Analytical Study of ANN Architectures for Identification of Chaotic Behavior

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Abstract-

Research into the ability to forecast the internal dynamics of chaotic systems is vital. The chaotic character of climatic systems is a major barrier to accurate climate prediction. Numerous studies have been conducted so far on the topic of numerical simulation approaches for the simulation and prediction of chaotic systems. Chaotic systems are difficult to anticipate with numerical simulation approaches due to issues like sensitivity to beginning values, error accumulation, and inappropriate parameterization of physical processes. Here, we looked into the architectures of Neural Networks. The present literature study has provided confidence in the efficacy of artificial neural networks as a powerful tool for predicting internal dynamics climatological data. Research demonstrates that ANNs have the potential for prediction of climatological analysis since they are ideally adapted to situations requiring complex nonlinear interactions.

keywords: Artificial Neural Network, Chaotic systems, Climatological data, Internal dynamics, Numerical Simulation

1. Introduction

The term "climate" refers to the average weather conditions throughout a certain time frame, and climatology is the scientific study of climates. Meteorology is a subfield of atmospheric science that examines both the day-to-day fluctuations and the seasonal patterns that shape our planet's climate. Climatology is crucial because it is used to predict how the climate will change in the future. Because of its impact on global air circulation, which in turn affects global temperatures and precipitation, ENSO is a crucial climate phenomenon. Climate exhibits chaotic behaviour because its properties (such as wind speed, temperature, humidity, precipitation, etc.) vary throughout time. The term "butterfly effect" has come to be used to describe this climate occurrence. In chaos theory, "the butterfly effect is the sensitive dependency on beginning circumstances in which a tiny change in one state of a deterministic nonlinear system can result in significant alterations in a later state". A seemingly insignificant rounding off of beginning condition data led to Edward Lorenz's discovery of the effect while observing runs of his weather model. He pointed out that simulations with the roughed-off starting conditions would provide different outcomes from those with the rounded ones in the weather model. The results had changed drastically due to a seemingly insignificant shift in the original conditions. Artificial neural networks (ANNs) are frequently used in the prediction of time-series phenomena, including hydrological variables. Because of the method's flexibility, it can account for inputs and outputs that aren't linearly related, and it can also automatically alter the link to account for new information about potential outcomes. In most cases, less computing power is needed for the process. The effectiveness of ANN models in predicting climate behaviour has been demonstrated in a number of previous studies (e.g., "Back-Propagation Network, Radial Basis Function Network, Feed forward Neural Network, Recurrent Neural Network, Convolutional Neural Network", auto regressive integrated moving average, etc.). The strategies we employ allow us to achieve desirable outcomes with increased precision.

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2. Literature Review

In past many researchers have done their work for analysis of Neural Network in context of climate data. Classification of different methods used by them are described below.

2.1 Back-Propagation Neural Network

To train Multi-layer Perceptrons, Backpropagation is used, which is a supervised learning algorithm (Artificial Neural Networks). Using the "delta rule (or gradient descent), the Backpropagation method searches for the smallest value of the error function in weight space". To solve the learning problem, we look for the weights that produce the smallest error function. Every BPN has three layers: input, output, and hidden. Accurate output prediction is based on the number of neurons in each layer of the network and the number of hidden layers.

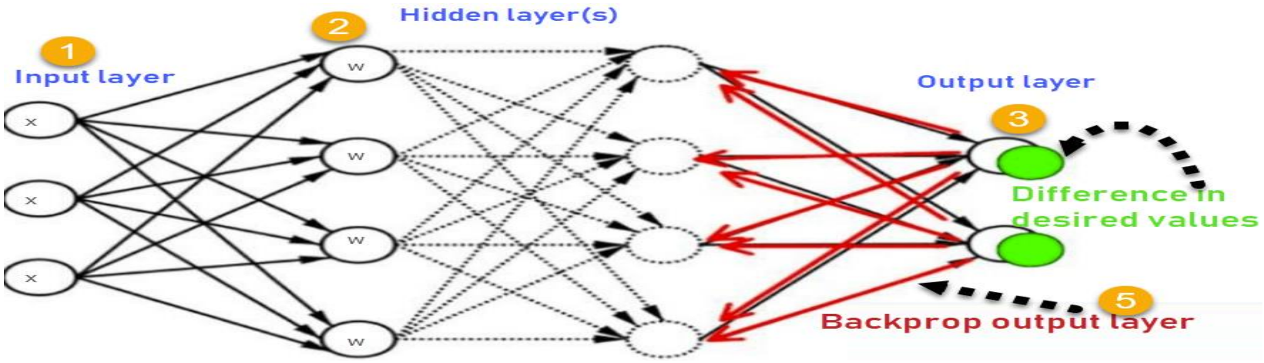

Fig.1 Back-Propagation Algorithm

Source: https://www.guru99.com/backpropogation-neural-network.html

The Backpropagation method used by many researchers for climatological data analysis is discussed below:

