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An intelligent pattern recognition model for assessment of terrorists' activities in Nigeria

Uduak David George *, Samuel Sunday Udoh and Okure Udo Obot

Department of Computer Science, University of Uyo, Nigeria.

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Abstract

Terrorism and its brutal tendencies constitute a major setback to the development process of the Nigerian economy leading to severe loss of lives, destruction of properties, and a decline of interest in investment by both local and foreign investors. Many models for assessment of terrorist's activities lack the ability of learning from previous patterns in order to guide pre-emptive actions against future occurrences, and there are no established regional pattern of weaponry, types of attack, as well as types of victims of terrorists' operations. This study seeks to build a robust intelligent model for recognizing several terrorists' patterns in each of the six geo-political zones of Nigeria. A data set of 5,503 instances of terrorists' activities in Nigeria was obtained and a pattern recognition model was built using Artificial Neural Networks (ANN) with 70%, 15%, and 15% data splits for training, validation, and testing respectively. A 10-10-6 ANN architecture was designed and trained using the scaled conjugate gradient backpropagation algorithm. The training was carried out using Matlab's neural network pattern recognition toolkit. In order to numerically represent categorical data, a sort-order scheme was developed by the authors and utilized. The results showed average percentage scores for accuracy, precision, recall and F1-score as 99.89, 99.96, 100 and 99.98 respectively. This showed acceptable performance. The developed model is therefore considered a robust one for recognition of terrorists' patterns in Nigeria. This would assist security agencies to deal with terrorists' incidences with high intelligent information and advanced preparation for prevention and control. The developed model is highly recommended for use by the security agencies in the country.

Keywords: Terrorism; Terrorists' pattern; Neural network; Pattern recognition; Cross-entropy; Geo-political zones

1. Introduction

In recent years, Nigeria has been subjected to almost uncontrollable spate of terrorists' activities that constitute serious setback to the development process of the Nigerian economy. This has led to severe loss of lives, destruction of properties, and a decline in investment opportunities both at local and foreign levels [1, 2]. Farm settlements and other business ventures have been dislodged and these have caused a spike in unemployment rate in the country. It is also noted that regional terrorism patterns have not been scientifically established as there is no pattern of weaponry per region, no pattern of types of attack per region, and no pattern of types of victims of terrorists' operations. The study of patterns of terrorism based on the geopolitical zones would provide significant insights into modes of operations, weapons used, and type of target. In a bid to emphasize the cruciality of study of regional terrorism, [3] presented global regional trends of impacts of terrorism, where it was revealed that seven of the nine global regions were greatly impacted in 2022. The report also stated that despite a 35% decline in the number of deaths between 2020 and 2022, Nigeria still faces a significant threat posed by armed extremist groups such as Boko Haram and ISWA. Although there have been some attempts by the government to curb the menace of terrorism, it seems to be a foul cry from what could be considered as victory over the crime. Terrorism is one of the most devastating crimes in the society. Very serious

* Corresponding author: Uduak David George

negative impacts have been imposed on Nigerian economy. Dibia [4] shows there is an 18.7% decrease in national development when there is a 1% increase in terrorism in Nigeria.

Terrorists run a very complicated network with peculiar modes of operation. Obviously, they engage in extensive planning activities as well as committing preliminary secondary crimes before the major terrorist act, hence it is needful for security agents to fight them by following their patterns of operations [2]. Several tactics of terrorists' operations exist which include bombing, kidnapping, assassination, armed attack, unarmed attack, and hostage taking. Grades of weapons include melee, firearms, and incendiary. Victim types include business, government, aircraft, and educational institutions [5].

There are patterns used for an attack varying from one group to another, and in effect, conferring the terrorist groups their distinctiveness. Nigeria, for some time now, has a fair share of acts of terrorism. The mode of operations of terrorists tends to be different from one geo-political zone to another, therefore making it necessary for the security agents to extend their intelligence gathering network to what happens in each of the six geo-political zones. This information can be useful in tackling the acts of terrorism and nib them at the bud before they are hatched. Data is very useful in this fight as vital information are hidden in them. Human beings might not be very efficient in discovering the hidden patterns and make sense of them as may be done by computers. Therefore, machine learning techniques are applied in the learning process with the data to discover the available hidden information. One of the machine learning tools to recognize hidden patterns is the ANN. Its capabilities include fault tolerance, using known information to infer some unknown information, learning from training data, recalling memorized information, and generalizing to the unseen patterns [6,5]. With enormous amount of data, NN can perform very well in prediction, pattern recognition and classification.

Nigeria is a country that is segmented into six geopolitical zones [7] for proper administrative control. Terrorists' activities occurring in the country at any time, definitely happen in one or more of the zones. Therefore, study of the patterns of terrorism based on the geopolitical zones would provide significant insights into modes of operations, weapons used, and type of target. The study therefore aims at building a robust intelligent model for recognizing several terrorists' patterns based on the six geo-political zones of Nigeria. This would assist security agencies to unravel potential patterns of operations of terrorists.

