

Research Article

Backpropagation Algorithm for Predicting Rainfall in Anyigba, Kogi State, Nigeria

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Abstract

Rainfall remains the primary supply of moisture for agricultural activities in Nigeria. Accurate and timely rainfall prediction is also essential for food security, better flood control, water resource management, and the wellbeing of the people. This research proposes a method for rainfall prediction based on metrological data and a machine learning technique. The machine learning technique is a hybrid of Levenberg-Marquardt (LM) back propagation and Artificial Neural Network (ANN) used to construct the rain fall forecasting model. Anyigba, in Dekina Local Government Area, Kogi State, Nigeria was used as a case study. The database from six years (2011-2016) of meteorological parameters made up of air temperature, relative humidity, and pressure were obtained from the Tropospheric Data Acquisition Network (TRODAN) of the Centre for Atmospheric Research, National Space Research and Development Agency (CAR-NASRDA) and used. The rainfall prediction model was trained using part of the data collected. The performance of the model was evaluated using metrics such as precision, recall, F1-score, and confusion matrix. The model achieved an accuracy of 0.88, indicating its robustness and reliability in predicting rainfall patterns. The high accuracy of the model demonstrates its potential application in real-time weather prediction, which can significantly benefit local farmers, water resource managers, and disaster response teams. The study identifies several limitations, including the dependency on the quality and availability of metrological data, and the potential impact of climate change on predictive accuracy. Future research could explore the integration of additional meteorological parameters, the use of ensemble methods, and the adaptation of the model to other regions with similar climatic conditions. This research presents a promising approach to rainfall prediction in Anyigba using the back propagation algorithm, offering a valuable tool for mitigating the adverse effects of unpredictable rainfall and enhancing the decision-making processes in agriculture and water management.

Keywords

Machine Learning, Anyigba, Rainfall Forecasting, Levenberg-Marquardt Backpropagation, Artificial Neural Networks

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1. Introduction

Planning for agriculture, disaster relief, and efficient water resource management all depend on accurate rainfall forecasting. Meteorological data is complex and non-linear, hence, traditional methods are not always effective in predicting rainfall pattern. This study looked into the prediction of rainfall patterns in Anyigba, Nigeria, using a neural network technique called the Backpropagation Algorithm. The goal is to create a model that can predict daily rainfall with enough accuracy to let local stakeholders make better decisions.

Predicting the amount of rain is crucial in the north central Nigerian state of Lokoja where heavy rainfall poses a risk of flooding in some places. After a period of intense rainfall, the people of Lokoja were shocked when they woke up on July 2, 2021, to find their homes completely flooded. The overflowing drainage channel caused traffic and pedestrians to be impeded during the whole incident. According to reports, two kids drowned while attempting to cross a flooded drain brought on by a lot of rain.

The issue above involves a number of crucial concerns related to rainfall prediction, including the inability to predict future patterns of precipitation with accuracy, the difficulty of anticipating and reducing the effects of extreme rainfall events, the difficulty of evaluating how better water resource management and disaster preparedness are facilitated by rainfall predictions, and the lack of knowledge regarding how data collection and technological advancements can improve rainfall prediction capabilities. Resolving these problems is crucial to creating forecasting techniques that are more accurate as well as to enhancing water resource management and catastrophe readiness plans.

This study's goal is to develop an algorithm that can forecast rainfall using parameters such as—rain, temperature, humidity, and wind—that affect rainfall forecasting. In order to forecast the occurrence of rainfall, the study used these identified features to train a model with the data gathered and used a machine learning backpropagation algorithm. Lastly, the performance of the model was evaluated by analysing the precision and efficacy of the projected outcomes.

1.1. Overview of the Algorithm for Backpropagation

Goal: To train artificial neural networks, the Backpropagation Algorithm to minimise the error between the target values and the anticipated output. It uses an error-correction procedure to modify the network's weights.

Elements: An input layer, one or more hidden layers, and an output layer make up the structure of a neural network.

Non-linear functions that are applied to each neuron's output in a network are known as activation functions. Some typical instances include Tanh, ReLU, and Sigmoid.

1.2. Crucial Actions

a. Propagation Forward:

Data Input: The algorithm takes in and processes data input over the network.

Layer Computations: Every neuron inside a layer applies an activation function, computes the weighted sum of its inputs, and forwards the result to the layer below.

Calculating Output: The network's output is generated by the last layer.

b. Calculating Errors:

Loss Function: Loss function (such as Mean Squared Error for regression tasks) was used to compare the expected output with the actual target values in order to compute the error or loss.

c. Reverse Propagation:

Error Signal: Using the chain rule of calculus, determine the gradient of the loss function with regard to each weight in the network.

Weight Update: Using gradient descent, the network's weights was modified in a way that makes sense given the loss function's negative gradient.

d. Repetition:

Epochs: Forward and backward propagation procedures were continued for several iterations, or epochs, until the loss function indicates that the network's performance is at an acceptable level.