Mishra et al., [27] have analyzed 141 years rainfall records in North India. Using monthly rainfall data, ANN approach has been utilised to construct forecasting models for rainfall prediction one month and two months ahead. Each of these models (M1 and M2) is based on a "Feed Forward Neural Network (FFNN) trained with the Levenberg-Marquardt function and the Back-Propagation technique. Regression Analysis, Mean Square Error (MSE), and Magnitude of Relative Error" have all been used to compare the two models' performances (MRE). Comparing the results of the proposed ANN model to those of another model, the proposed model performed better.

Saxena et al. [41] have offered a literature review of the various approaches taken by scientists who have used ANN for weather prediction. The authors argued the use of an ANN instead of conventional metrological methods for weather forecasting is effective. The study details the capacities of ANN to forecast a variety of weather phenomena, including temperature, thunderstorms, and precipitation, and draws the conclusion that key architectures like BP and MLP are well-suited to this task.

Singh et al. [45] have suggested using a BPN model they developed to predict 45 years' worth of rainfall data for the vindhya area. The LPA (long-term average) that has been measured is 956. During the testing period, it was found that the MAD (6.09) was lower than the SD (14.37). The training and testing period correlation coefficients are 0.89 and 0.95, respectively. The model's results are accurately observed. Identification of parameters for long-term rainfall data is a good use of Back-Propagation Neural Network.

As Shrivastava et al. [44] showed, the complexity of weather is a result of the chaotic behaviour of climatic data, and the presented BPN model is the best way to identify climatic parameters for prediction and forecast rainfall. The scientific community as a whole, however, has been advocating for the use of neural network-based numerical modelling for this purpose since 1986, and it has been successful enough to the point where a literature review covering a wide range of contributions from 1997 to 2017 has been presented. The results showed that soft computing, including neural networks, deep learning techniques, and associative classifiers from data mining, were effective. In the end, it is determined that BPN is all that is necessary to address this intricate issue. As a model, it has proven to be 90% accurate.

Long-range predictions of monsoon rainfall over a relatively limited area have been examined by Shrivastava et al. [43] using the BPN model. The coordinates of Ambikapur are 23° 07′ 23″ North and 83° 11′ 39″ East. Long-range forecasting (LRF) of monsoon rainfall in this area is the focus of this model's operation in 2012. In 2012, the model predicted a value of 94.4 (% of LPA), with a margin of error of 2.7 (% of LPA). This experiment yields highly accurate results, suggesting BPN's potential for use in weather prediction; however, designing BPN parameters such as "learning rate, momentum factor, initial weights, neurons in the hidden layer, number of input vectors, number of hidden layers, transfer function, training cycles, etc.", necessitated near-perfect observations.

Using "TMPA-v7 rainfall" records from the Kopili River basin in northeastern India, Kumar et al. [21] give a comparative analysis of three available methods for the aim of rainfall-runoff-sediment modelling. Artificial neural network backpropagation (ANNBP) methods were used to look into the "LM, SCG, and BR algorithms". They concluded that a combination of the LM and BR algorithms in an ANN model yields the best results. As far as validation goes, the ANN model incorporating BPN fares better than the alternatives.

Nourani and Fard [31] developed an ANN model to foretell the amount of water lost to evaporation each day in the cities of Tabriz and Urmia. The ANN models' output was compared to that of some more traditional methods. Higher and lower RMSE values for daily evaporation predictions were found in ANN models like BPN, MLP, respectively. However, when compared to other ANN models, the BPNN excels due to its easier-to-understand structure and shorter training period.

Kaur and Singh [19] showed how neural networks can be used to investigate the coldest time of year in Chandigarh. In order to simulate a forecasting system, they employed the Multi-layer Perceptron model and trained the network with the Back-Propagation algorithm. The suggested network is trained and tested using data from the meteorological department that spans the past decade. According to the findings, using MLP and BPN, minimum temperatures can be predicted with some degree of accuracy.

Srikalra and Tanprasert's [47] work illustrates the use of neural networks for predicting rainfall along the Chao Phraya River, with data being collected online. Their strategy employs a Back-Propagation Network. There are three steps involved in training a network via backpropagation: feeding forward the training pattern input, backpropagating the related error, and fine-tuning the weights. The BPN method discussed here is a viable option for improving the accuracy of weather forecasts.

