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FLOOD HAZARD ESTIMATION AND EVALUATION IN LAGOS STATE USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Floods threaten human life, infrastructure, and economic stability in Lagos State, Nigeria. Accurate flood hazard estimation is crucial for effective flood risk management and mitigation. This study employs machine learning techniques to estimate flood hazards in Lagos State. A dataset comprising historical flood events, meteorological factors (rainfall, temperature,

INTRODUCTION

The term "flood" refers to the temporary overflow of water onto normally dry ground. There are few natural calamities as catastrophic as flooding. Excessive precipitation, snowfall, coastal storms, storm surges, and the failure of dams and other water management systems are all potential flooding causes. By definition, a flash flood occurs when a river overflows its natural levels, inundating the land around it for a brief period (Xie et al., 2020). As a result of

humidity), topographical features (elevation, slope, land cover), and socioeconomic variables (population density, urbanization) is compiled. Feature selection and engineering techniques are applied to optimize model performance. Flooding is the most frequent and destructive natural catastrophe that may happen anywhere in the globe. The frequency and severity of flooding events have increased worldwide in recent years due to climate change and human activity. Flooding has caused widespread death and devastation of property, farms, and vegetation in several emerging Nigeria, including Lagos State, and has forced the relocation of many more. Flooding has been Lagos State's most common natural disaster during the last decade. Modern machine learning methods have shown great promise for improving flood Estimation and Evaluation. The optimum machine learning algorithm for flood Estimation and Evaluation is debated. To reduce the harm caused by floods, finding better ways to anticipate their occurrence is crucial. This paper initially applied 4 machine learning algorithms (Support Vector Machine SVM, Classification and Regression Trees CART, K-Nearest Neighbors KNN, and 4. Generalized Linear Model Network GLMNET) on the default dataset. The results reveal fair accuracy (over 60%) and kappa values (< 0.4). The same ML algorithms were again applied to the transformed dataset using the Boxcox transformation technique; the accuracy and kappa values improved but not significantly. Finally, Models for predicting floods were implemented using 3 different ensemble algorithms: Bagged CART (Bootstrap Aggregating BAG), Random Forest (RF), and Stochastic Gradient Boosting (Gradient Boosting Machine GBM). Compared to the other three models, the performance of RF (Area Under the Curve AUC = 0.93) and BAG (AUC = 0.92) indicated superior accuracy.

Keywords: Artificial Neural Network, Flood Hazard Estimation, Gradient Boosting, Machine Learning, Random Forest, Support Vector Machine.

several unfavorable environmental factors, including meteorological, hydrological, geomorphological, and human participation in the breakdown of flash flood protection measures, it is essential to remember that flash floods are a distinct phenomenon. A rise in the frequency and severity of worldwide flash flood dangers has been linked to continuing global climate change over the last several decades. Oloruntoba et al 2023. These challenges include the complex nature of weather patterns, inadequate historical data, limited monitoring, and early warning systems resources, and the need for localized Estimation and Evaluations due to variations in terrain and land use. Traditional methods of flood Estimation and Evaluation analysis often fall short of providing accurate and timely information for effective disaster management Gong, Y., Zhang, Y., Lan, S. and Wang, H.A. (2016). It has been reported that numerical forecasting of flood disasters in the 19th century lacked accuracy due to its inability to simplify complex atmospheric dynamics into simple equations Lynch, C.A. (2008). Although, the nonlinear modeling capability of Artificial Neural Networks (ANNs) has been used in developing nonlinear predictive models for weather analysis with the ANN approach Bose, I. and Mahapatra, R.K. (2001). Hoai, M., Lan, Z.-Z., and De la Torre, F. (2011) have shown limited accuracy and timeliness effectiveness. The critical challenge in flood disasters in the south-south of Nigeria includes poor attention to flood modeling and assessing vulnerability to flooding. Therefore, there is a need for novelty in the knowledge of machine learning (ML) model building for flood estimation and evaluation. Machine learning (ML) offers a promising approach to address this challenge by leveraging historical data, weather patterns, topographical information, and other relevant factors to develop predictive models for flood occurrences. The application of machine learning for flood Estimation Evaluation and analysis in Southern Nigeria has become an increasingly important area of research due to the region's vulnerability to flooding. Mathura, E., Manyena, S.B., Collins, A.E. and Manatsa, D. (2013) The review paper introduces the most promising Estimation and Evaluation methods for both long-term and short-term floods. Furthermore, the major trends in improving the quality of the flood Estimation and Evaluation models are investigated. Among them, hybridization, data decomposition, algorithm ensemble, and model optimization are reported as the most effective strategies for improving ML methods.

Devastating flash floods are caused partly by widespread human interference with natural systems, including forest ecosystems, as shown by deforestation, riverbed sedimentation, and the encroachment of human settlements and dam building on riverbeds. In recent years, there has been a shift in the severity pattern of flash floods due to the progressive growth of the world population, particularly in developing nations (Mosavi *et al*., 2017). Flash floods may cause significant socioeconomic losses. These damages include destroying homes and lives and critical infrastructure, including farms, factories, and communication networks. Several people are displaced, and many more are killed yearly due to flash floods. Nigeria happens to be one of the nation's most vulnerable to flooding. High rainfall intensity, the propensity to create runoff, the rapidity of the rainfall-runoff process, soil characteristics and infiltration rate, a poorly maintained flow pattern of a river system, and changes in land use are all contributors to the possibility of a disastrous flash flood. The literature demonstrates that floods have the highest fatalities among all-natural catastrophes (Panahi *et al.*, 2021). Maspo *et al.* (2020) reported that flooding is a major frequently occurring natural catastrophe with serious consequences on lives, infrastructure property, and the surroundings. While stopping flooding is difficult, one can reduce its impact through more accurate Estimation and Evaluations. This fact was corroborated by Mosaffa *et al.* (2022). Flooding has also caused irreversible harm to the ecosystem, property, human life, and infrastructure like bridges, buildings, roads, and many more (Egbinola *et al.*, 2017).

