Innovations

Prediction of terrorist activities in Nigeria using machine learning models

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Abstract
Problem*: Terrorism continues to be one of the most important threats to today's civilization. The different forms of terrorist attacks in Nigeria in the recent times are Boko-Haram attack, Fulani/Herdsmen attack, Inter/Intra-group conflicts, robbery and lack of intentionality. In order to curb or reduce these activities in Nigeria, there is a need to develop models that can be used to understand these terrorists' activities and prevent or reduce future occurrences.*
Objective: *The aim of this work is to predict terrorist activities in Nigeria using machine learning models (MLM).*
Methods: *The data used in this study was gathered from the daily terrorism incidents throughout Nigeria. The data consist of the different kinds of attacks, the success and the suicidal rates of the attacks and the different levels of weapon types used during the attacks. The targets or victims of the terrorist attack, perpetrators information, casualties and the incidents' consequences were also the highlights in the database. A Heterogeneous Neural Network(HETNN) model was used and its performance was compared with five other MLM namely: Logistic regression (LR), Support Vector Machine(SVM), K-Nearest Neighbour (KNN), Boosting and Random Forest classification models.* ***Findings:*** *The results show that HETNN performs better in prediction compared to the other models. It was also discovered that in determining the success of a terrorist attack, the factors to be considered in order of importance are the number of perpetrators, attack type, type of weapon, the type of victims targeted, and the state of the incidents.* ***Conclusion****: The information provided in this work will help the Nigeria government and the security agents in combating insecurity issues in the country.*

Keywords: 1.*Terrorism, 2.Machine Learning, 3.Transfer Functions, 4.Nigeria Terrorism Database, 5.Prediction.*

1.0 Introduction

Terrorism or terrorist activities could be defined as the use ofillegal and violent power for creating terror among a group of people. As stated by Llussá and Tavares (2011) in [1], these activities range from ethnically driven to politically-sponsored, from difference in religion to diversity in ideology. Terrorism has negatively affected different sectors, organizations, nations and the entire world in the recent times. Examples are its effect on airline performance (Guzhva and Pagiavlas (2004), [2]), major stock markets, evinced by the downward spikes in market prices [3-7], and global economy (Song*et al.*, (2022) [8]).The priority of the government of most countries that are faced with the problem of terrorism is to adopt methods that can best capture the different factors involved in terrorism, and providing possible ways of curbing or eradicating terrorist activities (Uddin*et al.*, (2020) [9]).

In the recent times, the invasion of terrorist groups in Nigeria has been so alarming and has resulted to numerous death cases. Specifically, the gruesome activities of the Boko Haram (a terrorist group in Nigeria and her environ, [10-14]), Fulani-Herdsmen and inter/intra conflict-groups (George *et al.*, (2022) [15]), robbers, bandits and kidnappers (Omeje*et al.*, (2022) [16]), have jeopardized the security state in Nigeria. According to the literature (McKendrick (2019) in [17]), the central focus of counterterrorism strategies is the adoption of some preventive measures. Novel technological developments have made their way into forcing authorities to re-examine how counterterrorism actions are conducted. Machine Learning Models (MLM), also known as Artificial Intelligence (AL) is one of these technologies (McKendrick (2019), [17]).

The advantage of using MLM in counterterrorism is mainly based on the accuracy of predictions, which in turn helps to redirect resources more accurately. Also,predictive MLM have been proven to minimize unnecessary intrusion on the population and reduce biased decisions made by human. Terrorism or terrorist activities are unpredictable in themselves since they are likely to be conducted by unknown persons in an unknown place and at unpredicted times. Hence, an effective method to counter terrorism depends possibly on accurate prediction. *The question is how accurate is the method of prediction of terrorism*. Therefore, this research focuses on the use of MLM, not just 'big data' analytics to provide counterterrorism solution, through the use of deep learning and traditional machine learning methods to build models based on data, and then make inferences from these models.

