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Application of Binary Classification Method of ANN in Rainfall Prediction of Minna, Niger State, Nigeria: The Multiple Thresholds Approach

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Abstract

In a previous work, an improved rainfall prediction model for Minna metropolis using Artificial Neural Network (ANN) was arrived at by the application of the default (single) threshold of 0.5 in the binary classification method of ANN. In this present work, attempt was made to further improve the work using the multiple (variable) thresholds method. The threshold was varied from 0.1 to 1.0 in steps of 0.1. Sensitivity rating was chosen as the performance metric for rain prediction. The best result was obtained using a threshold of 0.4 which has a 72.5% sensitivity rating against that of 63% of the default threshold as previously obtained, implying that with a 0.4 threshold, the network predicts (classifies) rainfall of Minna much better. Other metrics obtained are specificity and accuracy values of 85% and 73% respectively. This improved result has 60 rainfall days predicted out of 32 rainfall days available in the data set which is an indication of more rainfall and probable flooding. The Area Under the Receiver Operating Characteristics (ROC) curve value of 0.57% obtained correspond to the interval 0.5 > 0.59. This places the rainfall classification (prediction) carried out in this work in the "Good" category. More rainfall days predicted serves as an alarm to residents and relevant stakeholders to

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embark on mitigation in order to minimise the negative impact of heavy rainfall. It was recommended that for more accurate rainfall prediction, robust data encompassing more atmospheric parameters be used for network training.

Keywords: ANN, Multiple thresholds, Rainfall prediction, Terminal velocity, Binary classification

INTRODUCTION

The variability of rainfall is a crucial phenomenon in today's world. Making its prediction a topic of interest world over. Rainfall prediction is a challenging, dynamic and complicated process because it involves many factors of the atmosphere (Geetha and Nasira, 2014). Its forecast plays an important role in water resource management and therefore, it is of particular relevance to the agricultural sector, which contributes significantly to the economy of any nation (Abdulkadir, 2017). Therefore, it is important to predict how rainfall will vary in the future to minimise the negative impact of heavy rainfall and to increase the society resilience to hazards such as floods and erosions. To achieve this, researchers are developing and applying improved weather prediction models capable of accurately forecasting rainfall. Data mining techniques such as Artificial Neural Network (ANN) can effectively predict rainfall by extracting the hidden patterns among available features of past weather data (Aftab *et al.,* 2018). Weather data consists of various atmospheric features such as wind, precipitation, humidity, pressure, and temperature among others. These parameters are related to one another in one form or the other and as such can serve as inputs for the prediction of a parameter of interest using data mining technique. In classification prediction, the classifiers are used to find the class to which an unknown data belongs based on the information available from a set of data whose class is already known. Classification refers to a predictive modelling problem where a class label is predicted for a given sample of input data (Brownlee, 2020).

Previous studies have shown that among the entire climate elements, rainfall is the most variable element both temporally and spatially which can have significant impact on economic activities (Kowal and Kassam, 1978). Heavy rainfall can lead to numerous hazards, for example: flooding, including risk to human life, loss of crops and livestock and landslides which can threaten human life (Abdulrahim, Ifabiyi and Ismaila, 2013). Niger State, Nigeria has had her fair share of devastations resulting from heavy rainfall. The associated losses include those of flooding, landslides and erosion. Others are threat to human life, damages to buildings Having and infrastructure, disruptions to transportation and communications and cause losses to farm crops of the affected areas to mention just a few (NSEMA, 2018 & BBC, 2018). Due to this challenge, efforts to predict rainfall days were embarked upon by researchers in order to serve as early warnings. Having concluded in one of such previous works (Ibrahim *et al.,* 2022), that the best rainfall prediction with sensitivity of 63% and accuracy of 69% was obtained using a default threshold of 0.5. The values of the metrics obtained though good but requires improvement. It is therefore necessary to investigate using the multiple threshold method if there exist other thresholds with better performance indices other than 0.5. Therefore, the aim of this research is to predict the rainfall days of Minna metropolis using the multiple threshold classification method of ANN. The aim shall be achieved through the following objectives, which are to:

i. Predict Rainfall days using thresholds between 0.1 and 1.0 in the binary classification method of ANN.
ii. Determine the best performing threshold.
iii. Evaluate the performance of the rainfall classification using the Receiver Operating Characteristics (ROC) curve.

