Development of NARX Neural Network based Optimized Deep Learning Algorithm for Adaptive Rainfall Prediction in North-Western Himalayas

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Abstract

The paper proposes a Nonlinear Auto-Regressive with external input (NARX) neural network-based optimized deep learning algorithm for adaptive rainfall prediction in the North-Western Himalayas. The study focuses on examining the impact of the size of the training dataset and the number of neurons on the performance of the proposed algorithm in predicting monthly rainfall. This study presents a adaptive rainfall prediction model based on NARX Neural Network Model and Levenberg-Marquardt (LM) optimization algorithm to forecast the Indian summer monsoon rainfall (ISMR) using monthly seasonal time series data for Jammu &Kashmir and Indian rainfall data. The study finds that the algorithm's performance improves with an increase in the size of the training dataset and the number of neurons. Mean Squared Error (MSE) and Percentage Root Mean Square Difference (PRD) metric estimators are used to evaluate the performance of the proposed model with varying number of hidden neuron and varying training data size. The authors conclude that the proposed algorithm can be an effective tool for predicting rainfall in the North-Western Himalayas region and can aid in disaster preparedness and flood management. However, the study's limitation is that it focuses only on the North-Western Himalayas region, and further research is required to generalize the results to other regions. Overall, this study makes a valuable contribution to the field of rainfall prediction by showcasing the potential of NARX neural network-based optimized deep learning algorithms in predicting complex meteorological phenomena.

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Introduction:

Rainfall prediction using machine learning is an essential tool for the economy and agriculture practices. Accurate rainfall prediction can help farmers make informed decisions about crop planting, fertilization, and harvesting. It can also help in water resource management, flood prevention, and disaster management. Predicting accurate rainfall using artificial intelligence and machine learning is essential and beneficial for the economy and agriculture practices of a country.Rainfall prediction is essential for various applications such as agriculture, water resource management, and disaster management. Moreover, as we all know agriculture and allied sectors is extremely dependent on precipitation, and accurate rainfall prediction is essential for crop planning and management [1]. Agriculturalistsand farmers need to know the rainfall forecast to decide on crop planting, irrigation, and fertilization. For example, if the forecast predicts low rainfall, farmers may decide to plant drought-resistant crops or delay planting until there is enough rainfall. On the other hand, if the forecast predicts heavy rainfall, farmers may need to take measures to prevent flooding and soil erosion. Accurate rainfall prediction can also help in yield estimation and pest control [2]. Similarly the economy of any country is also greatly dependent on amount of rainfall, especially in countries where agriculture is a major contributor to the GDP like India. As, precise rainfall prediction can help in resource planning, disaster management, and economic growth. For example, if the forecast predicts low precipitation, the government can take measures to conserve water resources and prevent drought. On the other hand, if the forecast predicts heavy rainfall, the government can take measures to prevent flooding and infrastructure damage by taking smart decisions before time that will save the lives and minimize the destruction [3]. Accurate rainfall prognosis can also help in predicting energy demand and pricing. Therefore, rainfall prediction using machine learning and artificial intelligence techniques is essential not only for agriculture practices and farmers but also have a significant affects the economy and growth of country as a whole [4].

North-Western Himalayas is a region known for its complex topography and climatic conditions, which make rainfall prediction a challenging task. Traditional statistical models have limitations in accurately predicting rainfall in this region due to the non-linear and complex relationships between the meteorological variables [5]. Recently, deep learning models and optimization techniques have shown promising results in predicting rainfall with appreciable accuracy due to their ability to capture complex non-linear relationships between variables [6].In this paper, we propose a NARX (Nonlinear Auto-Regressive with external input) neural network-based optimized deep learning algorithm for adaptive rainfall prediction in North-Western Himalayas. The proposed model optimizes the NARX (Nonlinear Auto-Regressive with external input)Neural Network Model using optimized machine learning algorithm. The study uses a dataset of rainfall observations from different meteorological stations in North-Western Himalayas over the past several decades.

The paper is structured as: Section 1 provides the introduction and motivation of the study, Section 2examines the research work based on the existing techniques and approaches used to forecast rain, Section 3 provides the proposes NARX Neural Network based Optimized Deep Learning Algorithm for Prediction of Rainfall, Section 4 describes the results and discussions obtained through investigations and experiments performed on the various datasets exhaustively and Section 5 provides the conclusion centred on the proposed rainfall prediction model.