The main objective of this research is to explore novel techniques in deep learning so as to understand the behavior of terrorist activities in Nigeria. The Heterogeneous Neural Network (HETNN), Logistic regression, K-nearest Neighbour, Random forest, Support Vector Machine (SVM) and Boosting classification models were used to model and predict recent terrorist attacks in the Nigerian case. A comparative analysis was carried out to ascertain the best model to predict the Nigeria terrorist activities. The tools and results obtained can be useful to the Nigerian government and law enforcement agencies as effective counterterrorism mechanisms to understand the parameters of terrorism and to design strategies to help deal with terrorism. Second, it would reduce the chances of terrorist activities and particularly helpful for security agencies to make prediction in future terrorist activities. The remaining part of the paper is structured as follows: The next section presents related work concerning machine learning models that have been used for prediction in general perspective in the literature. In section three, the Nigeria terrorism activities data source and type, model variables, methods and models' performances using Accuracy, Precision, Recall and F1-score criteria were highlighted. The results, interpretation and conclusion were given in section four and five respectively.

2.0 Related works on machine learning models for terrorist attack prediction

Artificial Intelligence or machine learning applications cut across various fields of interest. These entail applications in transportation, medicine and finance [18-20]. However, in this review our focus here is on the aspect of machine learning techniques as well as its application to terrorist activities and their prediction.

The authors, JSPM and Tirwa (2018) in [25] categorized, using five machine learning algorithms the dataset obtained from global terrorism database (GTD) into three categories namely: type of attack, region of attack and weapon used in the attack. It was established that the occurrence of attack type depends upon weapon type used during the operation.

A comparative analysis of a class of machine learning algorithms was done by Agarwal*et al.* (2019) in [26] on the GTD for the prediction of some of the factors that might be responsible for increase in terrorist attacks. These include success rates, group type and the effect of some external forces.

Bangerter*et al*. (2020) in [21] identified terrorist groups by using the heterogeneous graph neural network based on the adopted knowledge graph.Jiang (2020) in [22] adopted tools for better prediction using artificial intelligence for representing objects having multiple structural data. IrfanUddin*et al.*, (2020) in [23] predicted future terrorist activities via five deep neural network models namely: single-layer neural network, five-layer deep neural network, and logistic regression, SVM, and Naıve Bayes algorithms. Their results prove that the five-layer deep neural network is a better tool for future prediction of terrorist attacks.Ogundunmade and Adepoju (2021) in [24] carried out an evaluation of the performance of two types of heterogeneous transfer functions (HTF) obtained via the convolution of three best proven homogeneous variants of HTF. This result could be applicable for modeling and predicting terrorist attacks. Ogundunmade*et al.*, (2022a) in [27] evaluated the predictive strength of five MLM under the categories of two cross validation (TCV) and no cross validation (NCV) techniques. The results obtained in their work prove that the MLM with TCV technique is stronger in terms of exact prediction than the MLM with NCV technique. Ogundunmade*et al.*, (2022b) in [29] considered the prediction of crude oil price in Nigeria via machine learning time series models.

This paper uses Nigeria terrorism data gathered from the daily occurrence of terrorism attacks, robbery, kidnappings, assaults etc. submitted to Nigeria Terrorism Database (NTD) through Google link made available to Nigerian citizens to report daily occurrence of terrorism activities in Nigeria. Our data for this study was extracted from this Nigerian database unlike other studies that used Global Terrorism Database. This paper also made use of a newly developed artificial intelligence model in the prediction of the terrorism activities in Nigeria for better prediction and accuracy and the performance of the model is also compared with other machine learning models used in the literature. This paper is very important as it gives insight into prediction of terrorism activities and this will help the government and security personnel to be able to curb or reduced these activities.

3.0 Materials and Method

Here, the data source for the Nigeria terrorism activities, type, model variables, methods and models' performances are presented.

3.1 Data source

The National Consortium for the Study of Terrorism and Responses to Terrorism (START) has a dataset known as Global Terrorism Database (GTD) which has been used by researchers to predict terrorism activities in the world (IrfanUddin*et al.*, (2020), [23]). However, data for predicting terrorism activities for Nigeria used in this study is a daily report of terrorist activities which occurs in Nigeria. The dataset used is a primary data, collected via an electronic medium, designed in a Google form and distributed randomly to different platforms in the six geopolitical zones (North east, North west, North Central, South East, South West and South South) in Nigeria. The form was designed in such a way that each respondent's personal information was not traced to their responses. This was done to keep the confidentiality of the respondents for obtaining exactness of correct information provided during the longitudinal survey.