The multiple threshold method of ANN algorithm which have become an attractive inductive approach in rainfall prediction owing to the non-linearity, flexibility and data learning is yet to be introduced into the rainfall prediction of Minna

Study Area

The area of study is Minna, Niger State, Nigeria. The area lies between Latitudes 09°40′ 7.63″ N and 09° 39′ 59.72″ N and Longitudes 06° 30′ 0.32″ E and 06° 36′ 34.05″ E. Based on the Koppen Classification Scheme, Minna is characterised by two climates and two seasons: the tropical continental wet and dry climate and the two distinct seasons are; the wet and dry season. The wet season begins around March and runs through October and dry season which begins from October to March. The city has a mean annual rainfall of 1334 mm with September recording the highest rain of close to 330 mm on the average, while the least amount of rainfall occurs in December and January which can be as low as 1mm (GEO FUTMinna, 2015). Figure 1 (a) and (b) is the map of the study area.

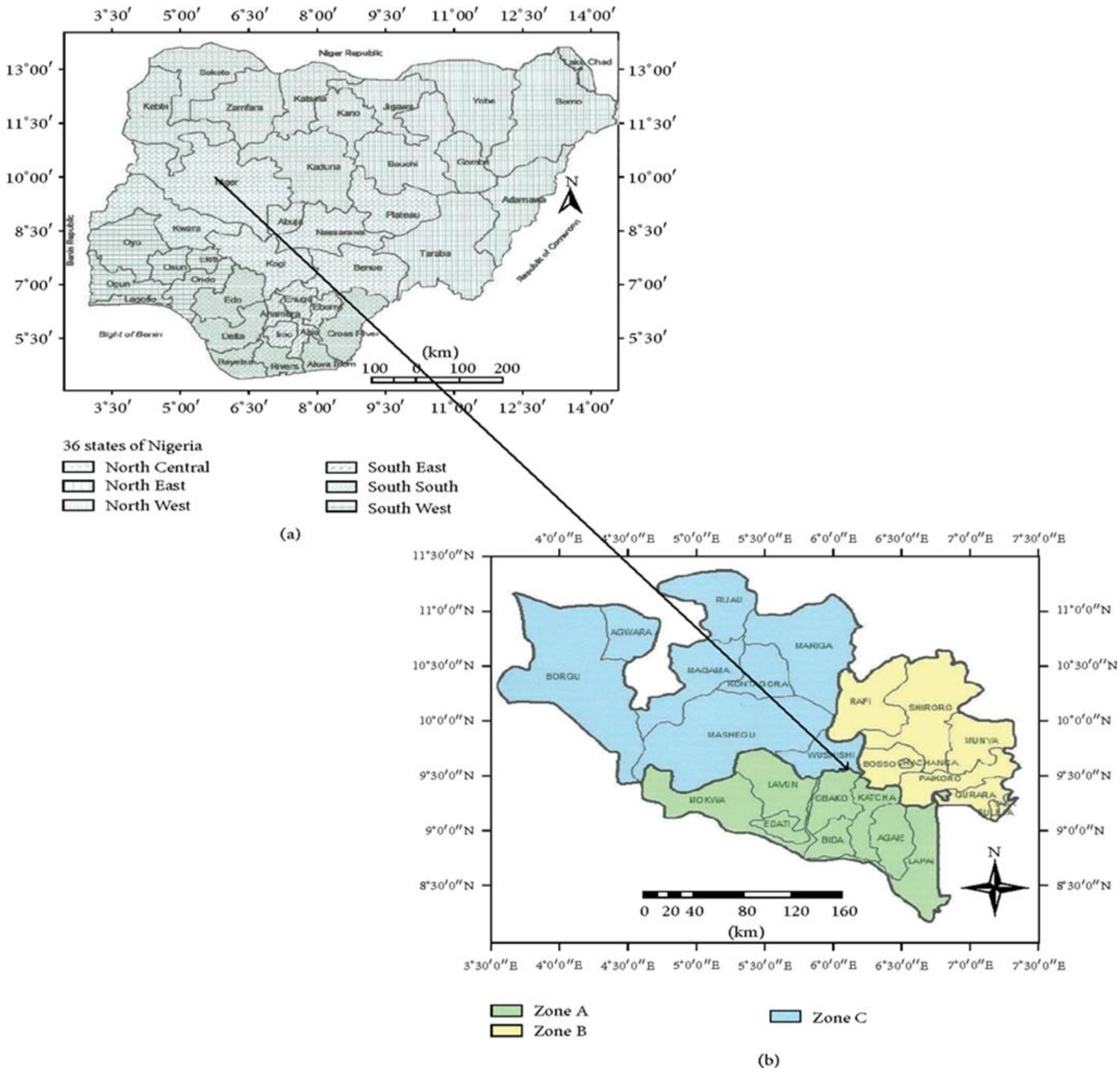

Figure 1. (a) Map of Nigeria and (b) Niger State showing the study area (GEO FUTMinna, 2015)

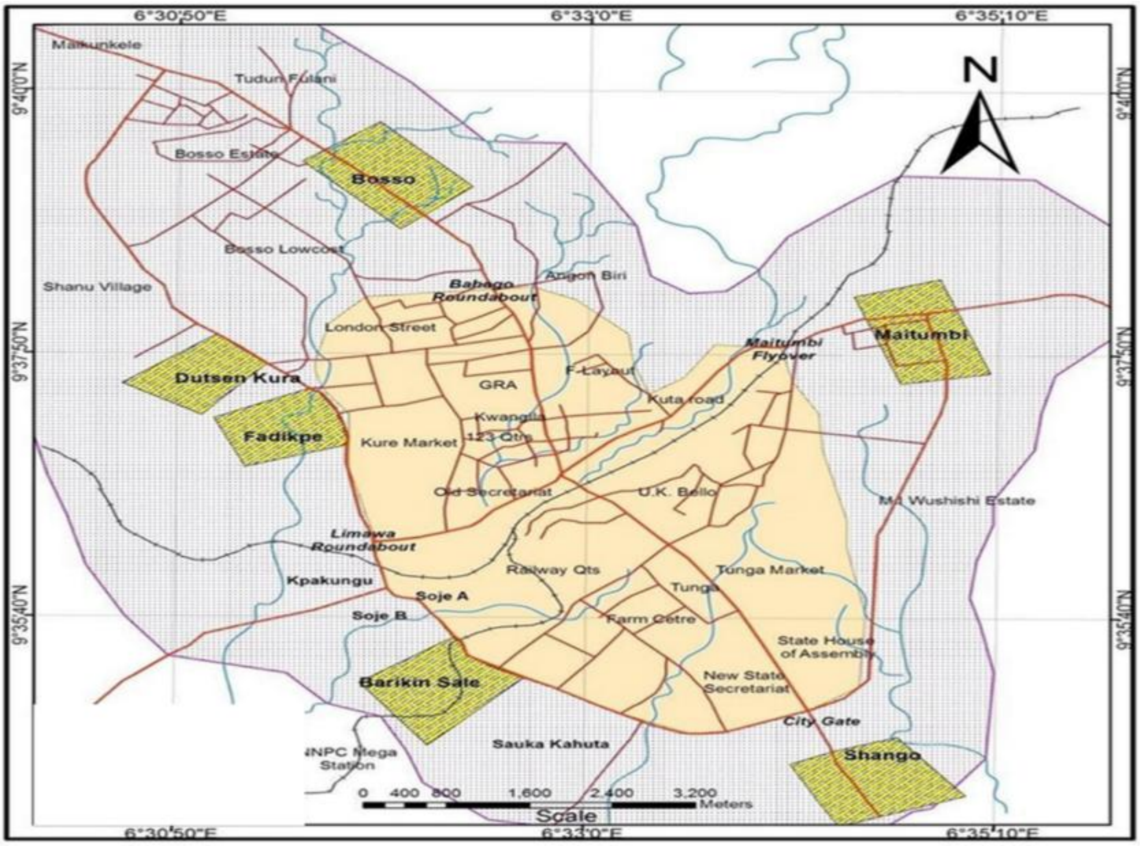

Figure 2. Map of Minna showing areas affected with flooding (GEO FUTMinna, 2015)