Literature Review

In [7], Mehmet Tektaş, et al, developed hybrid prediction model for weather forecasting by employing Adaptive Network Based Fuzzy Inference System (ANFIS) and Auto Regressive Moving Average (ARIMA) models-based data collected between year 2000-2008 of Göztepe, İstanbul, Turkey. It was observed that ANFIS has better prognostic fitness than ARIMA.
In [8], Chatterjee et al., proposed amalgamated neural network-based model for predicting rainfall. The rainfall data was taken from the Southern West Bengal, India. The model showed high rate of accuracy in predicting rainfall.

In [9], FazlinaAhmatRuslan, et al, proposed flood prediction model based on fluctuation water levels using NARX Neural Network Model which provides the prediction of flood water level before 10 hours precisely. The real time data for this work is collected from Department of Irrigation and Drainage Malaysia.
In [10], Vuong Minh, et al, proposed a rainfall prediction model using Nonlinear Autoregressive Neural Networks with external variables (NARX) Neural Network Model to forecast daily rainfall. Time series data of 8 years was collected from HoaBinh city, Vietnam. Root mean squared error (RMSE) and mean absolute error (MAE) metrics were implemented to measure the accuracy of the model which showed appreciable rate of daily rainfall prediction.

In [11], Asadnia, Mohsen, et al, proposed Levenberg-Marquardt neural network (LM-NN) with an improved particle swarm optimization (PSO) technique for forecasting water levels of Heshui Watershed, China. Day-to day data of rainfall and water level was collected for this analysis from year 1988-2000. It was seen that proposed optimized Levenberg-Marquardt neural network (LM-NN) model has better accuracy rate and prediction when compared with existing Neural Network Model. The main limitation of the model is that it didn't show good results during forecasting the low and peak water levels.

Methodology:

In the context of rainfall prediction, neural networks can be used to analyze historical rainfall data, weather patterns, and other environmental variables to develop accurate forecasting models [12]. Artificial neural networks can handle large volumes of data and can process multiple variables simultaneously, allowing for the incorporation of various environmental and meteorological data in the rainfall prediction models [13].One type of neural network that is commonly used for rainfall prediction is the Recurrent Neural Network (RNN), which is capable of learning from sequential data and capturing the temporal dependencies in time series data [14].Among various type of neural network that is widely used in rainfall prediction, the NARX (Nonlinear AutoRegressive with eXogenous inputs) neural network is also significant for its appreciable accuracy and adaptability. NARX neural networks are designed to predict a target output based on both past input and output data, making them ideal for time-series prediction problems like rainfall forecasting [15].The advantage of using neural networks for rainfall prediction is their ability to learn and adapt to changing patterns in the data, making them suitable for predicting weather patterns in dynamic environments like the Himalayan region [16].

The proposed rainfall prediction algorithm consists of two main components: a NARX neural network and Levenberg-Marquardt algorithm which is a numerical optimization method commonly used in nonlinear least squares problems based optimization technique. It is basically a modification of the Gauss-Newton algorithm, which iteratively solves a linear system of equations to update the estimate of the parameters [17]. However, the Gauss-Newton algorithm can be unstable if the Jacobian matrix (the matrix of partial derivatives of the model function with respect to the parameters) is ill-conditioned or if there are outliers in the data [18].The Levenberg-Marquardt algorithm adds a damping term to the Gauss-Newton update to ensure stability and convergence. When used with NARX Neural network, this damping term is controlled by a parameter that is adjusted iteratively based on the progress of the optimization for hyper-parameterization of Neural Network [19]. When the optimization is far from the minimum, the damping term is increased to stabilize the update and prevent overshooting. As the optimization approaches the minimum, the damping term is decreased to allow for faster convergence [19].
The NARX neural network is a type of recurrent neural network that uses past inputs and outputs to predict future outputs as shown in figure 1.The Levenberg-Marquardt (LM) algorithm can be used to train a NARX neural network [20]. The LM algorithm is an optimization algorithm that can be used to find the weights and biases of the neural network that minimize the difference between the predicted outputs and the actual outputs [21].