Predicting the likelihood of future flash floods based on the frequency of flash floods is a crucial part of flood risk assessment. As a result, many types of flash flood statistics, including discharge, rainfall, and runoff, have been used to quantify the recurrence of flash floods in the past (Xia *et al.*, 2017). Devastating flash flood damage necessitates various structural and non-structural methods for long-term mitigation and prevention. Floods are one of the most devastating natural catastrophes, not just in Nigeria but also in many other countries of the globe. Recent floods have significantly impacted damage to human life, property, infrastructure, and the economy and social fabric. Thus, creating flood forecasting models that can provide precise maps of potentially vulnerable locations is crucial, allowing for better measures to reduce and respond to flood risks (Mosavi *et al.,* 2018). Thus, cutting-edge technologies are crucial for short- and long-term flood forecasting. Hydrological event forecasting traditionally relies on physically based models (Mosavi *et al*., 2018). According to Akinyokun *et al*. (2020), several communities continue to experience the catastrophic effects of floods resulting from climate change, acute rainfall, rapid increase in population, and industrialization, among others.

The techniques for flood Estimation and Evaluation can be broadly categorized into three, namely, physical, statistical, and data-driven. The physical method combines hydraulic and computer hydrological models. It has a distinct physical basis. However, a significant amount of information about the river basin, which is typically scarce, must be deposited. According to Mosavi *et al.* (2018), the statistical method has limited performance capabilities and is typically not utilized to predict floods because it does not adequately expose the nonlinear underlying elements that are crucial to flooding processes.

The use of physical and statistical techniques for flood Estimation and Evaluation has several limitations, such as their susceptibility to ambiguous and subjective interpretation. Additionally, they don't provide quantitative flood Estimation and Evaluations, have a low level of Estimation and Evaluation capability, and are inaccurate. Modern data-driven models like machine learning are used as a result of the limitations of the physical and statistical models that were previously addressed.

Studies have revealed a gap in the short-term Estimation and Evaluation capability of physical models (Mosavi *et al.*, 2018). Machine learning methods for flood forecasting have emerged as a response to the limitations of physically based and statistical models. The following are some of the benefits that may be gained by using Machine Learning for flood Estimation and Evaluation: Faster development with fewer inputs; more straightforward implementation with low computation cost; faster training, validation, testing, and evaluation; relatively less complexity; and the ability to numerically formulate the flood's non-linearity based on historical data alone, without knowledge of the physical processes.

However, much research on the application of ML techniques is reviewed works that do not encompass most of the ML algorithms in one study. Hence, the current study seeks to apply five ML algorithms such as SVM, Random Forest (RF), Logistic Regression (LR), Naïve Bayes (NB), and Artificial Neural Networks (ANN) for flood Estimation and Evaluation and evaluation in Lagos State Nigeria.

Forecasters have attempted to anticipate floods in several ways, each with advantages and disadvantages and varying degrees of success. It's not like there's a model that everyone agrees on. The precision, speed, and datadistribution assumptions of available models vary widely. Most hydrological event forecasts have been made using physical models (Zhao et al., 2014). Yet, this often requires in-depth knowledge and skill regarding hydrological aspects, which may be complex and demanding. Research has shown that specific physical models cannot provide Estimation and Evaluations soon (Costabile and Macchione, 2015).

Several machine-learning methods have been employed for flood modeling. These include long short-term memory (Li *et al.*, 2021), linear models, fuzzy logic, artificial neural networks, multi-layer perceptron, Naïve Bayes, and decision trees (Pham *et al.*, 2021). Machine learning methods for flood forecasting have emerged as a response to the limitations of physically based and statistical models. Ardabili *et al.* (2019) wrote that conventional machine learning algorithms continuously advance and evolve quickly by introducing novel learning algorithms using hybridization and ensemble techniques. The hydrological strategy, which uses hydrological and hydraulic modeling, was the conventional one in the past. According to Tehrany *et al.* (2019), the qualitative model considers the influencing elements and their qualities while modeling. It uses expert knowledge and qualitative methodologies to associate independent variables with flood

incidence based on numerical expressions. The frequency ratio (FR), logistic regression (LR), and the index of entropy (IOE) are only a few of the standard statistical methods.
Nevertheless, Tehrany *et al.* (2019) pointed out that statistical techniques depend significantly on linearity assumptions, and flooding does not fit that description. Statistical methods such as statistical correlations using the gauge to gauge, gauge discharge data, multiple coaxial correlations using gauge, rainfall, and antecedent precipitation index (API) data are used by Nimet and NiHsa Nimet and NiHsa are the two sister agencies in Nigeria responsible for flood forecasting in Lagos State to provide the flood forecast. Hydrological event forecasts have been based on physically based models (Zhao *et al.*, 2014). To create a machine learning
Estimation and Evaluation model, historical flooding records are used in conjunction with data from several rain gauges. The dataset typically includes rainfall and water levels obtained from ground rain gauges or using remote sensing technologies.
Isaac *et al.* (2021) reported that findings indicate that during the past decade, machine learning researchers have used hybrid models more extensively than individual models. This is because the models' strengths and shortcomings complement one another. Statistical methods, physical models, and soft computing techniques are typically combined to create hybrid models.
According to Panahi *et al.* (2020), there is no general agreement on which machine learning method is best for flood Estimation and Evaluation. Hence new techniques, usually a hybrid of different algorithms, are often explored. Researchers in machine learning models for flood Estimation and Evaluation have used more hybrid models than stand-alone models in the last decade. Hybrid models complement each other in terms of strengths and weaknesses.