In order to forecast rain in India, Vamsidhar et al. [10] proposed a back propagation neural network model. The findings indicated that a backpropagation neural network may be used to reliably forecast precipitation. With the use of variables like humidity, dew point, and pressure, the amount of rainfall in the region can be determined using the BPN technique of prediction.

According to a literature assessment published by Karmakar et al. [18] Neural Networks are a viable tool for predicting and extrapolating climate. They concluded that Neural Networks, such as BPN and RBF, were most suitable for predicting the chaotic behaviour of climate variables like rainfall and rainfall runoff, and were also efficient enough for long-term predictions. When it comes to extrapolating average climate factors over large areas, they also discovered that Neural Networks are quite effective.

Table 1: Details of BPN method for Climatological data analysis

Author & Year	Classification Methods	Result
Mishra et al. (2018)	Feed Forward Neural Network Using BPN	M1 model is better than M2 model for one month ahead forecasting.
Saxena et al. (2013)	BPN, MLP	94.28%
Singh et al. (2016)	BPN	Better Accuracy
Shrivastava et al. (2017)	BPN	90%
Shrivastava et al. (2013)	BPN	94.4%
Kumar et al. (2013)	BPN	Better Accuracy
Nourani and Fard (2012)	BPN, MLP	Better Accuracy
Kaur and Singh (2011)	BPN, MLP	93.4%
Srikalra and Tanprasert (2010)	BPN	95.2%
Vamsidhar et al. (2010)	BPN	94.28%
Karmakar et al. (2016)	BPN, RBF	Better Accuracy

2.2 ARIMA Model

Autoregressive Integrated Moving Average is an abbreviation for "autoregressive" A model employed in time series analysis and econometrics. You can use the model to analyse existing data and make projections about the future of the series. It's utilised when a metric is recorded at predetermined times, such as seconds, minutes, days, weeks, or months. The ARIMA model makes forecasts about a time series by using the data from the series itself as input. It can be used to any sequence of numbers outside of a specific time period that shows regularity and is not a random sequence.

Read on for a breakdown of the ARIMA Model, a standard tool in the interpretation of climatological data used by many scientists:

Using a computer-intensive subsampling technique, Gluhovsky and Agee [14] presented meteorological and climatological time series. To shed light on the potential for estimate mistakes caused by nonlinearities in the underlying data-generating mechanism, a first-order autoregressive model with a nonlinear component has been chosen as "the default model for correlated time series in climate studies". It is demonstrated that statistical inference based on the linear model is erroneous due to the presence of nonlinearity that is unnoticed by standard diagnostic procedures. Time series analysis using ARIMA model determined to be appropriate.

Three models for predicting rain have been created and put into practise by Alhashimi et al. [2] based on historical data: an ARIMA-based time series model, an ANN-based model, and an MLR-based model. Root Mean Square Errors (RMSE) and the Correlation Coefficient (R) are two such parameters. Their data collection is composed of monthly observations of weather variables like precipitation, average temperature, wind speed, and relative humidity. The results confirm that, similar to other ANN models, the ARIMA and MLR models are effective for making predictions.

The research by Shukla et al. [46] aims to create a location-specific weather forecasting model for Pantnagar, Uttarakhand, by analysing historical data. To provide predictions for the winter season, an exponential smoothing model and a Seasonal Autoregressive Integrated Moving Average approach were used (SARIMA). The percentage of incorrect predictions and the mean square error have both been used in a comparative research . The study concluded that the SARIMA model was the best effective for forecasting monthly maximum/minimum temperatures and humidity levels on the basis of RMSE.

Based on "100 replicates on 100 generated data of the ARIMA (1,0,1) model shared by Haji et al. [15] we compare the ARIMA model with the Fuzzy Time Series (FTS) model to determine the most effective model for forecasting time series data. Three metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Bias Statistics Criterion", were used to assess the models' performances and decide the best approach. In this case, ARIMA proved to be a reliable predictive tool.

Taking into account stationarity, seasonality, and trend, Athiyarath et al. [5] examined and forecasted using several time series models based on a wide range of discrete datasets. Evidence from the survey indicates that the models' efficacy varies across different temporal scales. CBLSTM gave good results for both mid- and long-range LSTMs, CNNs, ARIMAs, and MVFTS, while also performing admirably for short-range LSTMs.

Rainfall estimates utilising "a complex statistical model ARIMA (1,1,1) and three different kinds of Artificial Neural Network (ANNs) models, MLP, FLANN, and LPE", were presented by Nanda et al. [29] and they discovered that weighted MVFTS and CBLSTM are effective for predicting. The ARIMA (1,1,1) model was chosen to analyse the Rainfall Estimation data since "it is the best statistical model for time series models. Multiple Artificial Neural Network (ANN) models, including Multilayer Perceptron (MLP)", Faster-Layer-Annotated Network (FLANN), and Least Squares Expansion (LPE), This is where the ARIMA model shines.