Pattern recognition is one of the promising research areas and several authors have carried out some studies on it. [8] proposed a pattern recognition system using neural networks. Kohonen Self-Organizing Map (SOP) (also known as Self-Organizing Feature Map (SOFM)) neural network was used to perform pattern recognize of human faces from the 400 images extracted from the AT&T database. The result showed a successful recognition of 40 persons at an accuracy of 85.5%. Prediction of terrorist activities using deep neural networks was proposed in [9]. Five models were used to understand the pattern of terrorist activities such as, the success or otherwise of an attack, the probability of being suicide attack, the type of weapon used, the attack type, and the region the attack will occur. The models were single-layer neural network (NN), five-layer Deep Neural Network (DNN), and three traditional machine learning algorithms, namely, logistic regression, support vector machine (SVM), and Naıve Bayes. The results demonstrated that deep neural networks (DNN) performed above 95% in accuracy, precision, recall, and F1-Score, while ANN, logistic regression, SVM, and Naïve Bayes achieved a maximum accuracy of 83%.

Li *et al.* [10] proposed a wavelet transform-based pattern recognition to predict terrorist group's behavior. The study designed a framework that hybridizes Social Network Analysis (SNA), wavelet transform, and the pattern recognition approach to investigate and predict the attack pattern of terrorist group. Data from the JJATT database was obtained. JJATT is a transnational terrorism database on a selection of radical Islamists, their associates, and case studies of their collective behavior. The behavior of the group is recognized based on the correlation between the network and behavior. The results indicated that the proposed framework obtained a very high accuracy.

Kaya and Algul [11] proposed the use of deep learning to predict potholes on highway. A deep learning algorithm, Yolo-v4, was used for the study. A dataset that consisted 681 highway images, 329 highway potholes images and 352 normal highway images, was used for the study. From the result, the potholes on the highway were detected with an accuracy of 87.5%. Chen *et al.* [12] proposed a failure pattern recognition of wafer map by the use of Deep Convolutional Neural Network (DCNN). The DCNN model for the research included the convolutional layer, batch normalization layer, Relu layer, maximum pooling layer, full connection layer, Softmax layer and classification layer. It was an end-to-end 19-layer network, which can actively learn and automatically extract effective classification features. The results of the model in the actual wafer map database WM-811K showed that the model exhibited good performance in identifying nine kinds of common failure patterns, where the dual-source DCNN structure had a better recognition accuracy than the single-source DCNN structure. Mirboda and Shoar [13] proposed a system that detects surface cracks using computer vision, pattern recognition, and Artificial Neural Networks (ANN). The research aimed at providing a reliable method for inspecting sensitive structures like bridges using an intelligent system consisting of a camera and intelligent software. The Utah State University image dataset that contains more than 56,000 images of cracked and non-cracked concrete bridge decks, walls, and pavements were used for experiment. The result indicated the ability of the proposed method to recognize cracking images from non-cracking images with accuracy of 84.88%.

Iwuoha and Onuoha [14] examined the current trends in Boko Haram's terrorism as well as counterintelligence and counterterrorism strategy of Nigeria military. Qualitative data collection and analysis method was adopted in the study. The outcome of the study was not impressive as the efforts by the military suffered great setbacks. The study revealed that the security forces did not utilize quantitative or scientific approach to the fight. Furthermore, [15] examined the trends and prospects of African security regionalism to figth against terrorism and para-terrorism. The work beamed its searchlight on the socio-spatial reasoning and the challenges of regional security mechanisms. The study revealed that the response to terrorism in Africa could move from the military hardware focus to adopt preventive measures since the former approach was saddled with serious challenges. The rest of the work are organized into material and methods, results and discussion, as well as conclusion.

2. Material and methods

System implementation follows some stages of development to arrive at the results. The stages are represented in the system architecture shown in Figure 1.