Methodology
The main focus of this study is Flood Hazard Estimation and Evaluation in Lagos State Using Machine Learning Techniques based on the flood type, location, duration, begin/end location, begin/end latitude and longitude, injuries direct/indirect, death direct/indirect, and property and crop damage in - Surulere, Kosofe, AjeromiIfelodun, Apapa, Shomolu, Ikeja, Amuwo-Odofin and Oshodi-Isolo. It consists essentially of five steps, namely: data collection and data pre-processing, the definition of the training set (data splitting and training), application of machine learning algorithms on untransformed features, application of algorithms transformed with Box- cox and advance to better performance using ensemble algorithms.

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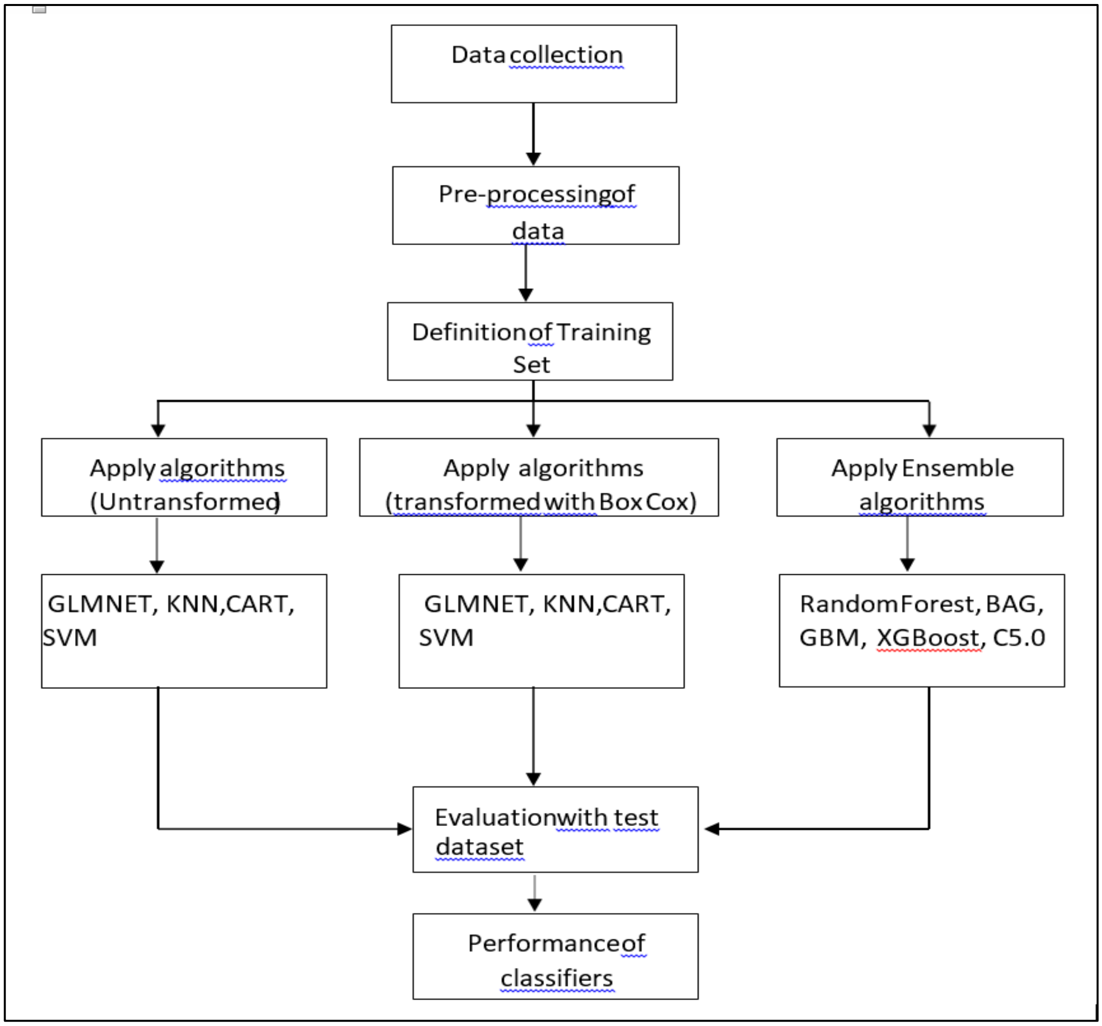

Figure 1: Workflow of the Flood Prediction Model

Data collection

Information used in the analysis was obtained from the Lagos Bureau of Statistics website. The bulletin was analyzed for the following details: precipitation, maximum and minimum temperatures, average radiation and evaporation, relative humidity, and flood reports. Data were included from 2014 to 2020. The size of the informational file is 21 kilobytes. The variables are listed in the columns, while the yearly data for the 8 Local governments in Lagos state are shown in the rows. In this study, we used annual rainfall, mean radiation, mean evaporation, relative humidity, minimum and maximum temperature, and the number of reported flood cases as the dependent variable and the number of reported flood cases as the outcome variable.

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Data Pre-Processing

The variables required for this analysis have been retrieved from the original dataset, and they are as follows: annual rainfall, mean radiation, mean evaporation, relative humidity, minimum and maximum temperature, and reported flood incidents from 2014-2020. A longitudinal sample was obtained from 8 Local Governments in Lagos State. After being extracted, the dataset was entered into an Excel spreadsheet and saved using a comma-delimited filename (.csv). The information is sent to R Studio and placed in the "Ensemble data" data frame. When dealing with missing data in R, the mean feature was used to fill in the gaps.