The study area shows increase in decade anomaly of rainfall (Akinsanola and Ogunjobi, 2014; Akinyemi *et al*., 2021 and Daramola *et al*., 2017). According to the Nigerian Meteorological Agency (NIMET, 2018), there are more wet years in the South and middle (North-central) Belt of Nigeria which are prone to the occurrence of flooding. One of such occurrences came to pass on the 25th to 26th August, 2014, when heavy downpour in most parts of Minna, the Niger State capital, caused serious damages. It was gathered that houses, fences, mini bridges were washed away by the heavy rain. Some of the affected areas were Barikin Sale and Farm centre in Tunga. Others are Niteco, Nykangbe and Kpankungu areas (Babalola, 2014). These areas are further shown in Figure 2.

Other areas such as Fadikpe, Barikin-Sale and Shango that were previously affected by heavy rains are still prone to flooding in Minna metropolis. Hence, this study is necessary based on the flooding history of Minna. A prediction of more rainfall days will serve as an alarm to individual, communities and relevant government agencies.

1.2 Theoretical background: Terminal Velocity of Raindrop

In a previous work (Ibrahim *et al*., 2022), the escape velocity V_e, of water molecules from the surface of water bodies to form rain was computed as;

$$V_e = \sqrt{\frac{9KT}{4\pi\rho r^3}} \qquad (1)$$

where;
K = Boltzmann constant
T = temperature of the water molecules
ρ = density of water and
r = radius of raindrop

Similarly, the terminal velocity of raindrop can be computed. It is defined as the constant speed that a freely falling raindrop eventually reaches when the resistance of the medium through which it is falling prevents further acceleration (Ibrahim, 2020). At cloud level, the condensed water molecules will fall down back to the earth through gravity, but it rather remains suspended through weightlessness and experiences free fall in the atmosphere. The process continues and gradually the mass of the cloud grows heavier and heavier and with time, the weightlessness is overcome by the rising weight of condensing water molecules; eventuating in the collapse of the clouds so formed. Soon, after the collapse of weightlessness; the condensed clouds begin to fall under the influence of gravity as rain and the whole Potential Energy (P.E) of the molecules once more are transformed to Kinetic Energy (K.E) with some energy lost in the form of heat due to air friction. The drag force experienced by the condensed water molecules at point of saturation, is equal to its weight. Equation (2) shows the saturation formula (Amajama, 2016).

$$mg = 6\pi\eta r V_T \tag{2}$$

where,
m = mass of suspended water (ice form)
g = acceleration due to gravity
n = coefficient of viscosity of air
r = radius of raindrop
V_T = terminal velocity of raindrop
solving for V_T;

$$V_T = \frac{mg}{6\pi\eta r} \tag{3}$$

The mass of water molecule is given as (Usman, 2021);

$$m = \frac{4}{3}\rho\pi r^3 \tag{4}$$

Substituting (4) in (3) yields;

$$V_T = \frac{2\rho g r^2}{9\eta} \tag{5}$$

Equation (5) is the terminal velocity with which the rain drops back to the earth surface. The size of the raindrop affects the terminal velocity; small objects falls slowly and large objects fall quickly. When the cloud droplets become large enough, under the influence of gravity, they fall as drizzle or rain (Awodi, 2021).

MATERIALS AND METHODS

Data Acquisition, Data preparation and Data Splitting

Ten years meteorological data of Rainfall (mm), Relative Humidity (mmHg), Minimum Temperature (°C) and Maximum Temperature (°C) for Minna metropolis was acquired from the Geography Department's weather station, Federal University of Technology Minna for the period spanning from 2015 to 2024. The data were collected on daily and annual total basis. A total of 1242 dataset were used for this work.

To reduce errors, the missing values were replaced with the fields mean and for large gap, the fields were omitted. Min-max normalization was used to fill missing values. The splitting proportions are usually decided according to the size and type of the data available (Kumar, 2020). In this work, splitting ratio of 70:15:15 was used to split the dataset, that is, the dataset was split into three parts: 70% for train data, 15% for testing data and 15% for validation data. The training set is the largest with 870 data set because a large data sample is required to fit the network so it can observe and learn from the data and optimise its parameters. 186 data sets were used for the testing and validation respectively.