The "Seasonal Autoregressive Integrated Moving Average (SARIMA) Stochastic model, the Support Vector Regression (SVR), and its merged type with the Firefly optimization algorithm (SVR-FA) as a meta-innovative model", Aghelpour et al. [1] have compared in terms of their ability to accurately predict the average monthly temperature over long time periods. With the help of the best models, we can now predict the average monthly temperature for the years 2012-2017. According to the findings, the SARIMA model is more effective than competing methods.

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Pham et al. [32] detail the potential of five data-driven "models for multi-station prediction of daily rainfall in the Vu Gia-Thu Bon River basin in Central Vietnam: Multilayer Perceptron (MLP), Least Square Support Vector Machine (LSSVM), Neuro-fuzzy, Hammerstein-Weiner (HW), and Autoregressive Integrated Moving Average (ARIMA)". The findings were measured against standard performance metrics including R-squared, RMSE, MAE, and CC to find that hybrid ARIMA-NF and ARIMA-HW models performed better than their single-model counterparts when it came to prediction accuracy.

Table 2: Details of ARIMA Model for Climatological data analysis

Author & Year	Classification Methods	Result
Gluhovsky and Agee (2009)	ARIMA	Good Accuracy
Alhashimi et al. (2014)	ARIMA, MLR	Better Accuracy
Shukla et al. (2014)	SARIMA	Temperature, Humidity forecasting is approx 94%.
Haji et al., (2018)	ARIMA	Good Accuracy
Athiyarath et al. (2020)	ARIMA, MVFTS, CBLSTM	Better Accuracy (Mid. and Long range)
Nanda et al. (2013)	ARIMA, MLP, FLANN, LPE	Approx 89% accuracy by ARIMA.
Aghelpour et al. (2016)	SARIMA, SVR	Better Accuracy with SARIMA
Pham et al. (2017)	MLP, LSSVM, NEURO FUZZY, HW, ARIMA	Better Accuracy by hybrid ARIMA- NF, ARIMA-HW compared to single model.

2.3 ANFIS Model

"Through highly interconnected processing units and information linkages, which are weighted to map the numerical inputs into an output, ANFIS is a straightforward data learning technique that use Fuzzy Logic to transform provided inputs into a desired output. The advantages of Fuzzy Logic and Neural Network, two machine learning methods, are combined in ANFIS". An ANFIS is a Fuzzy Inference System that uses Neural Network learning techniques to fine-tune the system's parameters (FIS).

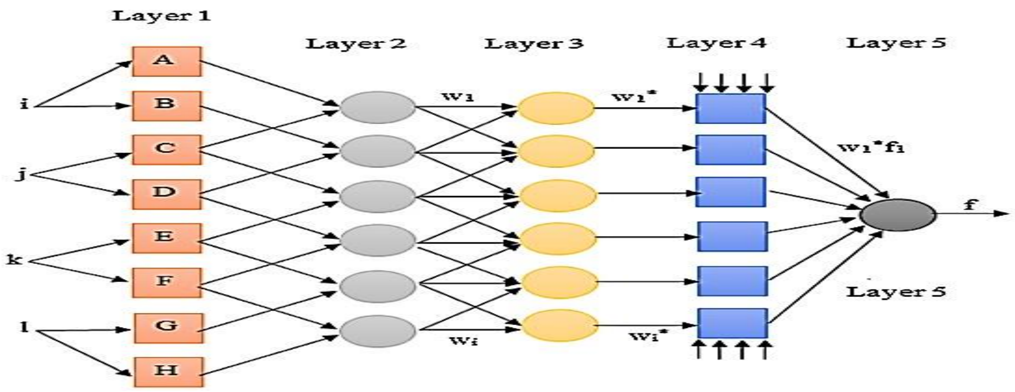

Fig.2 ANFIS Model

Source: https://www.researchgate.net/figure/Adaptive-neuro-fuzzy-system-ANFIS-model_fig2_336261180

The ANFIS Model used by many researchers for climatological data analysis is discussed below:

Nayaka et al. [30] proposed an ANFIS implementation for modelling hydrologic time series, with an example application simulating the river flow of the Baitarani River in the Indian state of Orissa. To evaluate how well ANFIS and ANN models perform in comparison, a suitable ANN model is built for the same basin. As can be shown, the ANFIS model is able to maintain the time series' observable statistical features.

