1
23	mintempm_2
24	mintempm_3
25	maxdewptm_1
26	maxdewptm_2
27	maxdewptm_3
28	mindewptm_1
29	mindewptm_2
30	mindewptm_3
31	maxpressurem_1
32	maxpressurem_2
33	maxpressurem_3
34	minpressurem_1
35	minpressurem_2

36	minpressurem_3
37	precipm_1
38	precipm_2
39	precipm_3
40	Weather_Class (rain, no rain)

4.2 Performance Analysis of the Proposed Optimized ANN Classifier

The performance of the Proposed Optimized ANN classifier is evaluated with performance metrics like Accuracy, True Positive Rate (TPR), False Positive Rate (FPR), Precision, Miss Rate and Specificity by comparing with different classifiers like Artificial Neural Network, Random Forest, and Naïve Bayes. Table 2 gives the performance analysis of the proposed Optimized ANN classifier, ANN, RF and NB for the given weather dataset. Figure 2 depicts the graphical representation of the performance analysis of the Proposed Optimized ANN classifier, RF, and NB for the given weather dataset. From the table 2, and figure 2, figure 3, figure 4, figure 5, figure 6, and figure 7, it is clear that the proposed Optimized ANN classifiers gives more accuracy, TPR, Precision, Precision and it reduces the error rates like FPR, Miss rate than the other existing classifiers for the given weather dataset.

Table 2: Performance Analysis of the Proposed Optimized ANN classifier, RF, and NB for the given weather dataset

Performance Metrics (in %)	Classification Techniques			
	ANN	RF	NB	Proposed Optimized ANN
Accuracy	45.65	43.1	41.85	75.3
TPR	54.62	50.46	49.51	76.89
FPR	67.62	70.11	73.82	40.12
Precision	63.13	56.34	57.82	72.24
Miss Rate	26.79	49.54	50.49	20.52
Specificity	32.38	29.89	26.18	73.63