Rainfall Prediction using variable thresholds

Confusion matrix was used for the prediction analysis while binary classification prediction method of ANN was used to predict the rainfall days (1) and no rainfall days (0). In this work, the input data are those of relative humidity, minimum temperature and maximum temperature while the class label to be predicted is Rainfall. The class label is often string values, for example "rain", "no rain", and must be mapped to numeric values for example, "rain" = 1, 'no rain" = 0, before being provided to an algorithm for modelling. This is often referred to as label training, where a unique integer is assigned to each class label. In binary classification prediction, there are four major prediction (Confusion Matrix) outcomes that could occur as shown in Table 1.

Table 1. Confusion Matrix (CM) Outcomes in Binary Classification Prediction (Larose, 2005).

Actual rain day	Predicted rain day	CM Outcome
0	1	False Positive (FP)
0	0	True Negative (TN)
1	0	False Negative (FN)
1	1	True Positive (TP)

The four outcomes of the prediction analysis were used to evaluate the classifier for each threshold. The evaluation standards as applicable to this research were discussed below (Usman, 2021):

Accuracy: Accuracy is defined as the percentage of correct predictions of the rain days and dry (no-rain) days. It can be calculated easily by dividing the number of correctly predicted rain days and no-rain days by the number of total predicted days.

$$Accuracy = \frac{TP+TN}{N} \tag{6}$$

Sensitivity: Sensitivity is defined as the percentage of predicted rain days. This mean that when it actually rains, how often goes the classifier correctly predicts rain days. This parameter is more relevant to this work since rainfall prediction is the main objective.

$$Sensitivity = \frac{TP}{TP+FN} \tag{7}$$

Specificity: Specificity is defined as the percentage of predicted dry (no-rainfall) days. This implies that when it's actually a no-rain day, how often does the classifier correctly predicts dry (no-rainfall) day.

$$Specificity = \frac{TN}{TN+FN} \tag{8}$$

Misclassification: Misclassification is defined as the percentage of wrong prediction of the rain days and dry (no-rain) days. It can be 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.

$$Error\ rate = \frac{FN+FP}{N} \tag{9}$$

Determination of the Best Performing Threshold

Although, in rainfall prediction, sensitivity value is the best indicator since it provides the probability of having rainfall. However, it will not be considered in isolation as a high sensitivity value can be associated with low accuracy or specificity values and vice-versa. The three parameters will therefore be analysed simultaneously in order to determine the best performing threshold.

Prediction Performance Evaluation
To evaluate the performance of the rainfall prediction carried out, the Receiver Operating Characteristics (ROC) curve which is a plot that shows the diagnostic capacity of a binary classification prediction as its threshold is varied. The area under the curve is computed and the rule applied. The rule is, the higher the Area Under the Curve (AUC) on a scale of 0 – 1, the better the classifier, that is, Area under the curve close to 1 indicates a better performance index. It helps to find the best classifier and how well the chosen threshold will work in the future to make good and accurate rainfall predictions.

RESULTS AND DISCUSSION

Rainfall Prediction using variable thresholds
As typical with multiple threshold approach, various thresholds ranging from 0.1 to 1.0 (in steps of 0.1) were selected from the software and applied in the classification of which day will have rainfall and day with no rainfall. This is to find out if there exist a particular threshold within the interval that will outperform the others. The number of rainfall days and no rainfall days were predicted using the Binary classification prediction method of ANN. The network was trained using 70% (870) of the entire 1242 data set for a particular threshold. After adequate training of the network, it was followed by testing using 15% (186) of the entire data. This was done for all the threshold and a summary of the result after several iterations are presented in Table 2. It shows the four Comfusion Matrix outcomes and the four outcomes of the prediction analysis as the Threshold Value (TV) was varied from 0.1 to 1.0.