1.3. Weather and Its Parameters as Variables of Rainfall

Every morning, one of the first things we generally notice is the atmosphere. We experienced several effects of the weather. Weather variations from day to day can affect how we feel and how we perceive the world. Because of the destruction they could inflict, severe weather might interfere with people's plans, including tornadoes and hurricanes. The temporary conditions of the atmosphere, the layer of air that surrounds the Earth, are referred to as "weather." The atmosphere in our own region of the world is typically how we conceive of weather. But when a pebble is put in water, the ripples eventually affect water far from the original location. The weather is always changing. From one hour to the next or day to the next, it moves and changes. Over many years, certain weather patterns become common in a place.

1.3.1. Precipitation / Rainfall

Any kind of moisture from the atmosphere that descends to the earth is referred to as "precipitation". Included are hail, sleet, snow, rain, and glazing. When water vapor in the atmosphere condenses into droplets that are too small to stay suspended in the air, it produces rainfall, one type of precipitation. Rainfall is the total amount of precipitation that falls in a certain location over time. Rainfall is the main source of moisture, or water. Raindrops are droplets of water that fall

from clouds. Rainfall occurs when hot, saturated air that has reached the dew point rises due to frontal activity, conventional currents, or a mountain. As saturated air or water vapour rises, it cools. It forms connections with atoms of smoke, seed, salt, and tiny dust particles in the atmosphere. These particles are often referred to as condensation nuclei. Condensation happens when water droplets gather on condensation nuclei to form raindrops. As raindrops get bigger, clouds are finally formed [1].

Forecasting rainfall is an important part of meteorological research, especially in areas like Anyigba, Kogi State, Nigeria, which is not prone to flood but majorly an agrarian environment with agriculture as the main industry. Effective planning and decision-making in agriculture, water resource management, and disaster preparedness all depend on accurate rainfall predictions. The ability to forecast rainfall can mitigate the negative effects of droughts, floods, and other weather-related hazards in regions with unpredictable weather patterns like Anyigba [2]. Since crop yield and food security are significantly impacted by rainfall variability, accurate forecasting is essential for sustainable development.

By adjusting the network's weights, the backpropagation algorithm, a supervised machine learning method, reduces prediction error in artificial neural networks. The algorithm was first presented in 1986 [3]. The algorithm allows the network to learn from its mistakes by propagating errors backward from the output layer to the input layer [3]. Pattern recognition, classification, and prediction tasks are just a few of the many uses for this algorithm. Backpropagation has been used to build models that can use historical data to predict how rain will fall in the future, improving the accuracy of weather forecasts [4].

Using the backpropagation algorithm, patterns and trends in the rainfall data can be used to make predictions for the future [5]. By contrasting the actual recorded data with the forecasted rainfall values, the model's performance can also be evaluated. The model's ability to accurately predict rainfall will be demonstrated by the high correlation between the predicted and actual values. The findings in this study suggest that the backpropagation algorithm can be a useful tool for predicting rainfall in Anyigba, assisting in improved planning for agriculture and disaster response. However, factors such as the length of the training period, the complexity of the neural network, and the quality of the data can have an impact on the accuracy of the model [6].

1.3.2. Air Temperature

Temperature is the amount of heat or cold that is sensible. In most cases, the distribution of rainfall reflects the distribution of temperature. Temperature has a significant impact on rainfall because it increases evaporation, which raises atmospheric moisture levels, which when they reach a certain level take other factors into account and result in rainfall. A device called a thermometer is used to measure temperature, which refers to how hot or cold the atmosphere is at any one time. There are two ways to measure temperature: in Celsius

(C) and in Fahrenheit (F). While most countries across the world use the Celsius system, the United States employs the Fahrenheit system. The Celsius scale is almost universally used by scientists to measure temperature. A related measurement is temperature. For instance, a day at 70 °C might appear warm after several days of temperatures around 32 °C, but a day at 70 °C would seem cool after several days of temperatures around 95 °C. The Polar Regions typically experience the coldest weather, while the equator typically has the warmest weather [7].

1.3.3. Air

Air packets go in this manner. Wind arises from differences in atmospheric pressure and temperature between nearby locations. Winds often flow from areas of higher pressure that are colder to areas that are warmer and less pressured. Wind is simply air in motion. It is the outcome of solar radiation's uneven heating of the Earth's surface. Because the Earth's surface is made up of so many various kinds of land and water, the sun's energy is absorbed by it at varying rates. Water usually does not heat up or cool down as quickly as land does because of its physical properties.

Wind has a big impact on crop evapotranspiration, which affects how much water the crop uses. Therefore, studying crop growth and electricity production requires measuring wind [8].

Direction of Air

It's crucial to remember that wind direction refers to the direction the wind blows from rather than the direction it moves. A north wind blows south from the north. "Wind-rose" is a popular meteorological technique that can be used to assess the main flow directions and wind velocity ranges that naturally exist at a wind monitoring station. A wind vane is composed of a brass arm positioned on a vertical axis and secured on a ball bearing. The brass arm has two flat vanes forming a 20 ° acute angle on one side and an arrowhead on the other. The bearing house, which houses the ball bearings, has an oil hole. It is tightened. The brass sleeve, a brass covering, holds the screw in the bearing housing beneath the bearing. A brass boss secures the four direction arms to the vertical axis beneath the wind vane. The area between the direction arms is where the corner indicators are situated. The corner indications and direction arms are fastened to the brass boss using check knots. The direction arms are parallel to N, S, E, and W. The vertical axis is built by means of an iron support [8, 9].