Different variables were gathered in the data collection. The nature of the terrorist attack was categorized into different levels of attack, namely: armed assault, assassination, bombing/explosion, facility/infrastructure attack, hijacking, unarmed assault and unknown type. Obviously, terrorist attack cannot be achievable without the application of some forms of weapons. The dataset also shows the targets of the terrorists (educational institution, government, media, military, NGO, police, private business organization, private citizen and property, religious institutions, and political parties). The perpetrators' information which include name, number of perpetrators, and mode for claim of responsibility were also included in the data. And finally, the information about the casualties and consequences of the terrorist attacks, such as, mortality rate, number of people injured, number of perpetrators injured, were also gathered.

3.2 Model variables

In this study, the factor to be considered for prediction using the machine learning model is the "success" factor. This indicates the success of a terrorist strike. The data is categorized into "Yes" or "No"(Level "Yes" coded as 1). The variables used as feature variables are: weapon type, location of the event, number of perpetrators, target of the terrorist and the type of the terrorist attack (kidnapping, assassination, Armed Assault etc.). The data is divided into 60 percent for training, 20 percent for validation and the rest 20 percent for Testing.

3.3 Methodology

The statistical neural network (SNN) model is given as

$$y = f(x) + e_i = \sum x_i w_i + e_i \qquad (1)$$

where, y is the dependent variable, which can be continuous or dichotomous qualitative variable $x_i = (x_0 = 1, x_1, \ldots, x_n)$ is a vector of independent variables, where w = is the network weight and e_i = is the stochastic term that is normally distributed (that is, e ~ N(0,$\sigma^2 I$)). The model for a neural network model with a homogeneous transfer function is given as:

$$\psi(x,\ \vartheta) = \mu x + \sum_{j=1}^{n} \nu_j \left[\kappa\left(\sum_{i=1}^{m} \gamma_{j_i} x_i\right)\right] + e_i \qquad (2)$$

where, $\kappa(.)$is the transfer function, ϑ is the network weight with a vector of (μ, ν, γ) equation (1) above is called an Homogeneous Statistical NN (HSNN) model. Given a convoluted form of the transfer function, model (1) given above is transformed using the product convolution to get:

$$\psi(x,\ \vartheta) = \mu x + \sum_{j=1}^{n} \nu_j \left[\kappa_1\left(\sum_{i=1}^{m} \gamma_{j_i} x_i\right)\kappa_2\left(\sum_{i=1}^{m} \gamma_{j_i} x_i\right)\right] + e_i \qquad (3)$$

where, $\kappa_1(.)$and $\kappa_1(.)$are transfer functions, which are homogeneous but combined in equation (3) above to make an Heterogeneous Transfer (HET) function. Equation (3) above is called the Heterogeneous Neural Network (HETNN) model.

Two convoluted HET functions were derived using the principle of convolution, that is, $g_1(.) x g_2(.)$, such that the newly derived transfer functions are also a probability density function. The two derived using the convolution of Symmetric Saturating Linear Transfer Function and the Hyperbolic Tangent Transfer Function (SSLHT) and the convolution of the Symmetric Saturating Linear Transfer Function and the Hyperbolic Tangent Sigmoid Transfer Function (SSLHTS) [24]. In this study, the convolution of Symmetric Saturating Linear and Hyperbolic Tangent Sigmoid (SSLHTS) was used as the transfer function for our neural network model with hidden neuron of 5. We also compared the performance of Heterogeneous Neural Network (HETNN) alongside with five other machine learning models like Logistic regression, Support Vector Machine, K-Nearest Neighbour (KNN), Boosting and Random Forest classification models. These machine learning models were studied in past works [30-35] and discovered high performed classification models.

3.4 Model Performance

The performance of the models will be based on these four criteria: Accuracy, Precision, Recall and F1-score. The mathematical expressions for the criteria are discussed below:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \qquad (4)$$

$$Precision = \frac{TP}{TP + FP} \qquad (5)$$

$$Recall = \frac{TP}{TP + FN} \qquad (6)$$

$$F1\text{-}score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall} \qquad (7)$$

where, TN, TP, FN and FP given in equations (4)-(7), are respectively, True Negative, True Positive, False Negative and False Positive. These were obtained in the confusion matrix and then used to compute the performance criteria. The confusion matrix is a performance measurement in machine learning classification problems. It is a 2 by 2 table showing the true positive, true negative, false positive and false negative. When considering multi-class classification, the confusion matrix table takes the size equal to the number of class squared.