The training of a NARX network with the LM algorithm involves defining a cost function that measures the difference between the predicted outputs and the actual outputs for a given set of input-output pairs [20]. The LM algorithm then updates the weights and biases of the neural network to minimize this cost function. The update involves finding the minimum of a quadratic approximation of the cost function in the direction of the gradient [23]. The LM algorithm is particularly effective for training NARX networks because it is able to handle nonlinearities in the network and can also handle noisy or incomplete data [24]. Additionally, the feedback loop in the NARX network allows it to model complex nonlinear relationships between the input and output data.However, like all optimization algorithms, the LM algorithm can suffer from local minima and may not always find the global minimum of the cost function [25]. Therefore, it is important to choose appropriate initial values for the weights and biases of the network and to use appropriate stopping criteria to avoid overfitting [26].

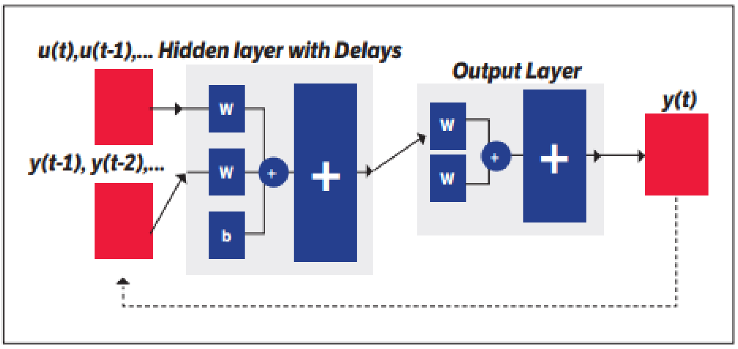

Figure 1: NARX Neural Network Model

Proposed Adaptive Rainfall Prediction Model based on NARX Neural Network and Levenberg-Marquardt (LM) algorithm

The proposed model is used for evaluating the time series prediction for rainfall. The model [27] consists of three vector layers, which involve the input layer, output layer, and the hidden layer. The input layer consists of three types of gathered information vectors, which are delayed regressed output vector, delayed the exogenous input vector and the exogenous input vector. The output vector is generated after processing the operation on the neural network denoted as:
o("i "+1) and is represented as:

$$o^L(i+1) = M[(o(i),\ldots,o(i-s_1);v(i),\ldots,v(i-s_2)]----------(1)$$

Where, $o(i)$ represents the rain drop data of the i^{th} series, $o(i-s_1)$ denotes the rainfall data of $(i-s_1)^{th}$ series, $v(i-s_2)$ denotes the delayed value of regressed output vector, and s_1, s_2 denote delayed factors adapted in prediction mechanisms.

Hybridization of NARX Neural Network model and LM algorithm is adapted efficiently for rainfall prediction. The proposed adaptive neural network model is based on error-based learning approach. The error minimization process is carried out between predicted output and ground data (actual value) by adjusting and computing the weights optimally.

The LM algorithm adapts the output of the neural network, and original ground truth for calculating the errors to train the networks and the error is represented as:

$$Err = \frac{1}{K}\sum_{n=1}^{K}\left(o_n^L - o_n^P\right)------------(2)$$

Where, o_n^L indicates the output of the neural network and o_n^P represents the expected output. The comparative analysis is performed on the errors at present iteration and past iteration, denoted as Err_{i+1} & Err_i.

If the value tends to be decreased then μ is increased with a factor d if the value tends to be increasing, then μ is decreased with a factor d. The evaluation is done recursively for i iterations, and the final computed weight is implemented as a trained weight for accurate rainfall prediction.

Results and Discussion

The proposed algorithm was implemented using Python programming language and deep learning libraries such as Keras and TensorFlow. The model was trained using the training dataset and optimized using the LM algorithm-based optimization technique with NARX Neural Network. The dataset used in this study is a time-series data which comprises of rainfall observations from different meteorological stations in North-Western Himalayas from 1900 to 2017 [28]. The dataset was preprocessed by removing missing values and outliers. The preprocessed dataset was then split into training and testing datasets in varying ratios.The collected rainfall database is divided into monthly, yearly and quarterly basis for India and Jammu & Kashmir. For this study we have considered only two datasets. Dataset 1 contains Indian database with monthly rainfall data and Dataset 2 contains Jammu and Kashmir database with monthly rainfall data.