Data Splitting and Training

Separating the dataset is the last step in the pre-processing phase of the data. The information is going to be divided into training and testing sets. The model will be trained on 80% of the data and verified using the other 20%. Both classification and regression are viable applications for machine learning algorithms. Since our outcome variable is binary, we used classification machine learning techniques in this investigation (0 or 1). Accuracy, Kappa, McNemar's Test, Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value, Prevalence, Detection Rate, Detection Prevalence, and Balanced accuracy are some of the performance metrics employed.
As can be seen in Figures 3 and 4 below, the dataset is not normally distributed, Most ML models perform better if the data is normally distributed. A box-cox transformation on the dataset is employed to make the prediction better. The analyses of the results of ML algorithms of untransformed dataset and transformed dataset are given in sections 4.4 and 4.5 respectively.

System Implementation

All the tests were run on a 1.8 GHz Intel Quad-Core i5-82500U with 8 GB of Memory and 64-bit Windows 10 Home Edition. We used 10-fold cross-validation with three repetitions to divide the datasets. The classifiers' efficacy is evaluated here using a 10-fold cross-validation method. Now, we break up the training dataset into 10 equal-sized subgroups and put each of those subsets through the classifier trained on the other nine. The computational cost of doing cross-validation is minimized by performing the procedure 10 times in a ten-fold cross-validation, which is one of its many benefits. In addition, because each data point is only tested once and used for training ten and a half times in other validation methods, 10-fold cross-validation produces less bias.

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Implementation Tool

The research used the statistical capabilities of the R-project software [R version 4.0.5 (2021- 03-31)]. The R Core Team and the R Foundation for Statistical Computing maintain R, a free software environment for programming, statistical computation, and graphics. Data miners and statisticians often use the R programming language for various applications, including creating statistical tools and examining large datasets. To complete the R-project, the CART library was included as a package. Classification And Regression Training (CART) is a collection of tools meant to simplify the development of prediction models. Data partitioning, feature selection for pre-processing, resampling for model tuning, assessment of variable relevance, and other features are all included in the package. To import the dataset into R-Studio for pre-processing and analysis, it was extracted from the portable document format (pdf) and then put into Microsoft Excel as comma-separated values (CSV).

Result and Decision

The present study's experimental analyses were carried out using a laptop equipped with an Intel® core i7-4340M CPU @ 2.90GHz (4 CPUs) 8GB RAM, and the Python programming language, together with the Scikit-Learn, matplotlib, pandas Pycaret, and seaborn libraries. In the following sections, we describe the findings from our experiments.

Unimodal Data presentation and Visualizations

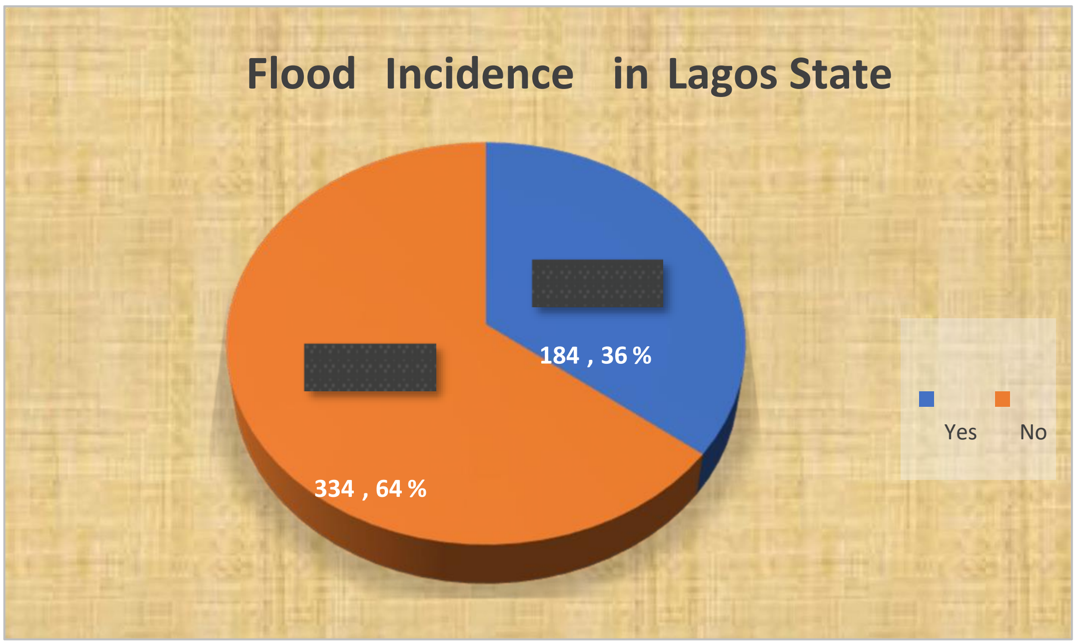
The research data is presented in Table 1. The whole data set is shown in Figures 1-4. Figure 1 shows the predictive variables of the flood. Figure 2 presents flood incidence in Nigeria, and Figures 3 and 4, present histogram and density plots for the independent variables, respectively.