4.0 Results and Interpretation

In this section, we present the confusion matrix results for each classification model considered and their performance measures. Tables 1 - 6 show the classification tables for the proposed model Heterogeneous Neural Network model (HETNN), Logistic regression model, K-nearest Neighbour model, Random forest model, Support Vector Machine Model(SVM), and Boosting classification models. Figure 1 and Figure 2 below shows the accuracy and the precision plots of the models. Table 8 shows the feature importance.

Table 1: Confusion Matrix for Logistic Regression Classification

	Predicted	
Observed	No	Yes
No	16	14
Yes	4	174

Table 2: Confusion Matrix for K-Nearest Neighbour Classification

	Predicted	
Observed	No	Yes
No	3	1
Yes	0	37

Table 3: Confusion Matrix for Support Vector Machine Classification

	Predicted	
Observed	No	Yes
No	1	6
Yes	0	34

Table 4: Confusion Matrix for Random Forest Classification

	Predicted	
Observed	No	Yes
No	3	4
Yes	0	34

Table 5: Confusion Matrix for HETNN Classification

	Predicted	
Observed	No	Yes
No	5	1
Yes	0	35

Table 6: Confusion Matrix for Boosting Classification

	Predicted	
Observed	No	Yes
No	2	4
Yes	1	34

Table 7: Performance metrics for Classification Models

Classification Models	Accuracy	Precision	Recall	F1-score	Area Under Curve (AUC)
HETNN	0.976	0.976	0.976	0.975	0.917
Logistic regression	0.913	0.926	0.917	0.951	0.755
K-Nearest Neighbour	0.975	0.975	0.975	0.974	0.875
Support Vector Machine	0.854	0.876	0.854	0.805	0.571
Random Forest	0.902	0.913	0.902	0.886	0.768
Boosting	0.878	0.861	0.878	0.86	0.636

Table 7 above shows the performance measures for the six models considered. The result shows that HETNN performs better compare to the other models while KNN classification models performs better for the terrorist data compared to Support Vector Machine, Random Forest and Boosting classification model. This shows good performance of these models in predicting the willingness of the consumers on payment of electricity consumption. The proposed model HETNN, produced 97.6% accuracy, K-Nearest Neighbour produced 97.5% accuracy, Logistic regression, Support Vector Machine, Random Forest and Boosting classification models produced 91.3%, 85.4%, 90.2% and 87.8% accuracy respectively. For precision, HETNN, Logistic regression, K-Nearest Neighbour, Support Vector Machine, Random Forest and Boosting model produced, 97.6%, 92.6%, 97.5%, 87.6%, 91.3% and 86.1% respectively. For Recall performance, the models produced, 97.6%, 91.7%, 97.5%, 85.4%, 90.2% and 87.8% respectively. Their F1-score results show 97.5%, 95.1%, 97.4%, 80.5%, 88.6% and 86.0% respectively. Lastly, area under curve values show 91.7%, 75.5%, 87.5%, 57.1%, 76.8% and 63.6% respectively.