Performance Metrics Evaluation and Analysis:

The performance analysis of the proposed adaptiverainfall prediction model is done in terms of two metrics, Percentage Root Mean Square Difference (PRD) and Mean Square Error (MSE) [16]. The values of MSE and PRD should be in minimum for a model to provide effective performance. The method with the least MSE and PRD is considered to be the best.

Experimental Study of Indian Database for Monthly Rainfall Prediction Using MSE and PRD Metrics:

Analytical results of monthly rainfall prediction for Indian rainfall database (dataset1) using MSE and PRD metric measured by proposed model is shown in figure 2 (a) &(b) and table 1.

Analytic results based on MSE values with varying size of training data:

1. When training data 0.80 (80%):

The corresponding MSE values calculated by proposed model with Hidden Neurons 20 is 0.0024, with Hidden Neurons 40, is 0.0026, with Hidden neurons 60, is 0.0028, with Hidden Neurons 80, is 0.0028, and with Hidden Neurons 100 is 0.0023 respectively.

2. When training data size is 0.70 (70%):

The MSE values measured for Hidden Neurons 20 is 0.0044, for Hidden Neurons 40 is 0.0046, for Hidden neurons 60 is 0.0049, for Hidden Neurons 80 is 0.0048, and for Hidden Neurons 100 is 0.0043 respectively.

Analytic results based on PRD values with varying size of training data:

1. When training data size id 0.40 (40%):

The PRD values generated by the proposed model for Hidden Neurons 20 is 2.836, for Hidden Neurons 40 is 2.835, for Hidden neurons 60 is 2.839, for Hidden Neurons 80 is 2.838, and for Hidden Neurons 100 is 2.818 respectively.

2. When training data size 0.50 (50%):

The corresponding PRD values measured using AALM-NARX for Hidden Neurons 20 is 2.819, for Hidden Neurons 40 is 2.819, for Hidden Neurons 60 is 2.822, for Hidden Neurons 80 is 2.821 and for Hidden Neurons =100 is 2.801 respectively.

Hence, Hidden neuron 100 provides the least MSE and PRD values.

Hidden Neurons	**20**	**40**	**60**	**80**	**100**
MSE (0.8)	0.0024	0.0026	0.0028	0.0028	0.0023
MSE (0.7)	0.0044	0.0046	0.0049	0.0048	0.0043
PRD (0.4)	2.836	2.835	2.839	2.838	2.818
PRD (0.5)	2.819	2.819	2.822	2.821	2.801

Table 1: MSE & PRD values for varying size of training data for Indian Monthly Rainfall Prediction.