It has been shown by Maitri and Tiwari that groundwater level predictions can be compared. Scaled-conjugate-gradient (SCG)-optimized artificial neural networks (ANN.SCG), and SCG-optimized Bayesian neural networks (BNN) (BNN.SCG). They employed measures of robustness such as “root mean square error, reduction of error, the index of agreement (IA), and Pearson's correlation coefficient” (R) to evaluate the models. The results of these tests show that the ANFIS model outperformed the BNN.SCG and the ANN.SCG when it came to simulating data with no background noise.

Moosavi et al. [24] have analysed the accuracy of groundwater level forecasts made 1, 2, 3, and 4 months in advance using “ANN, ANFIS, Wavelet-ANN, and Wavelet ANFIS models” for two different case studies in two different sub-basins. They discovered that it's possible these models can't account for the nonlinearity and seasonality of data. Following this initial stage, the data underwent a wavelet transform, and the pre-processed data was sent into the ANN and ANFIS models in step two. The Wavelet-ANFIS hybrid model performed the best, according to the results.

As shown by Rezaeianzadeh et al. [37] “maximum daily flow at the outlet of the Khosrow Shirin” watershed in Iran's Fars Province may be predicted using a variety of statistical methods, including ANNs, ANFISs, MLRs, and MNLRs. The RMSE and the R2 were used to assess the models' accuracy. The data demonstrates that both ANFIS and MLR are capable of producing reliable forecasts.

For modelling evaporation from meteorological data, Salih et al. [40] offer a new method they name the “co-active neuro-fuzzy inference system (CANFIS)”. Three well-established artificial intelligence (AI) models are used to verify the CANFIS model's prediction ability. According to the findings, CANFIS models provide more accurate predictions than the alternatives. By far the most accurate model for predicting evaporation given merely mean temperature and relative humidity is CANFIS, with a Nash-Sutcliffe efficiency of 0.93.

Sabzi et al. [38] showed how to use data processing and data mining to make more precise predictions about streamflow. Four models were developed and used in a “streamflow prediction process on Elephant Butte Reservoir based on easily accessible Snow Telemetry data (SNOTEL): an autoregressive integrated moving average (ARIMA), an artificial neural network (ANN), a hybrid-model of ANN and ARIMA (ANN-ARIMA), and an adaptive neuro fuzzy inference system (ANFIS)”. ANFIS outperformed the other three models in terms of predicting daily streamflow with a higher degree of accuracy.

Table 3: Details of ANFIS Model for Climatological data analysis

Author & Year	Classification Methods	Result
Nayaka et al. (2009)	ANFIS	Better Accuracy
Maitri and Tiwari (2012)	ANFIS, ANN, BNN	Better Accuracy by ANFIS

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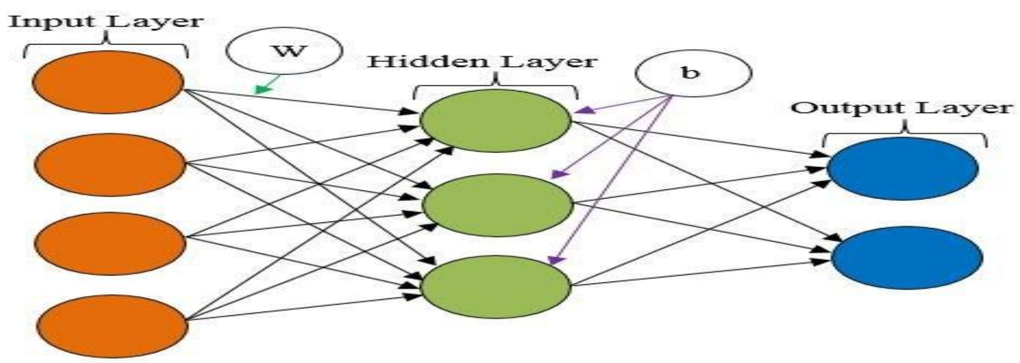
Moosavi et al. (2013)	ANFIS, Wavelet-ANN, Wavelet ANFIS	Better Accuracy by Wavelet ANFIS
Rezaeianzadeh et al. (2013)	ANFIS, MLR, MNLR	Better Accuracy by ANFIS, MLR
Salih et al. (2019)	CANFIS	Better Accuracy
Sabzi et al. (2017)	ARIMA, ANN, ANN-ARIMA, ANFIS	ANFIS is better than other models

2.4 Artificial Neural Network

The number of ANN nodes, often known as neurons, is essentially an engineering approximation of a biological neuron. ANN is structured in a hierarchical manner. Layers of input, hidden, and output data are used to illustrate them. There is a hidden layer in the network, and all the neurons there get their information from the neurons in the input layer. Weights and constants are determined during the training phase to indicate the relative strengths of each signal and biases. The output is a function of the transfer function applied to the sum of the inputs after they have been weighted. The activation functions can be anything from a sigmoid to a tanh.