Table 2: Rainfall Prediction Result using Multiple Threshold

TV	P	N	TP	TN	FP	FN	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)	FPR (%)
0.1	169	17	32	17	137	0	0.26	1.0000	0.3469	0.65306
0.2	110	76	30	74	80	2	0.56	0.9375	0.7115	0.28846
0.3	87	99	27	94	60	5	0.65	0.8738	0.7769	0.22314
0.4	60	126	20	114	40	12	0.73	0.7250	0.8507	0.14925
0.5	30	156	15	139	15	17	0.83	0.4688	0.9026	0.09740
0.6	11	175	2	145	9	30	0.79	0.0625	0.9864	0.01361
0.7	6	180	1	149	5	31	0.81	0.0313	0.9933	0.00667
0.8	4	182	2	152	2	30	0.83	0.0625	0.9870	0.01299
0.9	0	186	0	154	0	32	0.83	-	1.0000	-
1	0	186	0	154	0	32	0.83	-	1.0000	-

Determination of the Best Performing Threshold
For each threshold, the three parameters of accuracy, sensitivity and specificity of Table 2 were analysed simultaneously in order to determine the best performing threshold. As stated earlier, in rainfall prediction, sensitivity value is the best indicator since it provides the probability of having rainfall. Inspecting the sensitivity column and juxtaposing with the other two parameters. It can be seen that a higher sensitivity value of 93% and 87% of the 0.2 and 0.3 thresholds have corresponding accuracy values of 56% and 65% respectively. These

accuracy values are lesser than the accuracy of 73% associated with 72.5% sensitivity value of the 0.4 threshold. With a corresponding specificity value of 85%, it is clear that at 0.4, the three parameters have values greater than 70%. Only this threshold has these characteristics. Therefore, 0.4 is the best performing threshold for rainfall prediction in Minna metropolis.

3.3 Performance Evaluation of Rainfall Prediction Result

The Receiver Operating Characteristics (ROC) curve is a graph of sensitivity against False Positive Rate (FPR). The Area under the Receiver Operating Characteristics (ROC) curve shows the effectiveness of the rainfall prediction carried out in this work. It places the rainfall prediction under three categories. These categories are excellent, good or not good, using the criteria shown in Table 4. The False Positive Rate is evaluated by subtracting each specificity values from the number one, that is by using the relation (1 - specificity) as presented in the last column of Table 2. The ROC curve was plotted using values obtained in Table 2 and shown in Figure 3.

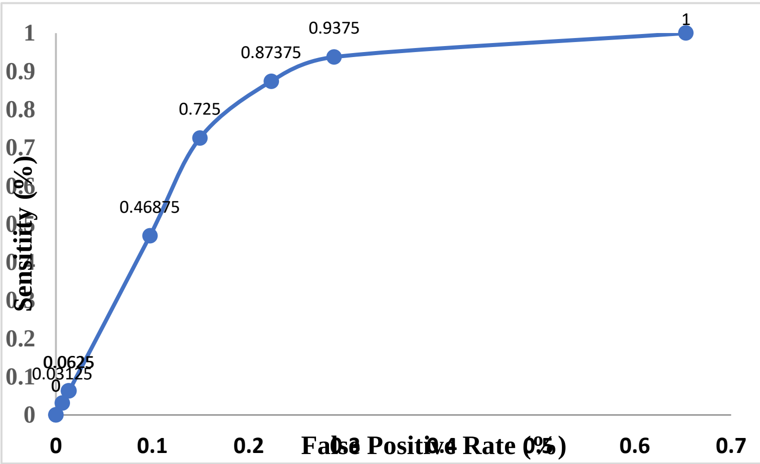

Figure 3. ROC Curve

The Area Under the ROC Curve having value close to 1 indicates a very good classifier. The Area Under the Curve (AUC) is obtained from the relation given in equation (10).

$$AUC = [(A1-A2) * (B1)] \tag{10}$$

where, A represent the false positive rate column (last column of Table 2) and B represent the sensitivity column. Equation (10) was computed from Table 2 and presented in Table 3.

Table 3: Area Under the ROC Curve

S/N	FPR (%)	SENSITIVITY (%)	AUC (%)
1	0.653061	1	0.3646
2	0.288462	0.9375	0.061238
3	0.22314	0.87375	0.064559
4	0.149254	0.725	0.037592
5	0.097403	0.46875	0.03928
6	0.013605	0.0625	0.000434
7	0.006667	0.03125	-0.0002
8	0.012987	0.0625	0.000812
9	0	0	0
10	0	0	0
		AUC	**0.568317**

The summation of the last column gives the AUC value of 0.568317 (approximately 0.57). As previously stated, the AUC categorizes the prediction into three classes: excellent, good or not good using the conditions of the classifier performance rating shown in Table 4.