2. Methodology

2.1. The Study Area

Anyigba, is a town in Okura district, Dekina Local Government Area of Kogi State, Nigeria. The town is located between Latitude 7 °27'-7 °31' North of the equator and between Longitude 7 °09'-7 °12' East of the Greenwich Meridian

and is 420 m above sea level in the derived Guinea Savanna vegetation zone of Nigeria, as shown in Figure 1 [10].

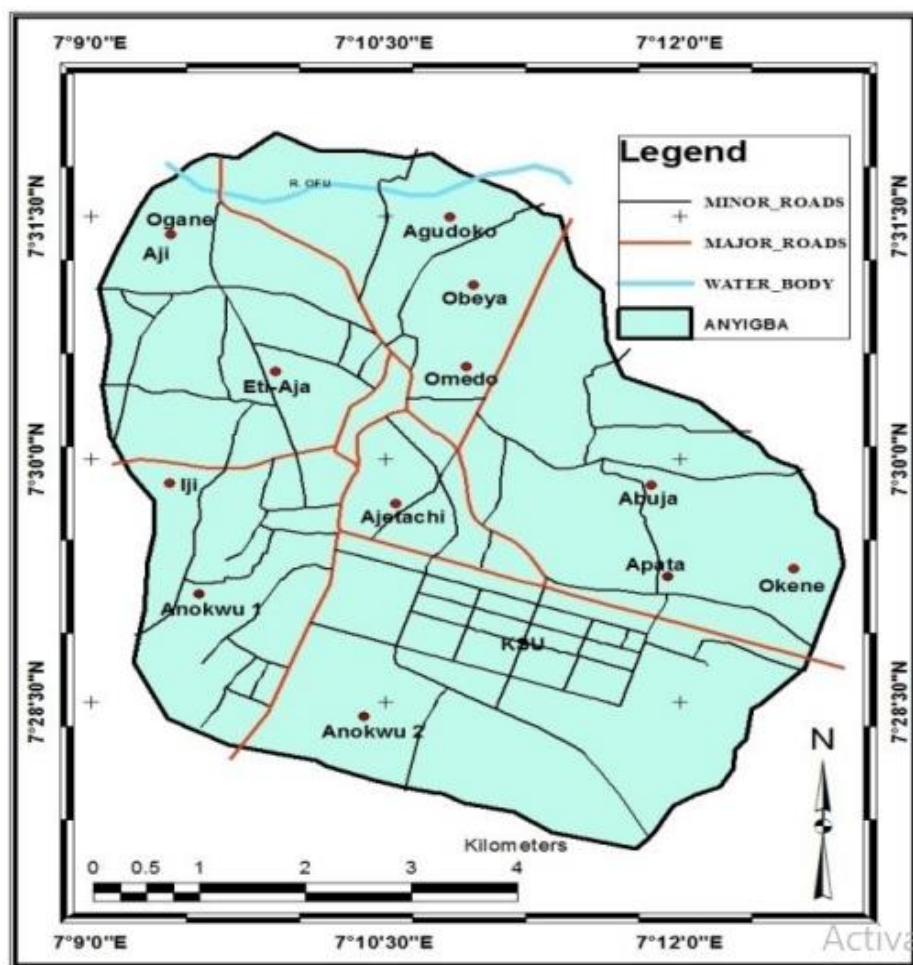


Figure 1. Map of Anyigba [11].

2.2. Data Collection / Gathering Stage



Figure 2. CAR_NASRDA Weather Station in Anyigba.

Meteorological data used in this work were obtained from an automatic weather station in Anyigba (7.29°N, 7.63°E, 186 m amsl), Central Nigeria as shown in Figure 2. The data set spanned over 6 years (2011-2016). The station is part of the Tropospheric Data Acquisition Network (TRODAN) operated and maintained by the Center for Atmospheric Research, National Space Research and Development Agency (CAR_NASRDA). The standard station is a fully configured, solar powered, automated weather station. It consists of a weatherproof enclosure which contains a highly reliable Campbell Scientific data logger, barometric pressure sensor, 12 V battery and charge controller. The weather station is equipped with a standard set of sensors which record: air temperature, relative humidity, wind speed and direction, soil temperature, moisture, rainfall, pressure at 5 min update cycle. The data logger is programmed using CR basic for the supplied sensors; when completely connected the weather station automatically starts to take measurements through each of the parameter sensors outside of the box. It is designed for long-term unmanned or unattended operation and is ideal for meteorological, weather monitoring and climate study applications as shown in Figure 2.

i. Data Transformative Stage

Raw data was transformed into a format that is more suited for model building. Data consolidation is another name for this stage. Meteorological data acquired from Tropospheric Data Acquisition Network (TRODAN) weather stations is automatically stored in excel format, which is in five (5) minute cycles as shown in the Figure 3 when collected. These five (5) minutes data was transformed into hourly data, daily and monthly.

ii. Pre-process Data

There are a number of steps involved in putting the back-propagation algorithm for forecasting rainfall into action. The first step is to collect and pre-process historical rainfall data from Anyigba, Kogi State, to get rid of any inconsistent or missing values. Cleaning, normalization and data splitting are the pre-processing tasks carried out [12]. Missing values were imputed using mean imputation. Data set was splitted into training and test data sets, 80% and 20%, respectively. The majority of the data (80%) were used for training the model after being divided into training and testing data sets. The backpropagation algorithm was used to minimize the error between the predicted and actual rainfall values after the neural network was initialized with random weights. This procedure entails adjusting the network's weights in accordance with the error gradient [13].

iii. Network Architecture

Input Layer: Contains nodes corresponding to the input features, such as Rain, Temperature, Humidity, and Wind.