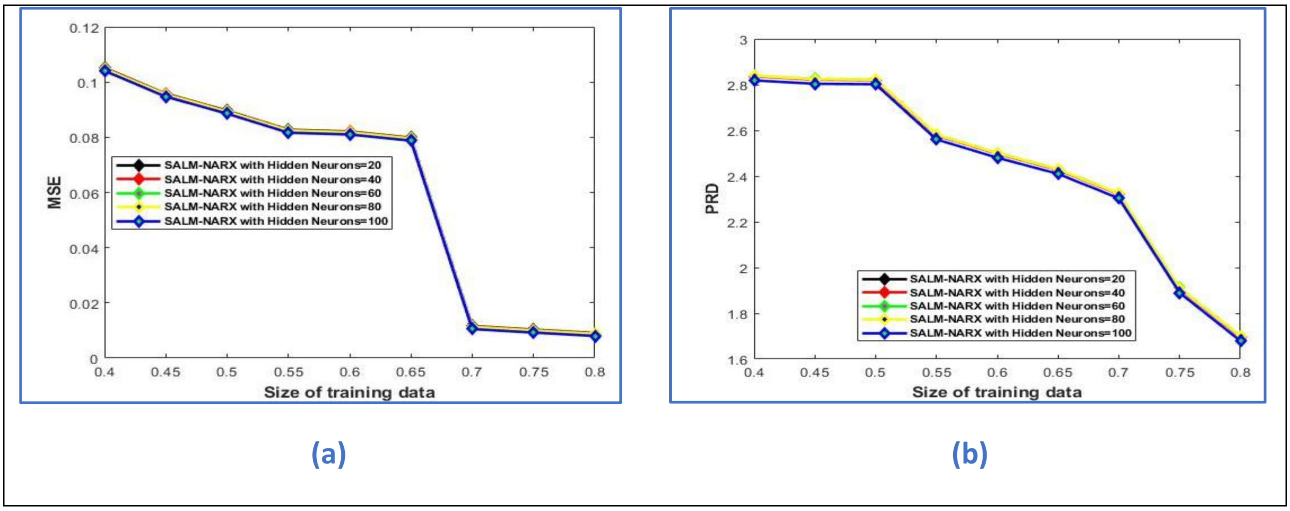

Figure 2: Analysis of Monthly Rainfall Prediction Using Indian Database (Time-series dataset1) based on a) MSE b) PRD values

Experimental Study of J&K Database for Monthly Rainfall Prediction Using MSE and PRD Metrics:

Predictive Analytics of monthly rainfall prediction for Jammu and Kashmir rainfall database (dataset 2) using MSE and PRD metric measured by proposed model isshown in figure 3 (a) & (b). The calculated values of MSE and PRD for varying size of training data are presented in table 2.

Analytic results based on MSE values with varying size of training data

1. When the size of training data is 0.5(50%):

It can be seen that after applying AALM-NARX model the MSE values for Hidden Neurons 20 is 0.0133, for Hidden Neurons 40 is 0.0133, for Hidden Neurons 60 is 0.0133, for Hidden Neurons 80 is 0.0135, and for Hidden Neurons 100 is 0.0129 respectively.

2. When the training data size 0.75 (75%):

MSE values measured by AALM-NARX for Hidden Neurons 20 is 0.0108, for Hidden Neurons 40 is 0.0109, for Hidden Neurons 60 is 0.0108, for Hidden Neurons 80 is 0.0110, and for Hidden Neurons 100 is 0.0104, respectively.

Analytic results based on PRD values with varying size of training data:

1. When the size of training data is 0.8 (80%):

PRD values calculated for Hidden neurons 20 is 4.285, for Hidden Neurons 40 is 4.282, for Hidden Neurons 60 is 4.280, for Hidden Neurons 80 is 4.286, and for Hidden Neurons 100 is 4.247 respectively.

2. When the training data size is 0.75 (75%):

PRD values measured using SALM-NARX for Hidden neurons 20 is 4.325, for Hidden Neurons 40 is 4.322, for Hidden Neurons 60 is 4.320, Hidden neurons 80 is 4.3260, and for Hidden Neurons 100 is 4.287 respectively.

It can be seen from the experimental results that employment of proposed model with Hidden neurons 100 yields better performance as MSE and PRD with values are minimum as 0.0100 and 4.2475, respectively.

Hidden Neurons	20	40	60	80	100
MSE (0.5)	0.0133	0.0133	0.0133	0.0135	0.0129
MSE (0.75)	0.0108	0.0109	0.0108	0.0110	0.0104
PRD (0.8)	4.285	4.282	4.280	4.286	4.287
PRD (0.75)	4.325	4.322	4.320	4.3260	4.287