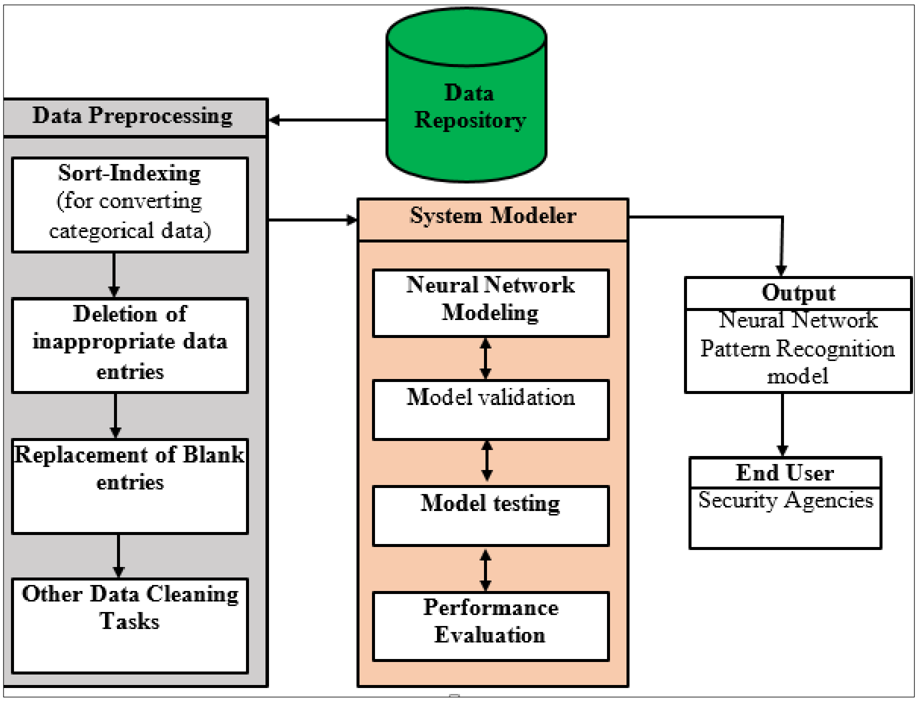

Figure 1 System Architecture

The system comprises four main modules, namely; Data Repository, Data Preprocessing, System Modeler, and Output. In the Data Repository, Nigeria terrorism incidents are acquired and stored in relevant databases. Data Preprocessing enables data cleaning processes such as categorical (non-textual) data conversion to numeric data since NN works primarily with numeric data. Other data cleaning activities include dealing with inconsistent data, blanks, outliers, duplicate data, and missing values. System Modeler module carries out the modelling process which performs training, validation and testing. Performance evaluation is also performed in the module, such that if the model performance is not satisfactory, the development process can be repeated with varied parameters. The Output module presents the developed model to the end users of the system, which are the security agencies.

2.1. Terrorists Dataset

The Global Terrorism Database hosted by the National Consortium for the Study of Terrorism and Responses to Terrorism (START), a Center of Excellence in the University of Maryland, provided the dataset which consists of 209,706 records on global terrorism incidents. However, for Nigeria's cases, five thousand five hundred and fifty (5,550) records were filtered out for the purpose of this research, covering a period of 45 years ranging from 1976 through 2020. The dataset is represented in comma-separated values (CSV) format presented in Table 1.

Table 1 Original Dataset

State	Multiple	Success	Suicide	Attack type	Weapon type	Number killed	Number wounded	Gpzone
Lagos	0	1	0	Assassination	Firearms	3	1	SOUTH-WEST
Kaduna	0	1	0	Unknown	Unknown			NORTH-WEST
Unknown	0	0	0	Assassination	Unknown	0	1	UNKNOWN
Lagos	0	1	0	Assassination	Unknown	1	0	SOUTH-WEST
Lagos	0	0	0	Assassination	Firearms	0	1	SOUTH-WEST
Lagos	0	1	0	Assassination	Firearms	1	0	SOUTH-WEST
Lagos	0	1	0	Assassination	Firearms	3	0	SOUTH-WEST
Katsina	0	1	0	Facility/Infrastruc-ture Attack	Incendiary	0	0	NORTH-WEST
Zamfara	0	1	0	Facility/Infrastruc-ture Attack	Incendiary	2	0	NORTH-WEST
Kano	0	1	0	Facility/Infrastruc-ture Attack	Firearms	8	34	NORTH-WEST
Katsina	0	1	0	Unarmed Assault	Melee	0	29	NORTH-WEST
Akwa Ibom	0	1	0	Armed Assault	Incendiary	80	0	SOUTH-SOUTH
Edo	0	1	0	Assassination	Firearms	1	0	SOUTH-SOUTH
Taraba	0	1	0	Bombing/Explosion	Firearms	20	0	NORTH-EAST
Lagos	0	1	0	Armed Assault	Incendiary	11	0	SOUTH-WEST
Ondo	0	1	0	Facility/Infrastructure Attack	Incendiary	0	0	SOUTH-WEST
Kaduna	0	1	0	Armed Assault	Firearms	10	0	NORTH-WEST
Kaduna	0	1	0	Armed Assault	Firearms	13	100	NORTH-WEST

Ten input parameters described in Table 2 constitute the dataset.

Table 2 Dataset Attribute Description

SN	Attributes	Data type	Status	Description
1	state	String	Input	The State in Nigeria where the incidence took place
2	multiple	Boolean	Input	The value 1 indicates that there were multiple terrorist attacks, and 0 indicates that there were no multiple attacks
3	success	Boolean	Input	Value 1 indicates that the attack was successful, 0 indicates a failed attack
4	suicide	Boolean	Input	Value 1 indicates that suicide attack tactic was deployed, 0 indicates that it was not a suicide attack
5	attacktype	String	Input	The type (tactic) of attack carried out
6	targettype	String	Input	The target of attack
7	terroristgroup	String	Input	Name of the terrorist group involved
8	weapontype	String	Input	The type of weapon used in the attack
9	numberkilled	Integer	Input	Number of persons killed
10	numberwounded	Integer	Input	Number of persons wounded
	gpzone	String	Target output	The geopolitical zone where the terrorist attack happened

2.2. Data Preprocessing

Preprocessing activities were carried out on the obtained dataset in order to have a clean data and present it in an appropriate form that would support neural network training. The attribute, "state", is very significant in the training and therefore 47 records labelled "Unknown" for the state of attack were deleted, while blank entries in all the attributes were replaced with "0". At the end of data cleaning, 5503 clean records were left.