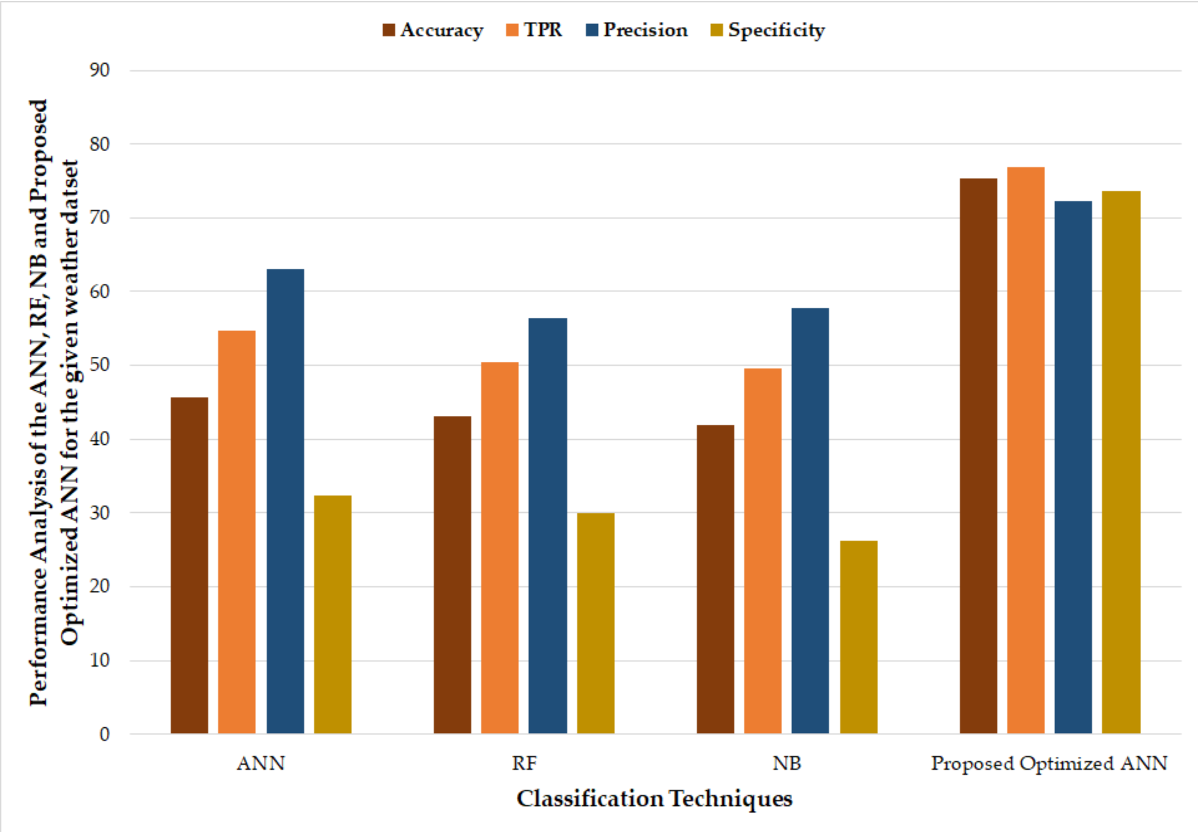

Figure 2: Graphical representation of the Accuracy, TPR, Precision, and Specificity of the ANN, RF, NB and proposed Optimized ANN classifier

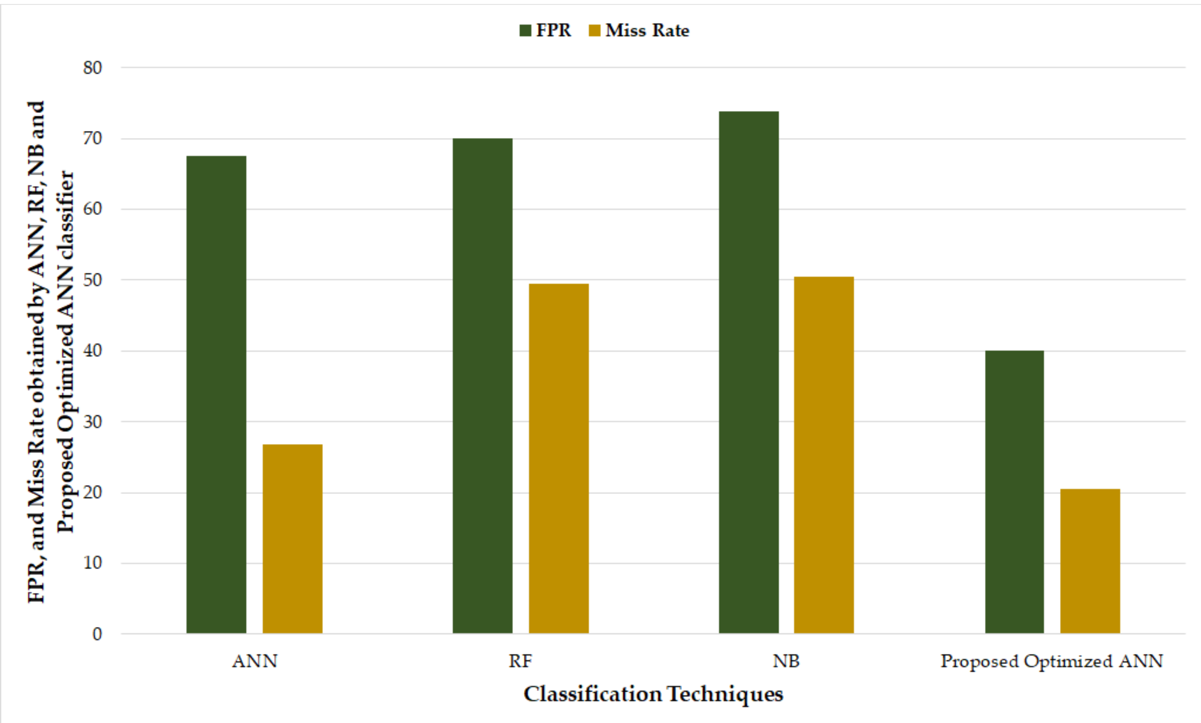

Figure 3: Graphical representation of the FPR, and Miss Rate obtained of the ANN, RF, NB and proposed Optimized ANN classifier

5. CONCLUSION

Rainfall affects agriculture and the regular routing of people, so precipitation for researchers is worth studying. The nonlinear and dynamic characteristics of precipitation cannot have a satisfactory impact on rainfall forecasting conventional methods such as numerical weather prediction (NWP) models or statistic models. Nevertheless an artificial neural network (ANN) can achieve complicated nonlinear relationships between variables that are suited for predicting precipitation. The weights optimised with the optimisation algorithm ABC by using the Gradient Decent algorithm to minimise costs are used to improve the performance of an ANN classifier in this research paper. To achieve the optimal solution, Greedy Search Selection algorithm is used. It is evident from the result achieved that the Optimized ANN classifiers proposed provide greater accuracy, TPR, Precision, Specificity and lower error rates such as FPR and the missing rate of the considered data set with no pre-processing technique at all.

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