Table 1: Descriptive Statistics of Predictor Variables over the Study Period

	Rainfall (mm)	MinTemp (°C)	MaxTemp (°C)	MeanRad (kW/m^2)	RelHum (%)	MeanEvap (mm)
Mean	1347.25	22.25	33.73	19.90	63.74	4.78
Std. Deviation	903.79	2.02	2.13	1.91	14.14	0.46
Minimum	109.00	15.40	27.40	15.+70	34.40	3.70
Maximu m	10719.00	27.00	41.10	24.00	85.50	5.90
Kurtosis	43.18	1.61	1.59	-0.84	-0.92	-0.59
Skewness	4.42	-1.09	0.32	0.21	-0.23	0.08

Table 1 presents the descriptive statistics of predictor variables over the study period. It shows that rainfall has a high deviation from the mean value. Also, relative humidity has high variability, so we can expect extreme rainfall values more frequently, which can cause hazards. In addition, the table also indicates that the distribution is highly skewed for rainfall, and min temperatures are approximately symmetric for the other predictor variables.

Figure 2: Pie-chart showing flood incidence in Lagos State over the study period.



The pie chart shows the flood incidence in Lagos State over the study period. It reported 184 (35.5%) cases of flood and 334 (64.5%) cases of no flood in different Local Governments of Lagos State.

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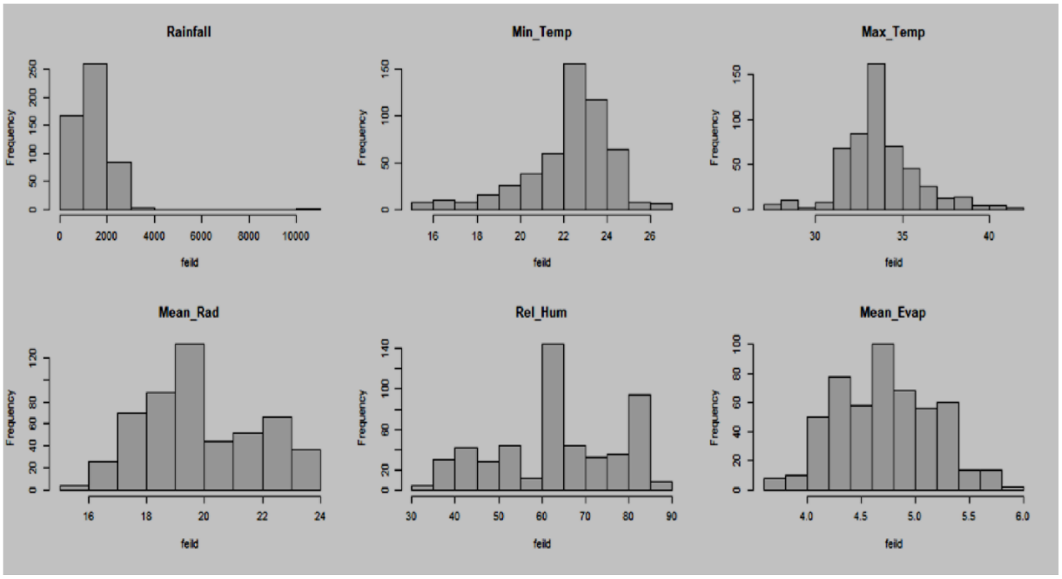

Figure 3: Histogram Plots for Each Independent Variable

Figure 3 above shows the histogram plots for each predictor. The histogram plots show virtually all the distributions have bimodal shapes, typically indicating deviation from normality. We employed the density plots to get a smoother look at the distribution.

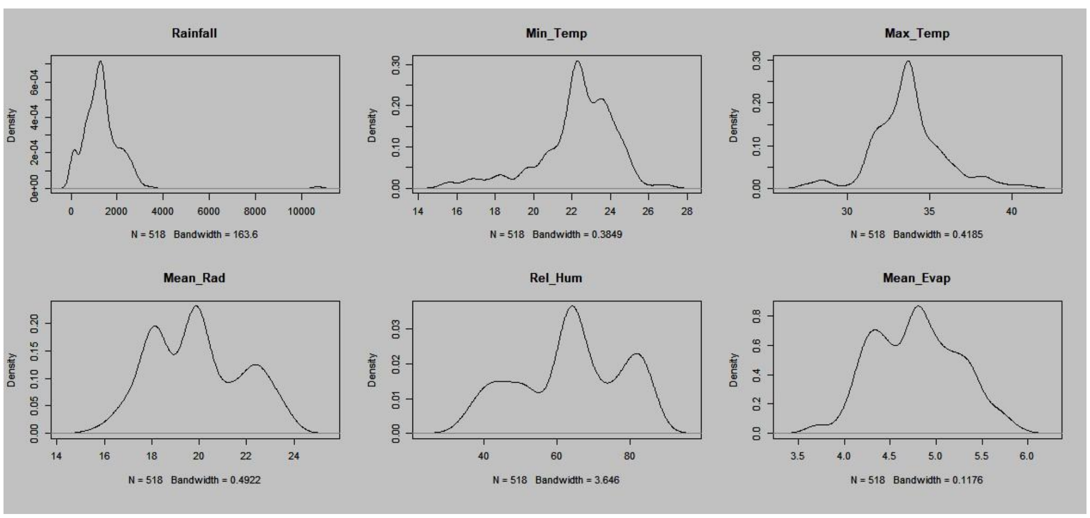

Figure 4: Density plots for each independent variable

Figure 4 shows the density plots for each of the independent variables. It shows that they all have multi-modal behaviors.