2.3. Sort-Index Scheme for Representation of Categorical Data

Neural network trains best with numerical data. Some attributes that were categorical (non-numeric, or textual) needed a coding scheme to represent them in numeric form. Therefore, a Sort-Index (S-I) scheme was developed by the researchers, where the entries in a textual attribute were sorted in ascending order, and the corresponding numeric code was assigned to them according to the sort order. The algorithm for the Sort-Index scheme is given as follows:

2.3.1. Algorithm (Sort-Index);

Begin

For a list of **n** items within categorical entries; (where **n** is the total number of items in the list)
Sort the list ascending;
Assign corresponding numeric value to each sorted item as: 1,2,…,n-2,n-1,n ;

End

The output attribute, gpzone, representing the six geo-political zones in Nigeria, had its entries sorted alphabetically in ascending order and coded from 1 to 6. Each State belonging to a geo-political zone were also alphabetically sorted and coded as shown in Table 3.

Attacktype and weaptype attributes were sorted and coded as presented in Table 4.

Table 3 Geo-political Zones Coding Scheme Using Sort-Index (S-I)

Zone	**S-I**	**Zone**	**S-I**	**Zone**	**S-I**	**Zone**	**S-I**	**Zone**	**S-I**	**Zone**	**S-I**
North Central	1.0	North East	2.0	North West	3.0	South East	4.0	South South	5.0	South West	6.0
States		**States**		**States**		**States**		**States**		**States**	
Abuja	1.1	Adamawa	2.1	Jigawa	3.1	Abia	4.1	Akwa Ibom	5.1	Ekiti	6.1
Benue	1.2	Bauchi	2.2	Kaduna	3.2	Anambra	4.2	Bayelsa	5.2	Lagos	6.2
Kogi	1.3	Borno	2.3	Kano	3.3	Ebonyi	4.3	Cross River	5.3	Ogun	6.3
Kwara	1.4	Gombe	2.4	Katsina	3.4	Enugu	4.4	Delta	5.4	Ondo	6.4
Nasarawa	1.5	Taraba	2.5	Kebbi	3.5	Imo	4.5	Edo	5.5	Osun	6.5
Niger	1.6	Yobe	2.6	Sokoto	3.6			Rivers	5.6	Oyo	6.6
Plateau	1.7			Zamfara	3.7						

Table 4 Coding Scheme for attacktype and weapontype

Attack type	**S-I**	**Weapon type**	**S-I**
Armed Assault	1.0	Chemical	1.0
Assassination	2.0	Explosives	2.0
Bombing/Explosion	3.0	Firearms	3.0
Facility/Infrastructure Attack	4.0	Incendiary	4.0
Hijacking	5.0	Melee	5.0
Hostage taking (Barricade Incident)	6.0	Sabotage Equipment	6.0
Hostage taking (Kidnapping)	7.0	Unknown	7.0
Unarmed Assault	8.0		
Unknown	9.0		

The targettype attribute, representing name of targets attacked by terrorists, is represented as shown in Table 5 which shows a segment of the entries.

Table 5 Target Type Representation

Target Type	**S-I**
Airports & Aircraft	1.0
Business	2.0
Educational Institution	3.0
Government (Diplomatic)	4.0
Government (General)	5.0
Journalist & Media	6.0
Maritime	7.0

Military	8.0
NGO	9.0
Other	10.0
Police	11.0
Private Citizens & Property	12.0
⋮	⋮
Violent Political Party	19.0

Similarly, the terroristgroup attribute with its 73 entries is represented in Table 6, where a segment of the entries is shown.

Table 6 Terrorist Group Representation

Terrorist Group	**S-I**
Al-Qaida in the Islamic Maghreb (AQIM)	1.0
Al-Sunna wal Jamma	2.0
Ansaru (Jama'atu Ansarul Muslimina Fi Biladis Sudan)	3.0
Anti-Government Group	4.0
Association of Mobil Spill Affected Communities (AMSAC)	5.0
Atyap militia	6.0
Bachama extremists	7.0
Bassa Kwomu extremists	8.0
Berom Militants	9.0
Biafra Zionist Movement (BZM)	10.0
Bini-Oru	11.0
Boko Haram	12.0
⋮	⋮
Zimbabwe Patriotic Front	73.0

A sample of the preprocessed clean dataset is presented in Table 7, where gpzone is the target output while the remaining 10 data attributes are the inputs.

Table 7 Preprocessed Dataset

Sta -te	**Multi -ple**	**Succe -ss**	**Suici -de**	**Attackt -ype**	**Targetty -pe**	**Terroristgr -oup**	**Weaponty -pe**	**Numberkill -ed**	**Numberwoun -ded**	**Gpzon -e**
6.2	0	1	0	2	5	16	3	3	1	6
3.2	0	1	0	9	4	73	7	0	0	3
6.2	0	1	0	2	5	22	7	1	0	6
6.2	0	0	0	2	5	70	3	0	1	6
6.2	0	1	0	2	4	70	3	1	0	6
6.2	0	1	0	2	3	70	3	3	0	6
3.4	0	1	0	4	6	34	4	0	0	3

3.7	0	1	0	4	5	70	4	2	0	3
3.3	0	1	0	4	12	43	3	8	34	3
3.4	0	1	0	8	11	62	5	0	29	3
5.1	0	1	0	1	12	18	4	80	0	5
5.5	0	1	0	2	5	70	3	1	0	5
2.5	0	1	0	3	13	44	3	20	0	2
6.2	0	1	0	1	12	4	4	11	0	6
6.4	0	1	0	4	12	70	4	0	0	6
3.2	0	1	0	1	12	33	3	10	0	3
3.2	0	1	0	1	12	25	3	13	100	3
6.2	0	0	0	1	2	26	5	0	0	6
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

The output attribute, gpzone, has six pre-labeled classes which is very critical to the neural network pattern recognition training and needed to be sub-divided into six categories, with the entry 1 representing the appropriate target output as shown in Table 8.