Table 4: Classifier Performance Rating

AREA UNDER CURVE	CLASSIFIER
0.6 > 1.0	Excellent (very good)
0.50 > 0.59	Good
0 < 0.49	Not good (weak)

The condition for the classification is based on the fact that the area under the curve (AUC) having value close to 1 indicates a very good classifier. It can be observed that the AUC value of 0.57% obtained correspond to the interval 0.5 > 0.59. Therefore, the rainfall classification (prediction) carried out in this work can be said to be in the "Good" category.

The multiple threshold classification method of ANN has pointed to 0.4 as a more suitable threshold for the area. This threshold has test result values for sensitivity as 72.5%, accuracy as 73% and specificity as 85% against those of 63%, 69% and 84% respectively obtained using the default or single threshold of 0.5 (Ibrahim *et al.,* 2022). The 72.5% sensitivity rating of 0.4 threshold against that of 63 % of the single threshold is a prove that with 0.4 threshold selected, the network predicts (classifies) rainfall of Minna much better. The AUC value of 0.57% obtained correspond to the "Good" category (Larose, 2005).

CONCLUSION

Rainfall occurrence in Minna metropolis has been predicted using the multiple threshold classification method of Artificial Neural Network and employing atmospheric parameters of relative humidity, minimum temperature and maximum temperature as input into the network. The threshold of 0.4 was found more suitable for the area. As shown in Table 2 for this threshold, 60 rainfall days were predicted out of 32 rainfall days available in the data set. An extra 28 days of rainfall have been predicted which is an indication of more rainfall days and probable flooding. To improve the result to the excellent category, it is recommended that: the atmospheric inputs be expanded to incorporate other relevant atmospheric parameters such as wind speed, wind direction, dew point, average temperature among others for a more encompassing rainfall prediction. Secondly, for higher accuracy of rainfall prediction in Minna, meteorological data for at least thirty years should be acquired. The performances of Artificial Neural Network improve when more and relevant input data are employed for initial training. This work serves as an alarm to relevant stakeholders to embark on mitigation in order to minimize the negative impact of heavy rainfall. This research is very important particularly to Minna residents, the Niger State Government Authorities and the research community as it will enhance the safety of lives and properties from rainfall hazards due to better awareness, preparedness and planning by farmers, aviation sector, construction firms and disaster managers.

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REFERENCES

Abdulkadir, T. S., Salami, A. W., Aremu, A. S. (2017). Assessment of Neural Network Performance in Modeling Rainfall Amount. *Journal of Research in Forestry Wildlife and Environment.* 9(1), 12-22.

Abdulrahim, M., Ifabiyi, I. and Ismaila, A. (2013). Time series analyses of mean monthly rainfall for drought Management in Sokoto, Nigeria. *Ethiopian Journal of Environmental Studies and Management.* 6(5) 461-470. DOI: 10.4314/EJESM.V615.3

Aftab, S. and Ahmad, M. (2018). Rainfall Prediction using Data Mining Techniques: A Systematic Literature Review (IJACSA) *International Journal of Advanced Computer Science and Applications,* 9(5), 143-150. DOI: 10.14569/IJACSA.2018.090518

Akinsanola A. A & Ogunjobi K. O (2014). Analysis of Rainfall and Temperature Variability over Nigeria. *Global Journal of Human-Social Science: B Geography, Geo-Sciences, Environmental Disaster Management. ISSN: 2249-460x*

Akinyemi, O., Faweye, O., Jide-Ashaolu, E. (2021). Trend and Variability Analysis of Rainfall and Temperature Trends in Ilorin Metropolis, Kwara State, Nigeria. *Journal of Human Ecology*. 74(1-3), 1-7. DOI: 10.31901/24566608.2021/74.1-3.3307

Amajama. R. (2016). Physics of Rainfall: Review Article. *Journal of Scientific and Engineering Research.* 3(1): 51-54. ISSN: 2394-2630.

Awodi, E. (2021). Development of a rainfall prediction model for Minna metropolis. M.Tech Thesis, Department of Physics, Federal University of Tecbhnology Minna, Nigeria.