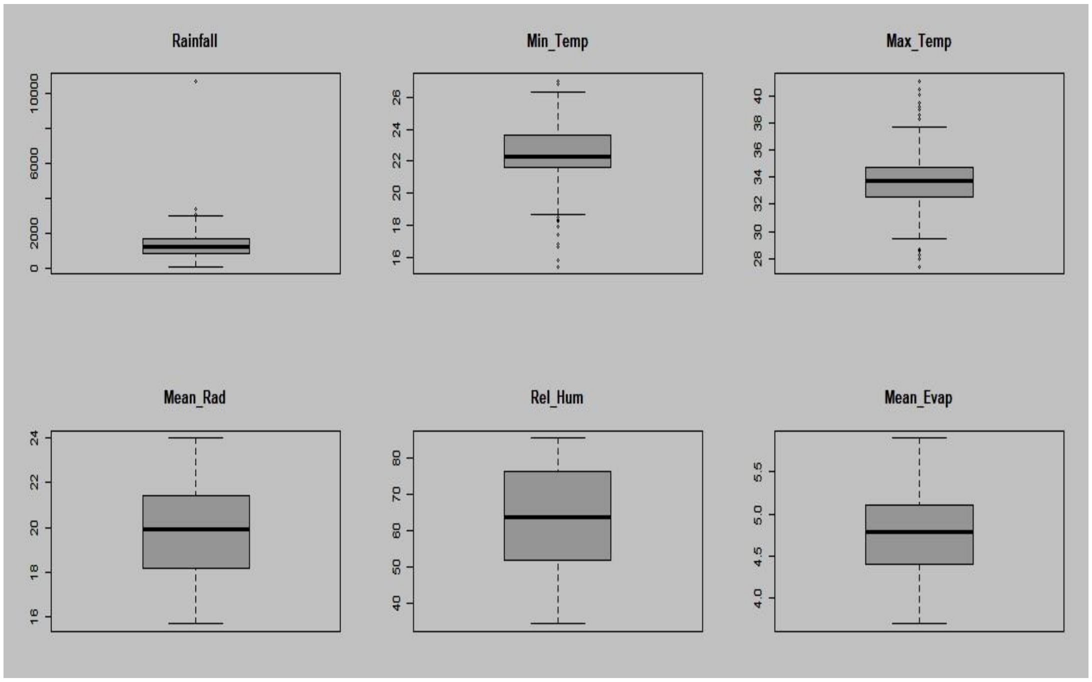

Figure 5: Boxplots for the Predictor Variables

Figure 5 shows the boxplots showing the distribution of the predictor variables. It shows that rainfall, minimum temperature, and maximum temperatures have outliers which shows the deviation of the dataset from normality.

Multi-modal Data Presentation and Visualizations

The research data of intercorrelation coefficients between independent variables is shown in Table 2. The other data set representing scattered matrix plots by flooding is shown in Figure 6 below.

Table 2: Intercorrelation coefficients between independent variables

	Rainfall	MinTemp	MaxTemp	MeanRad	RelHum	MeanEvap
Rainfall	1					
MinTemp	.236**	1				
Max Temp	-.121**	.349**	1			
Mean Rad	-.480**	-.438**	.320**	1		
RelHum	.463**	.462**	-.300**	-.840**	1	
MeanEvap	-.474**	-.318**	.400**	.866**	-.747**	1

**. Correlation is significant at the 0.01 level (2-tailed).		

Table 2 shows the intercorrelation coefficients between independent predictors. It shows that most of the variables have weak relationships. However, there were high correlations for Mean Radiation and Relative Humidity, Mean radiation and Mean evaporation, and Relative humidity and mean evaporation.

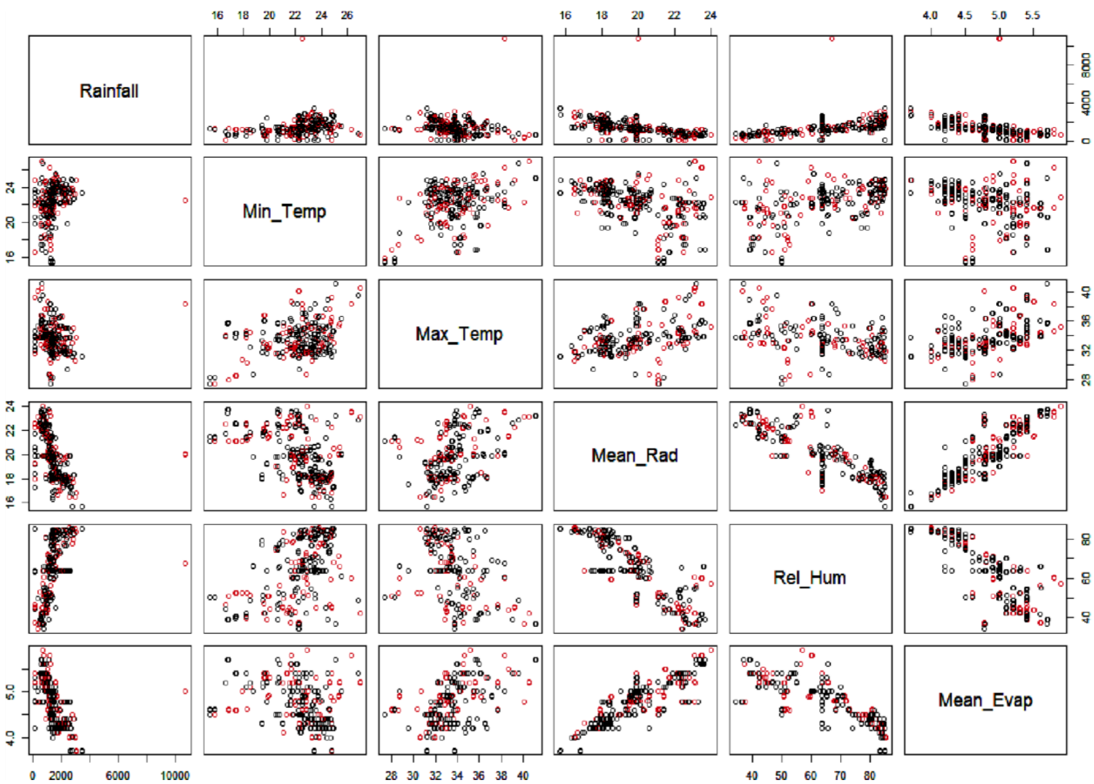

Figure 6: Scattered Matrix Plot by Flooding

Figure 6 shows the scattered matrix plot by flooding. It offers specific positive and negative linear correlations between the predictors, while rainfall didn't establish any relationships with other independent variables.