Table 8 Geopolitical Zone Class Representation

Geopolitical Zone Pre-labeled Class	**Geopolitical Zone Class Representation**					
	1	**2**	**3**	**4**	**5**	**6**
gpzone1	1	0	0	0	0	0
gpzone2	0	1	0	0	0	0
gpzone3	0	0	1	0	0	0
gpzone4	0	0	0	1	0	0
gpzone5	0	0	0	0	1	0
gpzone6	0	0	0	0	0	1

where:

gpzone1 = North Central, gpzone2 = North East, gpzone3 = North West, gpzone4 = South East, gpzone5 = South South, and gpzone6 = South West.

The training process requires the input and output patterns to be presented in two separate files. The output file corresponding to respective input pattern is presented in Table 9.

Table 9 Target Output Pattern

gpzone1	**gpzone2**	**gpzone3**	**gpzone4**	**gpzone5**	**gpzone6**
0	0	0	0	0	1
0	0	1	0	0	0
0	0	0	0	0	1
0	0	0	0	0	1
0	0	0	0	0	1
0	0	0	0	0	1

0	0	1	0	0	0
0	0	1	0	0	0
0	0	1	0	0	0
0	0	1	0	0	0
0	0	0	0	1	0
0	0	0	0	1	0
0	1	0	0	0	0
0	0	0	0	0	1
0	0	0	0	0	1
0	0	1	0	0	0
0	0	1	0	0	0
0	0	0	0	0	1
0	0	0	0	0	1
0	0	0	0	0	1
0	0	0	0	1	0
0	0	0	0	1	0
0	0	0	0	0	1

2.4. Neural Network Architecture

Neural Network (NN) is a supervized learning tool used to perform very interesting tasks. The input file, gpzInp, consisting of 5503 instances with 10 input attributes as well as the output file, gpzOut, consisting of 5503 instances with 6 output patterns representing the geopolitical zones of Nigeria were supplied to the network. The network adopted a 10-10-6 architecture comprising 10 neurons at the input layer, 10 neurons at the hidden processing layer, and 6 neurons at the output layer, shown in Figure 2.

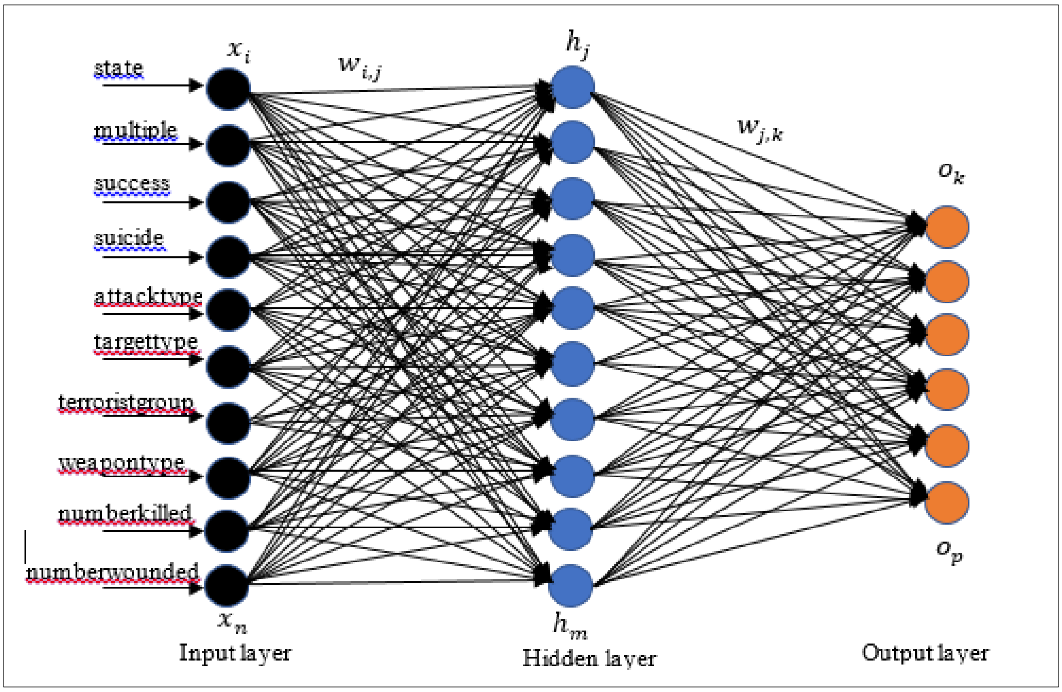

Figure 2 Neural Network Pattern Recognition Architecture

The architecture consists of the input layer, x_i: $i = 1,2,\dots,n$, hidden processing layer, h_j: $j = 1,2,\dots,m$, and output layer, o_k: $k = 1,2,\dots,p$, where $n = 10$, $m = 10$, and $p = 6$. The sum of product of each input value and the weight of connection between input and hidden layer constitute the value transmitted to the respective hidden layer node given as:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} w_{i,j}x_i = h_j \dots .(1)$$