. **Fig.3 Architecture of ANN**

Source: https://www.researchgate.net/figure/The-basic-ANN-architecture-Neuron-is-the-smallest-processing-component-of-the-ANN_fig1_337533434

Some important work done on Climatological data analysis using ANN is discussed below:

To find the best method for predicting monthly streamflow time series at 4 stations, Wu and Chau [48] have explored data-driven models such "Auto-Regressive Moving Average (ARMA), K-Nearest-Neighbors (KNN), and Artificial Neural Networks (ANN). In addition, a Moving Average Artificial Neural Networks (MA-ANN)" is proposed, which would take the average of streamflow series as its input. In comparison to the other four models, the results demonstrate that MA-ANN provides more reliable forecasts.

For the purpose of "predicting daily maximum air temperature in Canada during 1999-2009", Kumar et al. [23] looked into the viability of the "feed-forward neural network (FFNN)". Daily maximum air temperature readings were used as input data throughout a 10-year time period. When gauging the efficacy of neural networks, researchers experimented with a variety of transfer functions, neuron densities, and hidden layer depths. Finally, the findings demonstrated that the best maximum air temperature forecasts were made by "the ANN with 5 hidden layers, 10 neurons per layer, and a tan-sigmoid transfer function".

With data spanning from 1901 to 2015, Praveen et al.[34] analysed and projected long-term Spatial-temporal changes in rainfall across India at the level of meteorological divisions. The Mann-Kendall (MK) test and Sen's Innovative trend analysis were used to examine the precipitation pattern, while the Pettitt test was used to identify the moment of sudden shift. Rainfall predictions for the next 15 years in India were made using an Artificial Neural Network with a Multilayer Perceptron (ANN-MLP). The findings are considered to be satisfactory.

"Potential evapotranspiration over Gangetic West Bengal, India during the summer monsoon months of June, July, and August" has been estimated using a neurocomputing-based model provided by Chattopadhyay et al. [8] Surface temperature, vapour pressure, and precipitation are the only three meteorological variables that have been used in this modelling approach. Estimating monthly potential evapotranspiration has been made easier with the use of an artificial neural network (ANN) in the form of a multilayer perceptron trained using adaptive gradient learning. In terms of prediction, this Model performs better.

Id et al. [17] developed an ANN model to run real time change in water level prediction for Calabar River with lead time of 4 years in advance (from 2017-2020). Using the Levenberg-Marquardt as the training algorithm, the model was validated with R, R^2 and MSE to be 0.9705, 0.9418 and 0.0170 respectively. The ANN model shows better results in actual and predicted values, R^2 showed that the variation in water level was 94% influenced by rainfall, temperature and relative humidity.

Kushwaha and Kumar [20] built 8 artificial neural network models that use "daily discharge and suspended sediment concentration to forecast daily suspended sediment concentration in the Baitarani River at the Anandpur gauging station. With a sigmoid activation function and the Levenberg-Marquardt (L-M) learning algorithm", they employed multilayer feedforward back propagation neural networks. The artificial neural network-based model outperformed the sediment rating curve and the multiple linear regression in both qualitative and quantitative assessments.

Forecasts of weather conditions using ANN models have been made by Rajendra et al. [35] Air and soil temperatures, as well as relative humidity, have been examined in relation to climate change. The availability of weather data varies throughout the year, therefore hourly and monthly estimates would be quite beneficial. Compared to the MLR, both the MLP and RBF models performed better, which is a positive sign.

Input and output parameters, data sets for training and testing, "the number of hidden layers and the number of neurons in each hidden layer, the weights, the biases, the learning rate, and the activation function are all specified are specified in the Artificial Neural Network model provided by Selvin S. and Seetha N. [42] Measurement of accuracy is done by calculating the Mean Squared Error (MSE) between the predicted and actual output". This model's results are helpful in analysing climate patterns.

Ayodele and Precious [6] showed that it is possible to use non-linear methods for SRP, or seasonal rainfall prediction. They determined that ANN works well at transforming input patterns into output ones. Using a number of meteorological data, including: "sea surface temperature (SST), U-wind at (surface, 700, 850, and 1000), air temperature, specific humidity, ITD, and relative humidity". The results showed an MSE of 7174, RMSE of 84.7, and MAE of 18.6. The outcome demonstrated that the proposed ANN constructed network accurately predicted seasonal rainfall totals in Ikeja with low standard deviation.