Table 2: MSE & PRD values for varying size of training data Monthly Rainfall

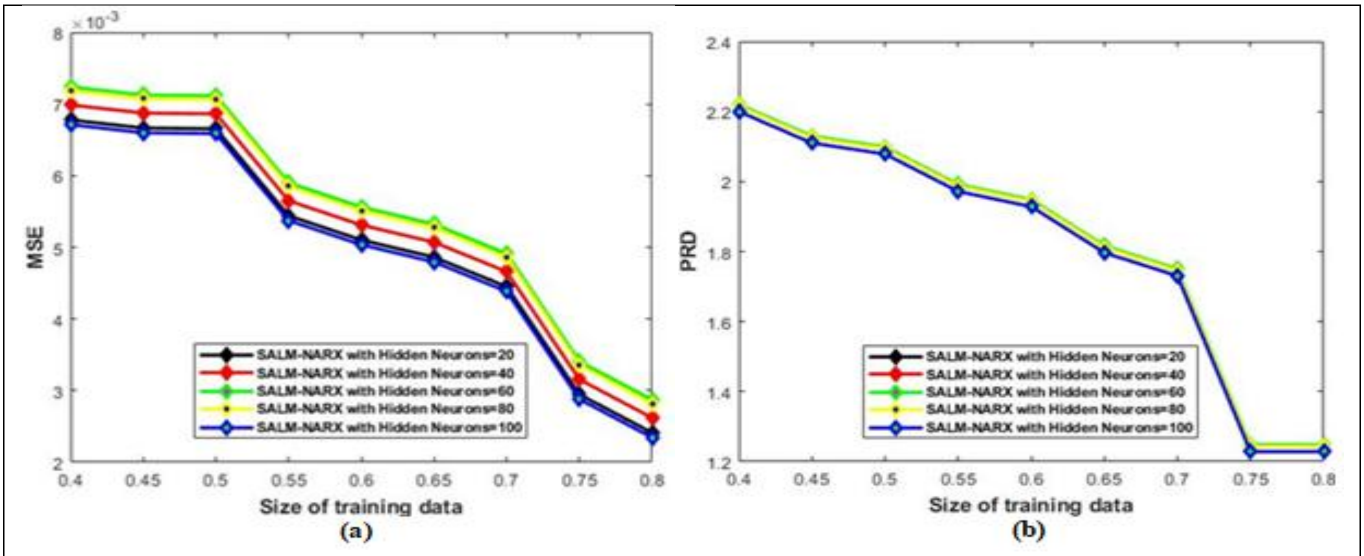

Figure 3: Analysis of Monthly Rainfall Prediction Using J&K Database(dataset 2) based on a) MSE b) PRD values.

Conclusion

Rainfall prediction and neural networks have a close relationship, as neural networks are increasingly being used to develop accurate and efficient rainfall prediction models.NARX neural networks are designed to predict a target output based on both past input and output data, making them ideal for time-series prediction problems like rainfall forecasting. NARX Neural Network based Optimized Deep Learning Algorithm for Adaptive Rainfall Prediction in North-Western Himalayas has been found to be an effective tool for predicting rainfall patterns in the region. This study aimed to investigate the impact of varying the training data size and the number of hidden neurons on the accuracy of the predictions.

Our findings suggest that increasing the training data size leads to improved prediction accuracy. This result is expected since a larger dataset allows the model to learn more about the rainfall patterns and make better predictions. However, it is also important to note that there is a limit to the benefit gained from increasing the training data size. After a certain point, further increase in the data size does not result in significant improvement in prediction accuracy.

Additionally, we found that increasing the number of hidden neurons in the NARX neural network also leads to improved prediction accuracy. However, this increase has diminishing returns, and after a certain point, the benefit of adding more hidden neurons is negligible.

Overall, our study highlights the importance of optimizing the training data size and the number of hidden neurons in the NARX neural network for accurate rainfall prediction. This research can provide valuable insights for future studies in this field and can be useful for decision-makers in agriculture and water resource management sectors. The NARX Neural Network based Optimized Deep Learning Algorithm can be further developed and applied in other regions and can be an essential tool for adaptive rainfall prediction.

References

[1] Sit M, Demiray BZ, Xiang Z, Ewing GJ, Sermet Y, Demir I. A comprehensive review of deep learning applications in hydrology and water resources. Water Science and Technology. 2020 Dec 15;82(12):2635-70.

[2] Roncoli C, Ingram K, Kirshen P. Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. Society & Natural Resources. 2002 May 1;15(5):409-27.

[3] Balica SF, Popescu I, Beevers L, Wright NG. Parametric and physically based modelling techniques for flood risk and vulnerability assessment: A comparison. Environmental modelling & software. 2013 Mar 1;41:84-92.

[4] Talaviya T, Shah D, Patel N, Yagnik H, Shah M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture. 2020 Jan 1;4:58-73.

[5] Kumar P. Assessment of impact of climate change on Rhododendrons in Sikkim Himalayas using Maxent modelling: limitations and challenges. Biodiversity and Conservation. 2012 May;21:1251-66.

[6] Mohapatra JB, Jha P, Jha MK, Biswal S. Efficacy of machine learning techniques in predicting groundwater fluctuations in agro-ecological zones of India. Science of the Total Environment. 2021 Sep 1;785:147319.

[7] Tektaş, Mehmet. "Weather forecasting using ANFIS and ARIMA models." Environmental Research, Engineering and Management 51.1 (2010): 5-10.