Similarly, the sum of product of each hidden layer value and the weight of connection between the hidden layer and output layer constitute the value transmitted to the respective output layer node given as:

$$\sum_{j=1}^{m}\sum_{k=1}^{p} w_{j,k}h_j = o_p \dots \dots (2)$$

Therefore, each of the six output patterns generated for the geo-political zones by the network took the following forms:

$$o_1 = 1\ 0\ 0\ 0\ 0\ 0$$

$$o_2 = 0\ 1\ 0\ 0\ 0\ 0$$

$$o_3 = 0\ 0\ 1\ 0\ 0\ 0$$

$$o_4 = 0\ 0\ 0\ 1\ 0\ 0$$

$$o_5 = 0\ 0\ 0\ 0\ 1\ 0$$

$$o_6 = 0\ 0\ 0\ 0\ 0\ 1$$

2.5. Neural Network Training Process

Prior to training, the dataset was randomly split into training (70%) consisting of 3853 instances, validation (15%) consisting of 825 instances, and testing (15%) consisting of 825 instances. The research adopted the scaled conjugate gradient backpropagation as the training algorithm. A two-layer feed forward neural network was designed with sigmoid activation function at the hidden layer and softmax activation function at the output layer. Pattern recognition training was carried out using Matlab R2015a software. The command, *nnstart* was entered at the Matlab command prompt to activate the Pattern Recognition App. This helped to select data, create, and train a network, then evaluate network performance using cross-entropy and confusion matrices.

3. Results and discussion

The neural network pattern recognition process was performed and training was stopped when the minimum gradient of $5.7\text{x}10^{-07}$ was reached, and the best validation performance (entropy) of $2.26\text{x}10^{-07}$ using cross entropy measure was obtained each at epoch 102, shown in Figure 3 and Figure 4 respectively.