Hidden Layers: One or more layers where computations are performed. Each neuron in a hidden layer applies an activation function to the weighted sum of inputs.

Output Layer: Produces the prediction, which in this case is

the forecasted amount of rainfall.

Forward Propagation

Input Data: The input features were fed into the network.

Weighted Sum:

Each neuron computes a weighted sum of its inputs.

$$z_j = \sum_i w_{ji}x_i + b_j$$

Where

w_{ji} is the weight from neuron i to neuron j ,

x_i is the input,

b_j is the bias.

iv. Activation Function

Apply an activation function $f(z_j)$ to the weighted sum to produce the neuron's output:

$$a_j = f(z_j)$$

Pass Output: The output of each layer is passed to the next layer until reaching the final output.

v. Error Calculation

Compute Error:

Calculate the difference between the predicted rainfall and the actual observed rainfall using a loss function (e.g., Mean Squared Error):

$$L = \frac{1}{2} \sum_k \left(y_k - \hat{y}_k \right)^2$$

Where

y_k is the actual value.

$\hat{y}_k$ the predicted value.

vi. Backward Propagation

Adjust the weights using gradient descent:

$$w_{ji}^{new} = w_{ji}^{old} - \eta \frac{\partial L}{\partial w_{ji}}$$

vii. Iteration

Epochs: The forward and backward propagation steps were repeated for a number of epochs until the network's performance (as measured by the loss function) stabilized.

viii. Evaluation

Model Test: Trained model was evaluated on the test set to ensure it generalizes well to new, unseen data. The test data set (20%) was used to evaluate the model, and Correlation coefficient, Mean Squared Error (MSE), Mean Absolute Error (MAE) and confusion matrix were used to measure how well it performed and the model's accuracy.

3. Results

3.1. Data Transformation

	A	B	C	D	E	F	G
1	TOAS	CPU:CR1000Standard3ayingba.cr1					
2	TIMESTAMP	AirTC_Avg					
3	TS	Deg C					
4		Avg					
5	1/1/2011 0:00		21.45				
6	1/1/2011 0:05		21.74				
7	1/1/2011 0:10		21.95				
8	1/1/2011 0:15		22.13				
9	1/1/2011 0:20		22.15				
10	1/1/2011 0:25		22.05				
11	1/1/2011 0:30		21.99				
12	1/1/2011 0:35		21.98				
13	1/1/2011 0:40		21.96				
14	1/1/2011 0:45		21.89				
15	1/1/2011 0:50		21.91				
16	1/1/2011 0:55		21.77				
17	1/1/2011 1:00		21.6				
18	1/1/2011 1:05		21.45				
19	1/1/2011 1:10		21.45				
20	1/1/2011 1:15		21.36				
21	1/1/2011 1:20		21.31				
22	1/1/2011 1:25		21.68				
23	1/1/2011 1:30		21.63				

Figure 3. Five minutes range data.

	A	B	C	D	E
1	TOAS	CPU:CR1000Standard3ayingba.cr1			
2	TIMESTAMP	AirTC_Avg			
3	TS	Deg C			
4		Avg			
5	1/1/2011 0:00		21.45		
6	1/1/2011 0:05		21.74		
7	1/1/2011 0:10		21.95		
8	1/1/2011 0:15		22.13		
9	1/1/2011 0:20		22.15		
10	1/1/2011 0:25		22.05		
11	1/1/2011 0:30		21.99		
12	1/1/2011 0:35		21.98		
13	1/1/2011 0:40		21.96		
14	1/1/2011 0:45		21.89		
15	1/1/2011 0:50		21.91		
16	1/1/2011 0:55		21.77		
17	1/1/2011 1:00		21.6		
18	1/1/2011 1:05		21.45		
19	1/1/2011 1:10		21.45		
20	1/1/2011 1:15		21.36		
21	1/1/2011 1:20		21.31		
22	1/1/2011 1:25		21.68		
23	1/1/2011 1:30		21.63		

Figure 4. Conversion from 5 minutes to hourly data.

Metrological data acquired from Tropospheric Data Acquisition Network (TRODAN) weather stations is automatically in excel format, which is in five (5) minute cycles as shown in the Figure 3 when collected.

These five (5) minutes data was transformed into hourly data, daily and monthly.

The procedures are as follows: Since, 60 minutes makes one

hour, therefore $60/5 = 12$, then take an average of 12 rows of the excel sheet to give single hourly data as shown in the Figure 4.

Again, this hourly data was converted to daily data by taking the average of 24 rows of the excel sheet to give single hourly data as illustrated in the Figure 5.