[8] Chatterjee, S., B. Datta, and N. Dey. "Hybrid neural network-based rainfall prediction supported by flower pollination algorithm." Neural Network World 28.6 (2018): 497-510.

[9] Ruslan, FazlinaAhmat, ZainazlanMdZain, and Ramli Adnan. "Flood water level modeling and prediction using NARX neural network: Case study at Kelang River." 2014 IEEE 10th International Colloquium on Signal Processing and its Applications. IEEE, 2014.

[10] Le, Vuong Minh, et al. "Daily rainfall prediction using nonlinear autoregressive neural network." Micro-Electronics and Telecommunication Engineering (2020): 213-221.

[11] Asadnia, Mohsen, et al. "Improved particle swarm optimization–based artificial neural network for rainfall-runoff modeling." Journal of Hydrologic Engineering 19.7 (2014): 1320-1329.

[12] Estévez J, Bellido-Jiménez JA, Liu X, García-Marín AP. Monthly precipitation forecasts using wavelet neural networks models in a semiarid environment. Water. 2020 Jul 4;12(7):1909.

[13] Han JM, Ang YQ, Malkawi A, Samuelson HW. Using recurrent neural networks for localized weather prediction with combined use of public airport data and on-site measurements. Building and Environment. 2021 Apr 1;192:107601.

[14] Liu Y, Gong C, Yang L, Chen Y. DSTP-RNN: A dual-stage two-phase attention-based recurrent neural network for long-term and multivariate time series prediction. Expert Systems with Applications. 2020 Apr 1;143:113082.

[15] Peña M, Vázquez-Patiño A, Zhiña D, Montenegro M, Avilés A. Improved rainfall prediction through nonlinear autoregressive network with exogenous variables: a case study in Andes high mountain region. Advances in Meteorology. 2020 Sep 17;2020:1-7.

[16] Ahmed K, Shahid S, Haroon SB, Xiao-Jun W. Multilayer perceptron neural network for downscaling rainfall in arid region: a case study of Baluchistan, Pakistan. Journal of Earth System Science. 2015 Aug;124:1325-41.

[17] Ranganathan A. The levenberg-marquardt algorithm. Tutoral on LM algorithm. 2004 Jun 8;11(1):101-10.

[18] Rymarczyk T, Kłosowski G, Kozłowski E, Tchórzewski P. Comparison of selected machine learning algorithms for industrial electrical tomography. Sensors. 2019 Mar 28;19(7):1521.

[19] Dhundhara S, Verma YP. Grid frequency enhancement using coordinated action of wind unit with redox flow battery in a deregulated electricity market. International Transactions on Electrical Energy Systems. 2020 Mar;30(3):e12189.

[20] Bukhari AH, Sulaiman M, Islam S, Shoaib M, Kumam P, Raja MA. Neuro-fuzzy modeling and prediction of summer precipitation with application to different meteorological stations. Alexandria Engineering Journal. 2020 Feb 1;59(1):101-16.

[21] Golafshani EM, Behnood A, Arashpour M. Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer. Construction and Building Materials. 2020 Jan 30;232:117266.

[22] Shamsudin SS, Chen X. Identification of an unmanned helicopter system using optimised neural network structure. International Journal of Modelling, Identification and Control. 2012 Jan 1;17(3):223-41.

[23] Sutskever I. Training recurrent neural networks. Toronto, ON, Canada: University of Toronto; 2013 Jan 1.

[24] Tung TM, Yaseen ZM. A survey on river water quality modelling using artificial intelligence models: 2000–2020. Journal of Hydrology. 2020 Jun 1;585:124670.

[25] Tatro N, Chen PY, Das P, Melnyk I, Sattigeri P, Lai R. Optimizing mode connectivity via neuron alignment. Advances in Neural Information Processing Systems. 2020;33:15300-11.

[26] Snieder E, Shakir R, Khan UT. A comprehensive comparison of four input variable selection methods for artificial neural network flow forecasting models. Journal of Hydrology. 2020 Apr 1;583:124299.

[27] MenezesJr JMP, Barreto GA. "Long-term time series prediction with the NARX network: an empirical evaluation "Neuro Computing, vol.71, pp.3335–43, 2008.

[28] Rainfall prediction dataset taken from “https://data.gov.in/catalog/rainfall-india”, accessed on September 2020.