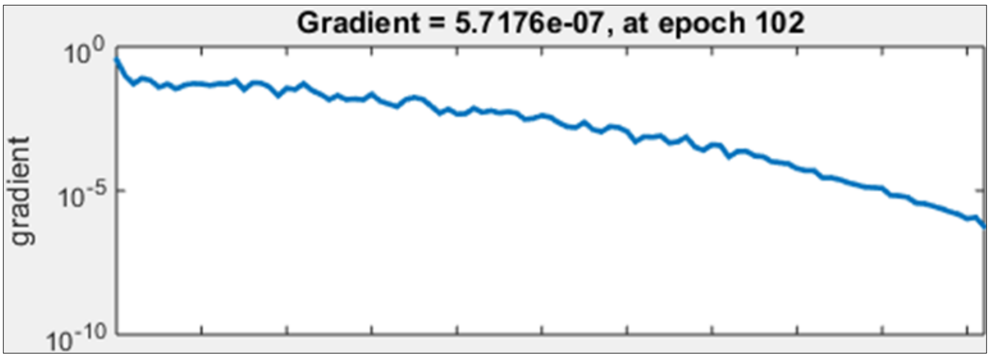

Figure 3 Best Gradient Check at Epoch 102

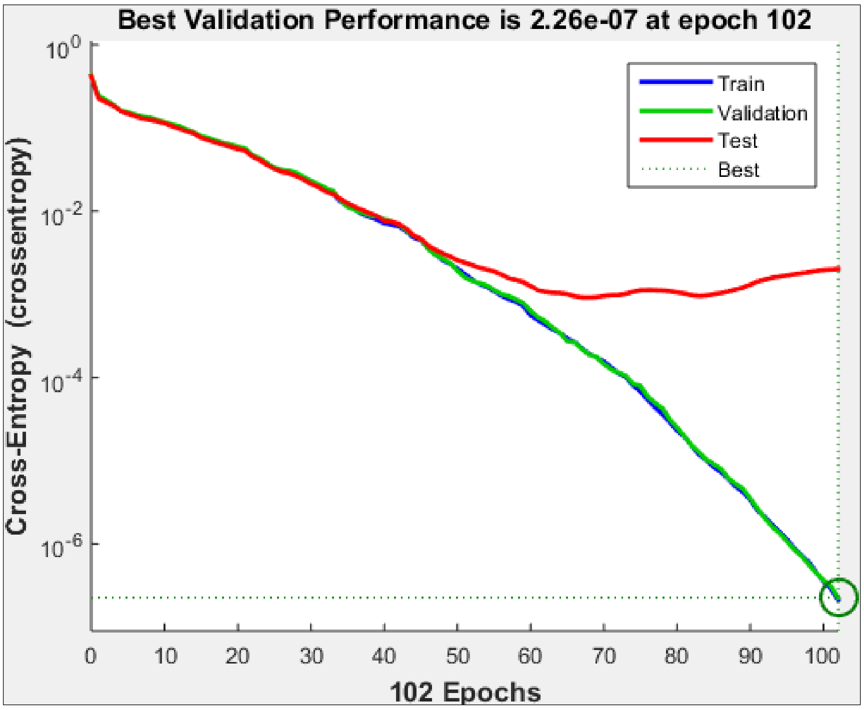

Figure 4 Best Validation Performance Using Cross Entropy at Epoch 102

A multi-pattern confusion matrix comprising six output patterns of the data pattern was generated as shown in Figure 5. Confusion matrix is a time-tested measure for determining the predictive performance of classification, prediction, or machine learning models. It is therefore a structured means of mapping the predictions to the original classes to which the data belong and assists in the calculation of accuracy, precision, recall, specificity and F1-score measures of a trained model. The confusion matrix also helps to compute other important metrics such as micro F1-score, macro F1-score, and weighted F1-score, which developers often use to evaluate their models.

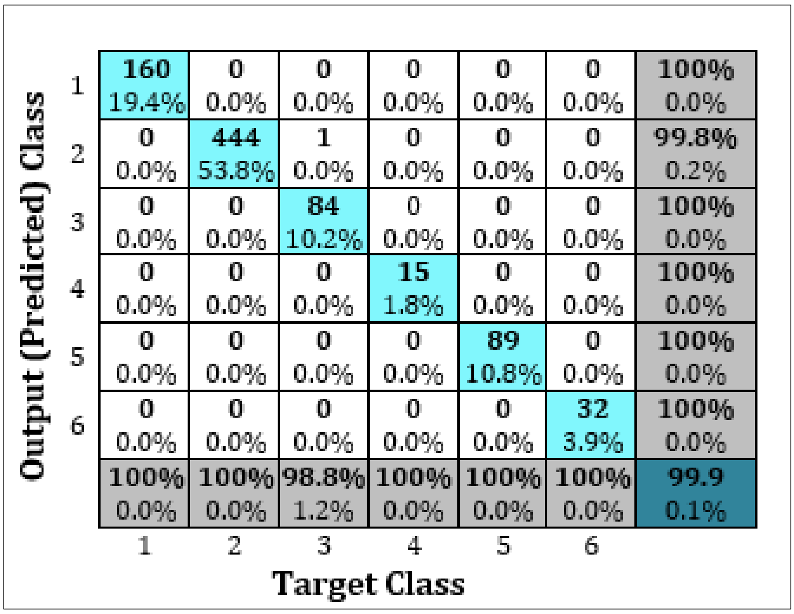

Figure 5 Multi-Class Confusion Matrix

To help in calculating pattern-wise measures such as accuracy, recall, precision, and F1-score, the multi-pattern confusion matrix was converted to a one-vs-all type matrix obtained for binary-pattern confusion matrix [16]. Conversion of the multi-pattern matrices for each of the patterns are shown in Figure 6.

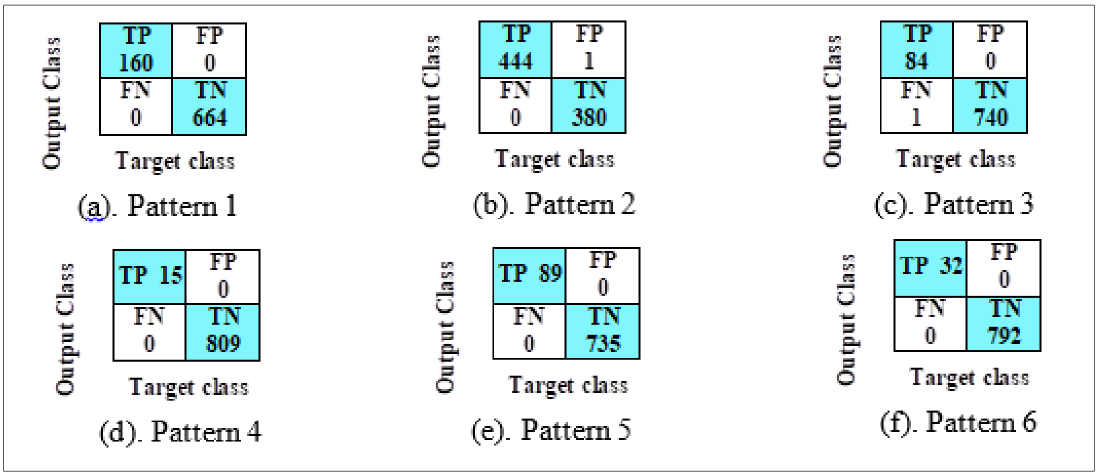

Figure 6 Converted Confusion Matrices

Model evaluation measures from the converted confusion matrices with their formulas defined in [17, 18] are shown in Table 10. Note that the F1-score can also be calculated as $\frac{2*TP}{2*TP+TP+TN}$.