Figure 5 shows a sample of the average of daily data for all metrological parameters that was used for this research work.

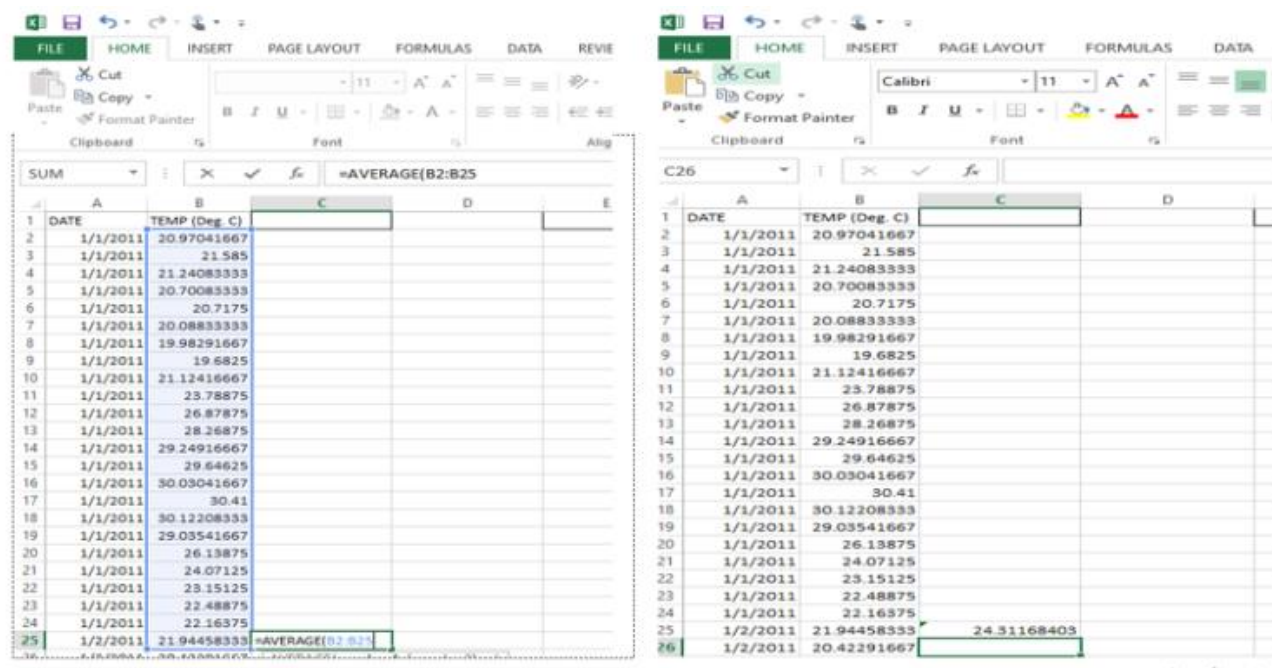


Figure 5. Conversion from hourly to daily data.