Evaluate Algorithms: Baseline

There is no prior knowledge of the performance of the different machine algorithms on the dataset. So, a spot-check on other methods was considered. We commenced this check by looking at linear and non-linear algorithms:

Linear Algorithms: Regularized Logistic Regression (GLMNET).

Non-linear algorithms: k-Nearest Neighbours (KNN), Classification and Regression Trees (CART), Naive Bayes (NB), and Support Vector Machines with Radial Basis Functions (SVM).

We have a good amount of data, so we used 10-fold validation with three repeats. This is an excellent standard test harness configuration. The dataset's outcome variable suggests we are dealing with a binary classification problem. We used Accuracy, Kappa Metrics, and ROC to select the best Machine Learning algorithms. In creating our fitting models, we used the default parameters without transformation, introduced a box-cox change, and advanced to better performance using the Ensemble algorithms. For each algorithm, the random number seed is reset before training to ensure that each algorithm is evaluated on the same data splits.

Untransformed Analysis of Machine Learning Algorithms

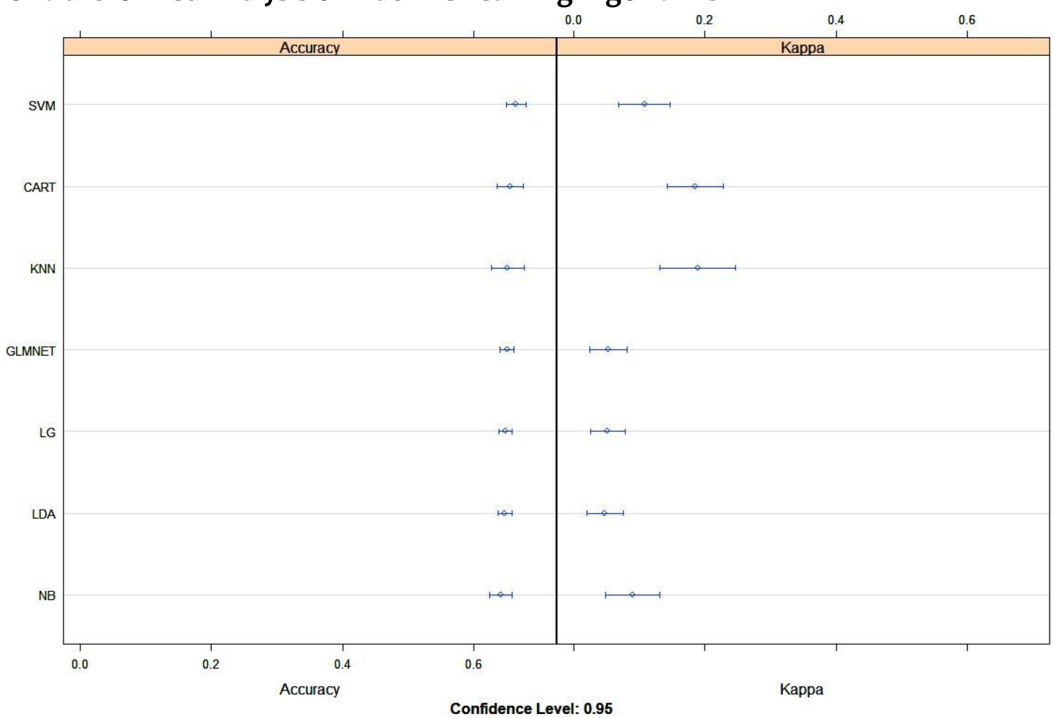

Figure 7: Performance chart of the Untransformed Analysis of Machine Learning Algorithms

We can see fair accuracy across the board. All algorithms have a mean accuracy above 60%, well above the baseline of 34.5% if we just predicted flood. This implies that the problem is learnable. We can see that KNN, CART, and SVM had the highest accuracy on the problem.

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Transformed Analysis of Machine Learning Algorithms

From the unimodal visualization, we saw that our predictors had skewed distributions. Hence, a transformation must be applied to adjust and normalize these distributions. Therefore, we used a transformation favoring positive input attributes, as in our case. The Box-Cox transformation was applied.