Ata [4] has demonstrated how neural networks can be put to use in a number of ways in wind power generation. Here we see how neural network approaches have been put to use in a variety of contexts, including but not limited to, prediction, identification, control, forecasting, modelling, assessment, and fault diagnostics of wind energy systems. Although the multi-layer perceptron (MLP) network has been the most popular choice, other neural models including the radial basis function (RBF) and hybrid models have also been employed.

A multilayer perceptron (MLP) neural network using gravitational search (GSA) with firefly olfactory encoding has been explored by Naganna et al. [28] (FFA). The proposed forecasting models made use of data collected on a daily time scale, including "wet bulb temperature (WBT), vapour pressure (VP), relative humidity (RH), and dew point temperature. By comparing the proposed hybrid MLP networks (MLP-FFA and MLP-GSA) to the performance of a standard MLP network tuned with a Levenberg-Marquardt back-propagation algorithm, an extreme learning machine (ELM), and a support vector machine (SVM), we were able to verify the efficacy of the proposed hybrid MLP networks. The hybrid MLP models suggested here provide very high precision in estimate".

The autoregressive method has been presented by Chattopadhyay et al. [7] to analyse "the monthly maximum temperature (Tmax) over northeast India. Based on the high values of Willmott's indices and the low values of the prediction error, a sixth order autoregressive model (AR (6)) is chosen as a good representation of the Tmax time series. A fourth order autoregressive neural network model (AR-NN (4)), implemented as a modular neural network (MNN), has also performed well with that of AR (6). As a result, AR-NN (4)-MNN will be preferable than AR (6) when making predictions about a time series".

Table 4: Details of some ANN Model for Climatological data analysis

Author & Year	Classification Methods	Result
Wu and Chau (2012)	ARMA, KNN, ANN, MA-ANN	Better Accuracy by MA-ANN
Chattopadhyay et al. (2018)	GFFNN, MLP, MNN	Approx. 89 % Accuracy by MNN
Kumar et al., (2016)	FFNN	Better Accuracy
Praveen et al. (2020)	MLP	Better Accuracy
Id et al. (2019)	FFNN, Levenberg-Marquardt	94%
Kushwaha an Kumar (2017)	FFBPN	Better Accuracy
Chattopadhyay et al. (2015)	MLP	Better Accuracy
Rajendra et al. (2019)	RBF, MLP, MLR	91-96% Accuracy by RBF and MLP
Selvin S & Seetha N (2019)	ANN	Good Accuracy
Ayodele and Precious (2019)	ANN	94%
Ata (2015)	MLP, RBFN	Better Accuracy can be achieved by Hybrid ANN models

Naganna et al. (2019)	MLP–FFA, MLP–GSA, SVM, Levenberg-Marquardt Back-Propagation, ELM	Hybrid MLP (MLP–FFA, MLP–GSA) performs better than other models

2.5 Other Classifiers

Zeng et al. [50] have studied chaos theory and its application in atmosphere and they use fractal dimensions (Monofractal and Multifractal) for strangeness of attractors. They studied about Lyapunov Exponent of strange attractors. The spectrum of Lyapunov exponents provides a quantitative measure of the sensitivity of non-linear system to an initial condition.

Hegrel et al. [16] provided examples of open questions about the identification and assignment of causes for climate change. Changes in other variables, on regional dimensions, and in climatic extremes are needed to evaluate model simulations of changes at societally important scales and variables. Methodologies were proposed by them. Fingerprinting that works well for identification. This is a maximum likelihood approach to generalised multivariate regression, where the amplitude of externally induced signals in observations is estimated. The outcome from using this strategy is satisfactory.

In their article, "Rainfall Data Reconstruction based on Chaotic Characteristics of Meteorological Factors," Li et al. [12] “Using the saturation correlation dimension method, they evaluate the chaotic features of the two groups of decomposition coefficients. The results of this experiment demonstrate conclusively that it is possible to use chaos theory to the reconstruction of rainfall sequence data that is absent from the Loess Plateau by instead using the temperature sequence.”

Using time series data for weather forecasting as an example, Mishra and Jain [25] have demonstrated the utilisation of Data Mining and statistical methods. Time series prediction is increasingly utilising Data Mining (DM) techniques in addition to more conventional statistical methodologies. Studies on how to pick the most useful features for DM are a promising area of study, especially in light of recent advances in computational intelligence and time series data processing. From a predictive and factual standpoint, these strategies have been successful.

Data mining methods and statistical techniques for predicting rainfall based on historical records have been surveyed in detail by Mishra et al. [26] Statistical methods and neural network-based methods were shown to be complementary during a thorough examination of data mining methodologies and statistical methods for time series data processing. However, improved outcomes could be discovered with the aid of soft computing methods.