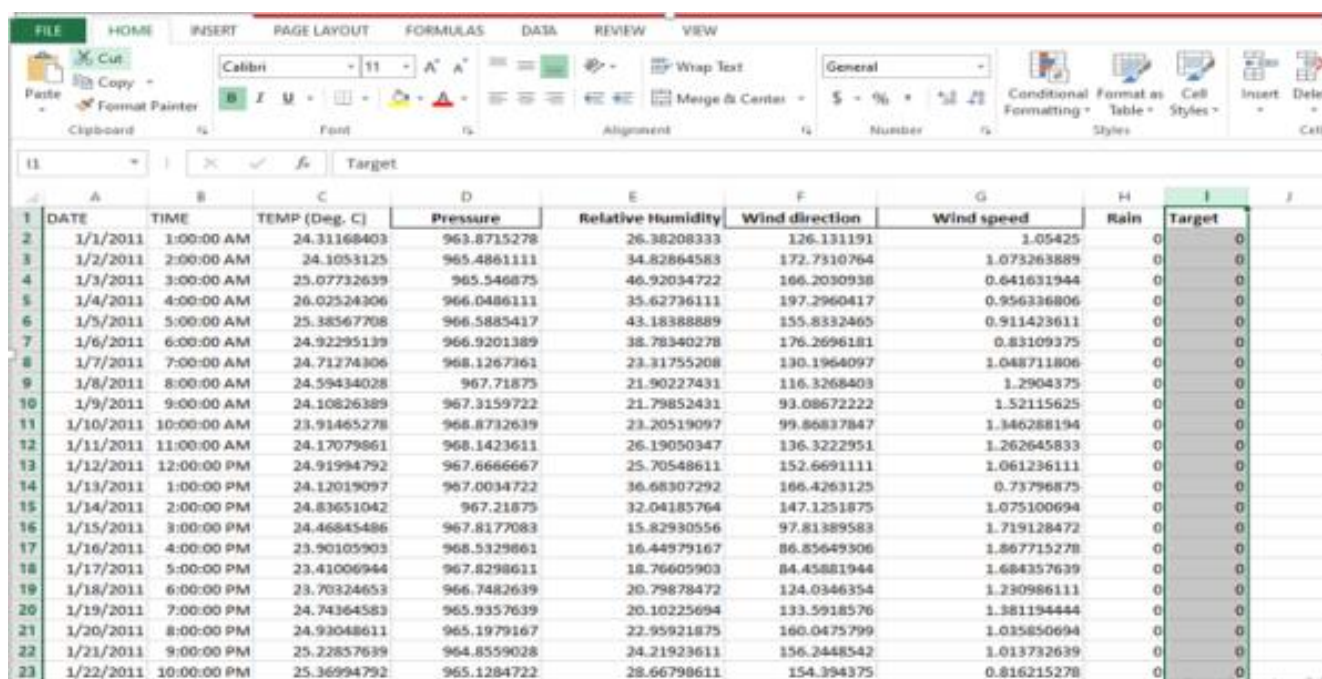


Figure 6. Average daily data for all parameters.

The system evaluates the model by using the prediction model with the processed training data, using the training dataset for rainfall prediction with actual values, and evalu-

ating the model performance through the confusion matrix as shown in [Figure 10](#).

Determining Rain or No Rain with Probabilistic Thresholds

Rain Prediction for the Next Day

Predict whether it will rain tomorrow by entering today's weather data. Fill in the details below and click the **Predict Rainfall** button.

Year	Temperature (°C)	Relative Humidity (%)
2014 - +	25.27 - +	81.44 - +
Day of Year	Pressure	Wind Direction (degrees)
279 - +	969.14 - +	186.27 - +
		Wind Speed (m/s)
		0.87 - +

The model predicts rain for the next day. ☁

Predict Rainfall

Figure 7. Screenshot of Sample Program Output Rain Prediction for the Next Day.

Rain Prediction for the Next Day

Predict whether it will rain tomorrow by entering today's weather data. Fill in the details below and click the **Predict Rainfall** button.

Year	Temperature (°C)	Relative Humidity (%)
2011 - +	26.69 - +	0.04 - +
Day of Year	Pressure	Wind Direction (degrees)
130 - +	968.16 - +	219.00 - +
		Wind Speed (m/s)
		1.18 - +

The model predicts no rain for the next day. ☀

Predict Rainfall

Figure 8. Screenshot of Sample Program Output no Rain Prediction for the Next Day.

3.2. Building and Evaluation Interface for ANN Multilayer Perceptron Classifier

The model building program module used the PIP of the Python machine learning library and the Jupyter Notebook IDE to implement the model for the training of the classification model. The system used the preprocessed dataset of students, feature set extraction, and classification model, and this preprocessed data set collected via meteorological records

was used to implement the model-building program module. The dataset has undergone 10-fold cross-validations, which mean 80% of the training set and 20% of the test set. The training set is for model building, and the test set is for model evaluation. The model building was trained with a random forest classifier, which has the Python library, for the implementation of the model for predicting rainfall with a multilayer perceptron classifier [Figure 9](#) shows snapshot of the is the Model Building and Evaluation Interface for ANN.

4 Machine Learning Algorithms

4.1 ANN Multilayer Perceptron Classifier

In [44]: `from sklearn.neural_network import MLPClassifier`

```
ANN_model = MLPClassifier()
ANN_model.fit(train_data, train_labels)
predictions = ANN_model.predict(test_data)
print(classification_report(test_labels, predictions))
print(f'The score for the ANN Multilayer Perceptron Classifier algorithm is {ANN_model.score(test_data, test_labels)}')
```

	precision	recall	f1-score	support
0	0.90	0.92	0.91	79
1	0.54	0.50	0.52	14
2	0.50	0.33	0.40	3
3	1.00	1.00	1.00	16
4	1.00	1.00	1.00	14
accuracy			0.88	126
macro avg	0.79	0.75	0.77	126
weighted avg	0.87	0.88	0.88	126

The score for the ANN Multilayer Perceptron Classifier algorithm is 0.8809523809523809

Figure 9. Model Building and Evaluation Interface for ANN.

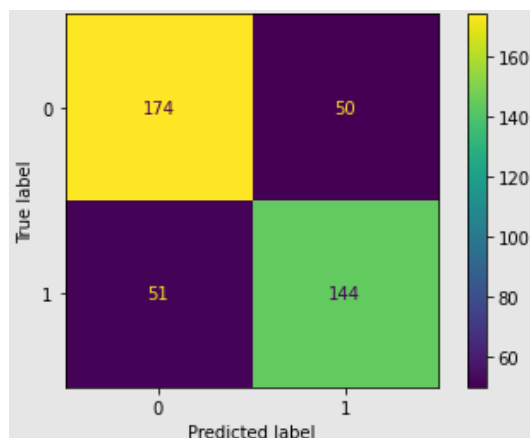


Figure 10. Confusion matrix.

Table 1. Model Performance metrics results.

Classifier	Test set Accuracy
ANN	0.88%

Table 2. Contingency Table for model Evaluation.

Algorithm	Precision	Recall	F-score	Support	Class
ANN	0.74	0.74	0.74	195	Yes
	0.77	0.78	0.78	224	No

Table 3. Summary of Confusion Matrix.