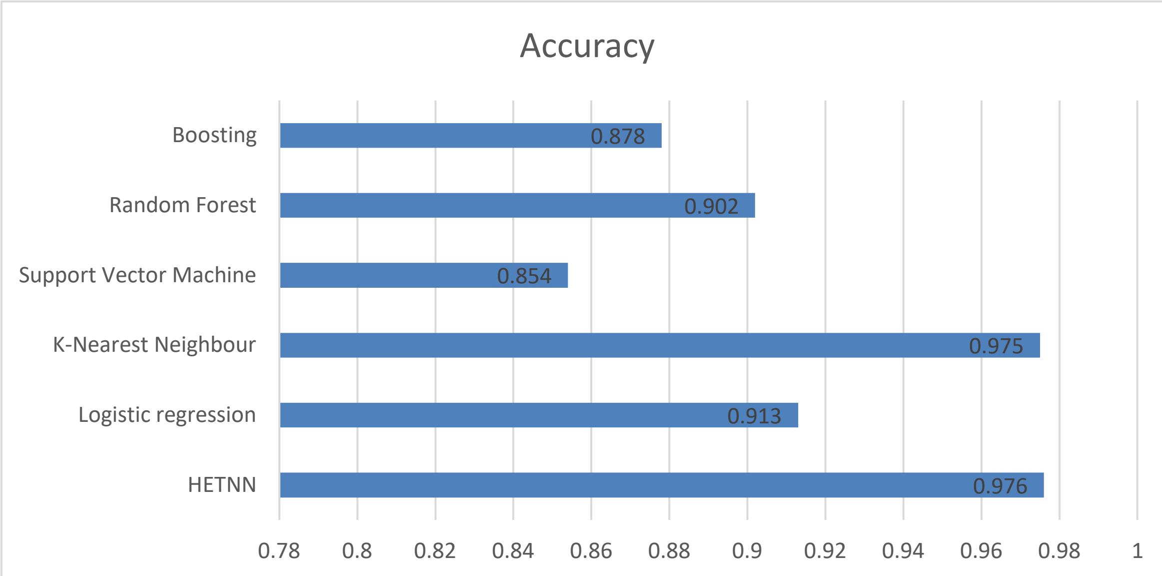

Fig 1: Accuracy of the models

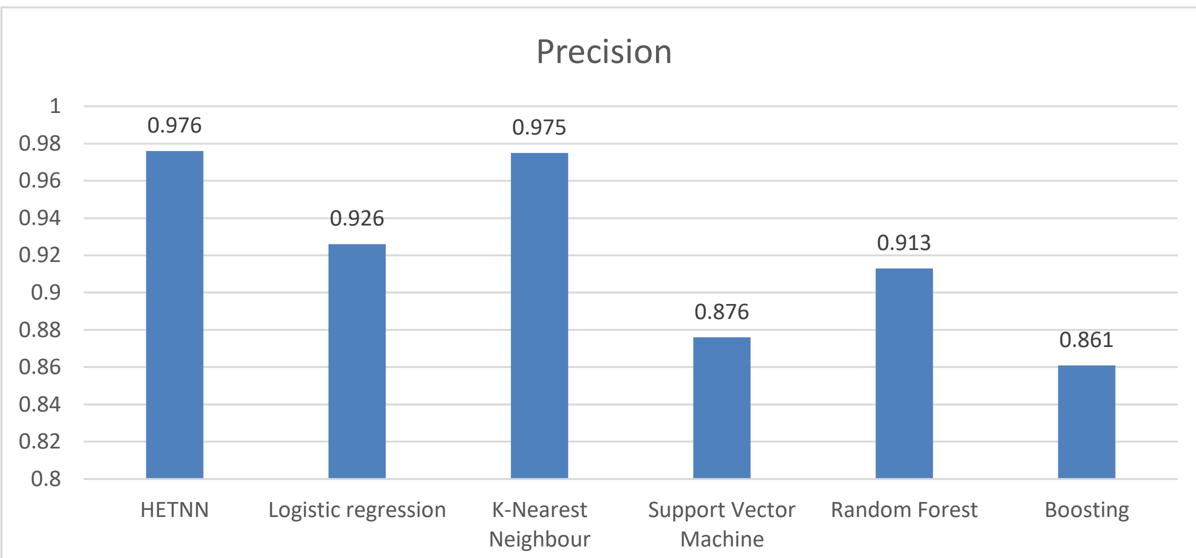

Fig 2: Precision of the models

Table 8: Feature Importance

	Relative Importance
Number of Perpetrators	62.320
Attack Type	17.852
Weapon Type	11.613
Target/Victim Type	8.215
State of the incident	0.000

Table 8 above shows the feature importance using Boosting classification models. It shows that, the Number of Perpetrators takes 62.320% determination on whether the terrorist attack will be successful or not.. Attack Type takes 17.852%, Weapon Type determines 11.613%, Target/Victim Type determines 8.215% and State of the incident determines zero percentage.

5.0 Conclusion

In this work, the machine learning models which are best in predicting the terrorist activities in Nigeria were determined. The study was able to deduce that, out of the six models considered, HETNN best predict the terrorist data followed by the K-Nearest Neighbour model. Also, we have been able to see that, in predicting the terrorist activities in Nigeria, the factors to be considered in order of importance are Number of Perpetrators, Attack Type, type of Weapon, the type of Victims targeted, and State of the incident. We believe that the information revealed in this research will help the government and the security agents in combating insecurity issues in the country and also help to guide and plan to reduce these insurgencies in the Nation.

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