“Short-term, high-dimensional data can be used to make accurate predictions, as described by Chen et al [9] Anticipated's Learning Machine (ALM). They use the theory of non-linear dynamical systems to demonstrate that ALM can be used to overcome the small-sample problem and make multi-step-ahead predictions by transforming the current correlation/spatial information of high-dimensional variables into the future dynamical/temporal information of any target variable”. Extensive studies using real data show that ALM is better than the other 12 approaches now in use.

Predictions for chaotic systems have been proposed by Yanan et al. [49] who use a strategy that incorporates deep neural networks and data assimilation. In order to estimate the amount of state in Lorenz96, the experimental findings reveal that the prediction method that mixes neural network and data assimilation is quite effective. Results from simulations and experiments corroborate the method's ability to accurately forecast the quantity of state in the lorenz96 system, with predicted values that are very near to the true value during a finite time interval.

Using data from four different sources, Fernandez et al. [13] created a Neuro-fuzzy model to compare with a deterministic model in terms of their capacity to model and predict water levels in the Magdalena River. Based on the data, it appears that the NMF approach is more effective in modelling and forecasting river levels than the DM approach. Ten days' worth of data from NFM is more stable than the three days' worth of data from any other method.

Scher and Messori [39] have discovered the utility of neural networks for "weather" forecasting in a variety of low-complexity climate models. They did this by employing Scher's deep convolutional encoder-decoder architecture, which was originally designed for a much simpler general circulation model with no seasonal cycle. Also, they did what they call "climate" runs, which involve starting the network in some arbitrary state derived from the climate model run and then having it generate daily fields for a number of decades.

3. Comparitive Analysis

The majority of researchers who have used Neural Network techniques for forecasting various weather phenomena have used the same architectures, as was discovered after reviewing a large number of ANN architectures for prediction of the internal dynamics of chaotic systems in the context of climatology. Thus, in the review of almost twenty-one years of studies. The vast majority of weather experts agree that BPN, RBFN, ARIMA, ANFIS, and MLP are the best techniques for making accurate forecasts. In order to forecast the internal dynamics of a chaotic system, ANN can be applied to climatic data because it is dynamic and non-linear. Overall, it has been seen that while comparing other prediction techniques, such as statistical and numerical modelling, over meteorological data, Neural Network has proven to be the most appropriate technique clearly for forecasting different climatic situations. The models are graded on how well they generally perform and how accurate their results tend to be on average. Machine learning was used in this paper to conduct an in-depth analysis of neural network architecture as it relates to weather prediction. Tables 1, 2, and 3 as well as fig. 4 show that the BPN model outperformed ANN and other techniques in terms of accuracy.

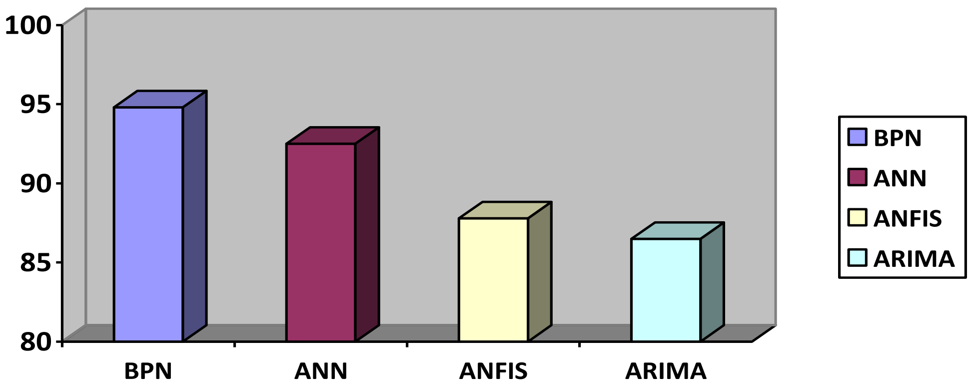


Fig 4. Comparative Analysis

4. Conclusion

The strengths of ANN are the primary focus of this research. It works well enough to detect chaotic motion in any non-linear data time series. This research has advantages since it confirms that ANN is well-suited for identifying the internal dynamics of highly dynamic non-linear systems and making predictions about them. From a comprehensive analysis of Neural Network architectures in practise, we know that BPN, RBFN, ARIMA, ANFIS, and MLP are the approaches most commonly utilised by researchers, with test results deemed sufficient in the absence of any rebuttal from the scientific community. In general, it has been seen that Out of the many prediction methods available, including statistical and numerical modelling over meteorological data, Neural Networks have proven to be the most effective.

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