N	Predicted No rain	Predicted Rain
No rain	TN (174)	FP (50)
Rain	FN (51)	TP (144)

In [Table 3](#), the true positives (TP) are the correct classifications of the positive class A; true negatives (TN) are the correct classifications of the negative class B. The false positives (FP) represent the incorrect classification of the negative class A into the positive class A; and false negatives (FN) are

the incorrect classification of the positive class B into the negative class B. Below is an illustration of a mathematical equation for rainfall prediction:

- The predictive *accuracy* of the classifier measures the proportion of correctly classified instances = $TP+TN/TP+FP+TN+FN$
- True Positive Rate (TPR or Recall or Sensitivity)*: measures the percent of actual positive class A that are correctly classified = $TP/(TP+FN)$
- True Negative Rate (TNR or Specificity)*: measures the percent of actual negative class B that are correctly classified = $TN/(TN+FP)$
- Positive Predictive Value (PPV)*: often called Precision, it is the percentage of the class predicted to be positive that were correct = $TP/(TP+FP)$
- False Negative Rate (FNR)*: The percentage of positive examples that were incorrectly classified = $FN/(TP+FN) = 1-TPR$
- False Positive Rate (FPR)*: The percentage of negative examples that were incorrectly classified = $FP/(TN+FP) = 1-TNR$

The machine learning algorithms were considered as a result of accuracy in classification, the Kappa statistic, and the mean absolute error. Initially, the classifiers were considered for evaluating the prediction results of sample data set instances, in which the results were observed and tabulated. Based on the results, an inference about rejecting the classifiers is reached. The Kappa statistic is a measure to show the agreement of predictions with true results. The numerical implications of the Kappa statistic are very high, which shows the coincidence or absorption of attribute values in predicting the results. The Kappa statistic varies from 0 to 1.

0 = agreement equivalent to chance.

0 - 0.20 = slight agreement.

0.21 - 0.40 = fair agreement.

0.41 - 0.60 = moderate agreement.

0.61 - 0.80 = substantial agreement.

0.81 - 0.99 = near perfect agreement.

1 = perfect agreement.

Here are some other factors in classifier output:

TP Rate: rate of true positives (instances correctly classified as a given class)

FP Rate: rate of false positives (instances falsely classified as a given class)

Precision: proportion of instances that are true of a class divided by the total instances classified as that class

Recall: proportion of instances classified as a given class divided by the actual total in that class (equivalent to TP rate)

F-Measure: A combined measure for precision and recall calculated as $\frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})}$.

3.3. Prediction Evaluation

The four outcomes of the prediction analysis were used to evaluate the classifier. The evaluation standards were discussed below:

cussed below:

a. Accuracy

Accuracy is defined as the percentage of correct predictions of the rain days and no rain days. It was calculated easily by dividing the number of correct predicted rain days and no rain days by the number of total predicted days.

$$\text{accuracy} = \frac{TP+TN}{N} \quad (1)$$

b. Sensitivity

Sensitivity is defined as the percentage of predicted rain days. This means when it actually rained, how often the classifier correctly predicts rain days.

$$\text{sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

c. Specificity

Specificity is defined as the percentage of predicted no rainfall days. This implies that when actually it was no rain day, how often the classifier correctly predicts no rainfall day.

$$\text{specificity} = \frac{TN}{TN+FP} \quad (3)$$

d. Misclassification

Misclassification is defined as the percentage of wrong prediction of the rain days and no rain days. It was calculated by dividing the number of wrong predictions of rain days and no rain days by the number of total predicted days. It is also known as error rate.

$$\text{error rate} = \frac{FN+FP}{N} \quad (4)$$

3.4. Neural Network System

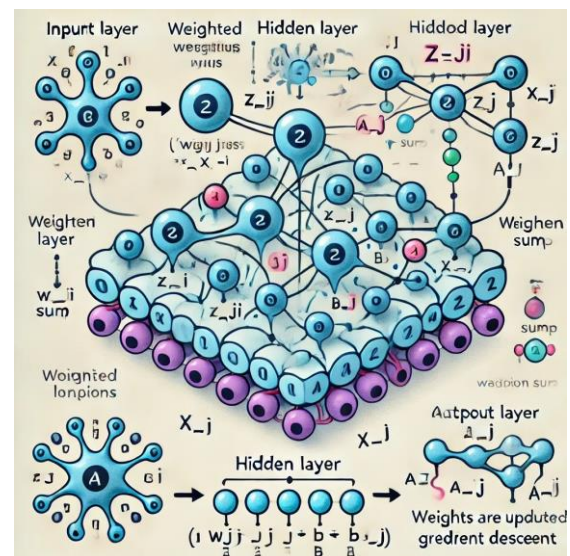


Figure 11. Model Diagram of the Neural Network System of back propagation.

The input layer, hidden layer, and output layer are all included in this visual representation, as are the forward and backward propagation processes.

The data flow diagram (DFD) representing the neural network model for rainfall forecasting is shown below in Figure 12. The DFD illustrates the flow of data between the various processes involved in the model, including input collection, weighted sum calculation, activation function application, prediction generation, error computation, and weight updating through back propagation.