Table 10 Evaluation Measures

Patterns	Accuracy $(\frac{TP+TN}{TP+FP+TN+FN} * 100)$	Precision $(\frac{TP}{TP+FP} * 100)$	Recall $(\frac{TP}{TP+FN} * 100)$	F1-Score $(\frac{2*Precision*Recall}{Precision+Recall} * 100)$
Pattern 1	100.00	100.00	100.00	100.00
Pattern 2	99.31	99.78	100.00	99.89
Pattern 3	100.00	100.00	100.00	100.00
Pattern 4	100.00	100.00	100.00	100.00
Pattern 5	100.00	100.00	100.00	100.00
Pattern 6	100.00	100.00	100.00	100.00
Average	99.89	99.96	100.00	99.98

The table clearly shows the testing of the model with similar data set that has never been presented to it before. It accurately recognizes all the 160 patterns for geo-political zone 1 (North Central), all the 84 patterns for geo-political zone 3 (North West), all the 15 patterns for geo-political zone 4 (South East), all the 89 patterns for geo-political zone 5 (South South), and all the 32 patterns for geo-political zone 6 (South West). The model however wrongly recognized one instance of geo-political zone 2 (North East) to be that of geo-political zone 3 (North West), resulting in accuracy of 99.31%, precision of 99.78% and F1-score of 99.89%.

The intelligent pattern recognition model for terrorism assessment performs outstandingly well with the presented data set of terrorism. A 100% pattern recognition was achieved during model testing for patterns 1, 3, 4, 5, and 6. It has however miss-recognized an instance of Pattern 2. Average percentage scores for accuracy, precision, recall and F1-score were obtained as 99.89, 99.96, 100 and 99.98 respectively. This showed acceptable performance.

The Receiver Operating Characteristic (ROC) curves, which are a plot of True Positive Rate (TPR) against False Positive Rate (FPR) are shown in Figure 7 (a) for training process and Figure 7 (b) for testing process.

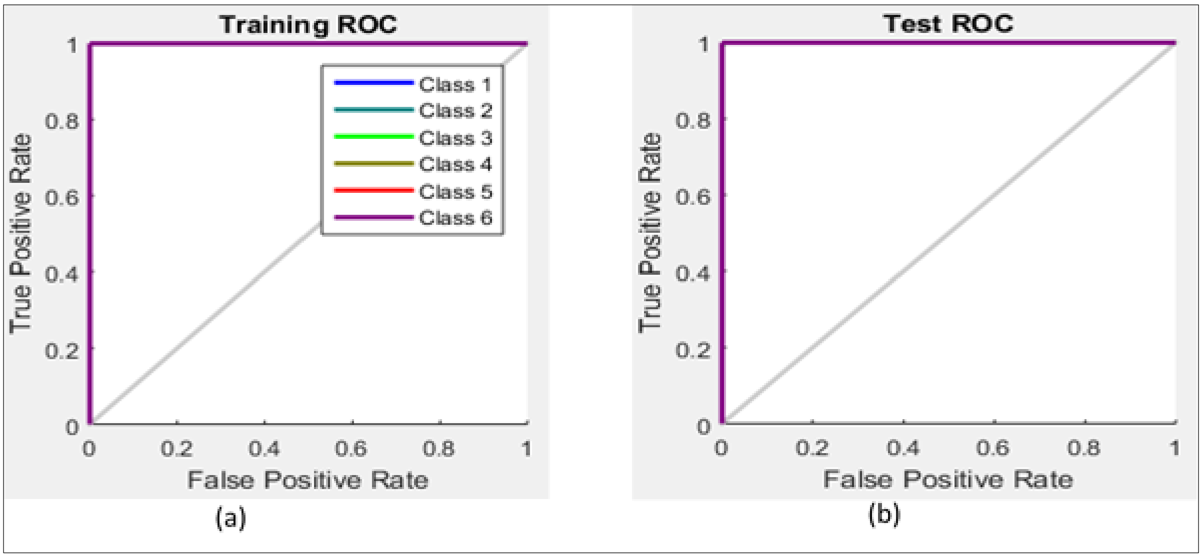

Figure 7 ROC Curves

The curves indicate a very impressive model for recognition of terrorists' attack patterns as both the training and testing curves for the six different geopolitical patterns are all approximately 100% of the true positive rate axes.

4. Conclusion and Recommendations

The menace of terrorism in Nigeria has resulted in severe loss of lives, properties, and investment opportunities. The aim of building a robust intelligent model for recognition of terrorist patterns was achieved, where a data set of terrorist activities in Nigeria was used for building a NN pattern recognition model with 70%, 15%, and 15% splits for training, validation, and testing respectively. A 10-10-6 NN architecture consisting of ten neurons at the input layer, ten neurons at the single hidden layer, and six neurons at the output layer was designed and trained using the scaled conjugate gradient backpropagation as the training algorithm. The six outputs of the network represented each of the geo-political zones in Nigeria.

It is clearly demonstrated that five patterns were perfectly recognized. Only geo-political zone 2 (North East) pattern was mis-recognized to be that of geo-political zone 3 (North West), resulting in average accuracy of 99.89%. The developed model is therefore considered a robust one for recognition of terrorist patterns in Nigeria. This would assist security agencies to deal with terrorist incidences with high intelligent information and advanced preparation vital for counterterrorism activities.

Therefore, the model developed in this research is highly recommended for use by the security agencies in the country. For further studies, this work can be extended by using other well-known machine learning tools in recognizing terrorists' patterns to provide the platform for comparative study.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest among the authors regarding this publication.

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