B. B. C (2018). British Broadcasting Corporation. Africa News Why does Nigeria keep Flooding? Retrieved from: https://www.bbc.com/news/world-africa-45599262

Babalola, P. (2014). Heavy Rain Sacks Minna, Residents Stay Indoors. Retreived from: https://theeagleonline.com.ng/heavy-rain-sacks-minna-residents-stay-indoors/

Brownlee, J. (2020). Four Types of Classification tasks in Machine learning. Retrieved from: www.machinelearningmastery.com

Bukka, U. A., Muhammad, B., & Yahaya, T. I. (2017). Effect of flooding on livelihood of Communities in Muwo District, Mokwa Local Government Area, Niger State, Nigeria. *International Journal of Scientific & Engineering Research Volume 8, 1615 ISSN 2229-5518*

Daramola1, M. T., Eresanya, E. O., and Erhabor, S, C. (2017). Analysis of Rainfall and Temperature over Climatic Zones in Nigeria. *Journal of Geography, Environment and Earth Science International ISSN: 2454-7352*

Geo FUTMinna (2021). Map of Minna, Geography Department. Federal University of Technology, Minna, Nigeria.

Geetha, A and Nasira, G. M. (2014). Artificial Neural Networks' Application in Weather Forecasting. *International Journal of Computational Intelligence and Informatics,* 4(3), 177-182.

Ibrahim, A.G., Oyedum, O.D., Abisoye, O, Usman, M. and Ughanze, I. J. (2022). An Improved Rainfall Prediction Model for Predicting the Number of Rainfall Days for Minna, Nigeria Using Artificial Neural Network. *Nigerian Journal of Physics.* Volume 31(2):151 – 159.

Ibrahim, A. G. (2020) Lecture note on "Physics of the Lower Atmosphere", Department of Physics, Federal University of Technology, Minna, Nigeria.

Ifabiyi, I. and Ashaolu, P. (2013). Analysis of Impact of Climate Variability on Public Water Supply in Ilorin, Nigeria. J*ournal of Meteorology and Climate Science.*11(1): 18 – 26.

Julie M. D., and Kannan B., (2010). Significance of Classification Techniques in Prediction of Learning Disabilities. Cochin- 683 107, India.

Kumar, S. (2020). Data Splitting Technique to fit any Machine Learning Model. Received from: www.towardsdatascience.com

Kowal, J. M. and Kassam, A. H. (1978). Agricultural Ecology of the Savanna: A Study of West Africa. Clarendon Press, Oxford. pp 102.

Larose, D. T. (2005). Discovering Knowledge in Data: An Introduction to Data Mining. Copyright C John Wiley & Sons, Inc. pp 60, 95.

Nayak, D. R., (2013). "A Survey on Rainfall Prediction using Artificial Neural Network", *International Journal of Computer Applications (0975 – 8887), Volume 72, No.16, pp. 32 – 40.*

NIMET (2018). An Overview of the Seasonal Rainfall Prediction. Nigerian Meteorological Agency (NIMET). Receieved from: http://www.nimet.gov.ng

NSEMA (2018). Niger State Emergency Management Agency. (https://www.vanguardngr.com/2018/07/over-60-houses-affected-by-flood-in-niger-nsema). Retrieved from www. https://www.vanguardngr.com

Oyewole, J.A, Thompson, A. M, Akinpelu, J.A & Jegede O. (2014). Variation of Rainfall and Humidity in Nigeria. *Journal of Environment and Earth Science ISSN 2224-3216 (Paper) ISSN 2225-0948*

Theerthagiri, P., Jeena, J., Usha, A, R., & Vamsidhar., (2020). Prediction of COVID-19 Possibilities using KNN Classification Algorithm. Received from: www. Researchsquare.com/articl/ rs-70985/v2 doi:10.21203/rs.3.rs-70985/v2

Tyagi, N. and Kumar, A. (2017). "Comparative Analysis of Backpropagation and RBF Neural Network on Monthly Rainfall Prediction, International. Conference Invention Computer Technology. ICICT vol. 1

Usman, M. N. (2021). Rainfall Prediction for Minna Metropolis using Artificial Neural Network. MTech Thesis submitted to the Department of Physics, Federal University of Technology, Minna. Nigeria.