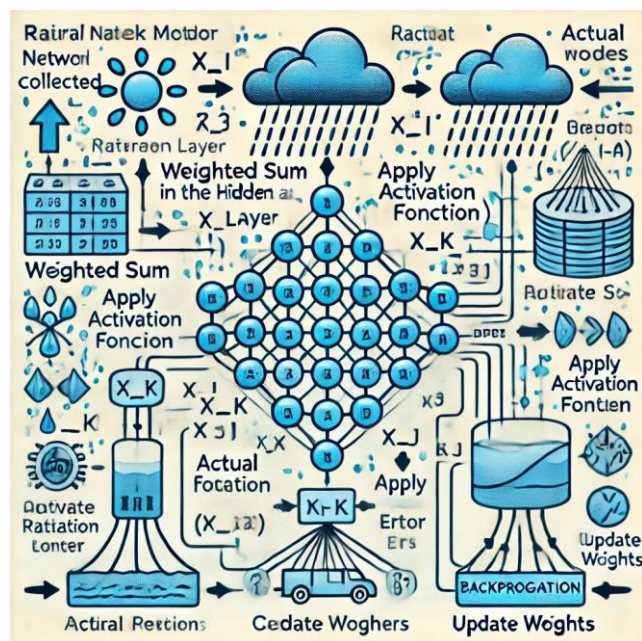


Figure 12. Data flow diagram (DFD) representing the neural network model for rainfall forecasting.

Rain fall prediction is difficult because of extreme climate variations. Machine learning predicted rainfall by extracting hidden pattern from historical weather data [14, 15]. Rainfall prediction based on meteorological data is complex but beneficial. The results shows that the Back Propagation Artificial Neural Network (BP-ANN) using Levenberg-Narquardt algorithm is good for rainfall prediction. BP-ANN could accurately predict rainfall under different meteorological features with high precision, recall and F-score.

4. Key Findings

Increased Precision: When compared to more conventional approaches, the Back propagation Algorithm has demonstrated a significant improvement in forecasting precision. This is because it can use historical rainfall data to model complicated, non-linear relationships. The algorithm effectively learns from previous data and improves its predictions by iteratively adjusting weights based on prediction errors. Forecasts are more reliable as a result of this increased preci-

sion, which reduces the margin of error and enables better preparation for varying rainfall conditions.

Effectively Using Historical Data to Learn: The Back propagation Algorithm's capacity to process and learn from massive datasets is one of its strengths. This indicates that the algorithm is capable of analysing numerous historical records to identify patterns and trends in the context of rainfall forecasting. Thus, it can cause forecasts that to mirror the basic elements of precipitation fluctuation in Anyigba, which may be disregarded by more straightforward models.

Enhanced Capabilities for Forecasting: For the purpose of capturing the intricate patterns associated with rainfall, the algorithm's capacity to deal with non-linearity is essential. Numerous factors, including atmospheric conditions, geographical features, and seasonal variations, influence rainfall. The advanced learning mechanisms of the Back propagation Algorithm enable it to incorporate these various factors into its forecasts, resulting in predictions that are more precise and relevant to the context.

Practical Consequences: Accurate rainfall forecasts are extremely useful for stakeholders in Anyigba, such as farmers, water resource managers, and meteorologists. Better planning and decision-making are the direct results of enhanced forecasting capabilities. Water resource managers, on the other hand, are better able to anticipate and manage the availability of water because they can use reliable forecasts to optimize planting schedules and irrigation strategies.

Potential for the Future and Suggestions: The Back propagation Algorithm's application yields promising results, but there is room for improvement. In order to improve forecasting accuracy, future research might concentrate on improving the algorithm by incorporating additional data sources like real-time weather observations or satellite data. Advanced neural network variants and the algorithm's integration with other predictive models may also contribute to more robust and reliable predictions.

Benefits to the Community: Accurate rainfall forecasting has benefits that go beyond the individual stakeholders. Communities can better prepare for and respond to extreme weather events like floods and droughts thanks to improved predictions. Additionally, the algorithm aids in the development and resilience of the community as a whole by fostering environmentally friendly farming methods and effective water resource management.

Finally, the use of the Back propagation Algorithm to forecast rainfall in Anyigba represents a promising step forward in meteorological prediction. It is a useful tool for local forecasting because it can handle complicated patterns, learn from previous data, and improve accuracy. The community and stakeholders in the region stand to gain significantly from the continued development and integration of this technology, which has the potential to further enhance forecasting capabilities.

5. Conclusion

Rainfall prediction model based on the Back propagation Algorithm was effective and suitable for predicting rainfall using different meteorological parameters in Anyigba, Nigeria's Kogi State. This strategy provides a number of significant advantages as well as insights into the foreseeable future of rainfall forecasting in the region by making use of the capabilities of artificial neural networks.

Abbreviations

ANN	Artificial Neural Network
TRODAN	Tropospheric Data Acquisition Network
CAR-NASRDA	Centre for Atmospheric Research-National Space Research and Development Agency
ReLU	Rectified Linear Unit
Tanh	Hyperbolic Tangent Function
C	Celsius
F	Fahrenheit
MSE	Mean Square Error
MAE	Mean Absolute Error
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
DFD	Data Flow Diagram
BP-ANN	Back Propagation-Artificial Neural Network

Conflicts of Interest

The authors declare no conflicts of interest.

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