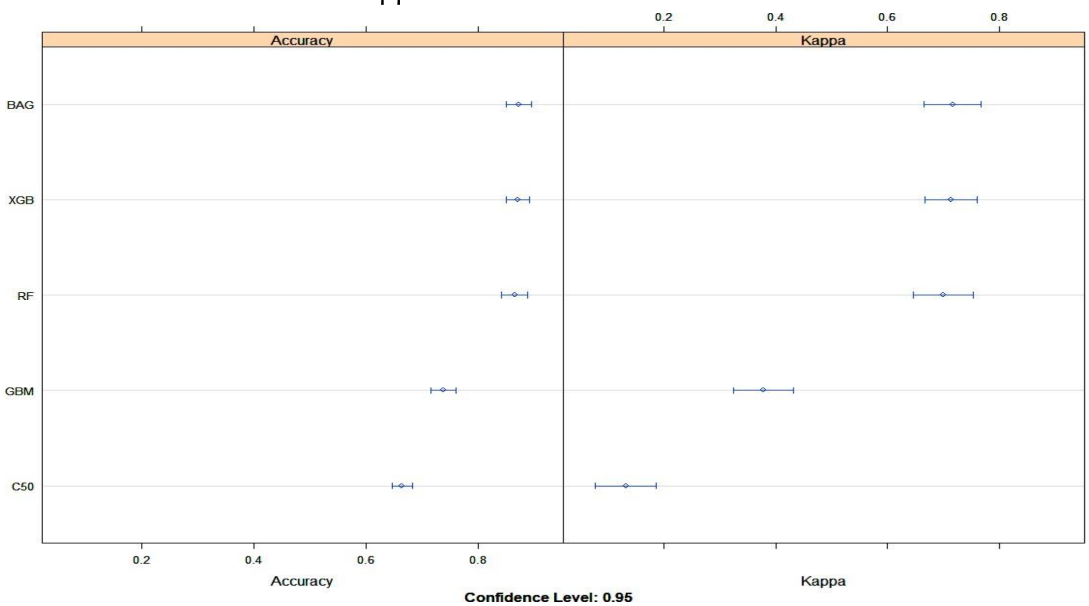

Figure 9: Ensemble Algorithms performance chart

Figure 9 shows the performance of the different ensemble algorithms. Random forest and BAG were the algorithms with the highest accuracy, and Kappa indicated better performance than the other three models (i.e. GBM, XGB, and C5.0).

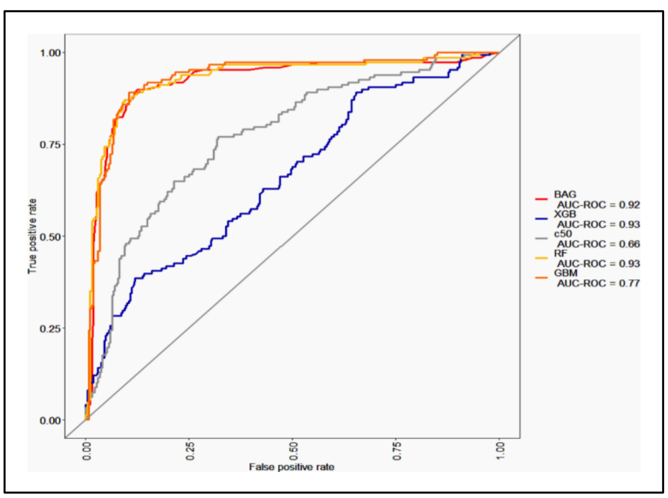

Figure 10: ROC Curve Assessing the Performance of the Different Ensemble Algorithms

Figure 10 shows the ROC assessing the performance of the different Ensemble algorithms. RF and XGB gave the best Area Under the Curve (AUC), followed by BAG. This shows that RG and XGB performed better than other models trained in this study (i.e. GBM, XGB Boost, and C5.0).

Table 4: Comparison of ensemble model performances

	Bagging			Boosting	
	RF	BAG	C5.0	XGB	GBM
Accuracy	0.91	0.89	0.68	0.91	0.78
No Information Rate	0.65	0.65	0.65	0.65	0.65
P-Value [Acc> NIR]	0.00	0.00	0.30	0.00	0.00
Kappa	0.80	0.75	0.20	0.80	0.50
Mcnemar's Test P-Value	0.05	0.02	0.00	0.05	0.06
Sensitivity	0.98	0.98	0.89	0.98	0.91
Specificity	0.78	0.72	0.28	0.78	0.56
PosPred Value	0.89	0.87	0.69	0.89	0.79
Neg Pred Value	0.97	0.96	0.59	0.97	0.77
Prevalence	0.65	0.65	0.65	0.65	0.65
Detection Rate	0.64	0.64	0.58	0.64	0.59
Detection Prevalence	0.72	0.74	0.83	0.72	0.75
Balanced Accuracy	0.88	0.85	0.59	0.88	0.73

Table 4 shows the Random Forest and the XGboost algorithms' performance based on the test dataset with an accuracy of 91%, a sensitivity of 98%, and a specificity of 78%.

Conclusion and further studies

In this study, we have gone through the process of predicting floods in Lagos State using ensemble machine-learning methods. The study employed linear and non-linear machine learning models to ascertain performance in the classification problem and further advanced the models using some ensemble algorithms. Comparing the models' performances showed that the ensemble algorithms performed better than the conventional machine learning algorithms**.** The random forest and BAG performed best in the training datasets from the different ensemble models based on their higher accuracy and Kappa. In contrast, the Random Forest and the XGboost algorithms performed better on testing with the test dataset based on their accuracy, specificity, and sensitivity.

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There is a need for NIMET and other agencies in Lagos State to improve their online data portal to be made readily available for researchers. This will make researchers faster and assist with better weather predictions and disaster predictions related to weather like floods. One way to improve their online system is to capture a daily log of meteorological changes. Daily capturing will go a long way to improve our machine learning algorithms with better performance since logging data generates a more significant mass of datasets. Nevertheless, further study is required to incorporate and operationalize the high-performance algorithms Random Forest, BAG, and XGboost as early flood warning systems. Several factors need to be thought about here. The first benefit is that a stochastic input may be utilized to estimate the probabilistic distribution across flood quantities, given the relatively short run time. Second, less severe than historical occurrences but still causing floods, precipitation projections should be used to assess the models further. If such precipitation occurrences are considered, the trained algorithms' tendency to overreact to very few swings may impair their effectiveness. The outcome variable in this study was a binary categorical variable which further analysis can adopt a count variable that follows a Poisson distribution. This time instead of predicting the incidence of the flood, it will be predicting the number of storms that occur in those states per year. The dataset in this study is more like time series data. Hence further work can look at machine learning algorithms that work with time series data better to capture the role of years in the model.

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