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Predictive Modelling of Crime Data using Machine Learning Models: A Case Study of Oyo State, Nigeria

Afolabi O. Adedamola[1]; Tayo P. Ogundunmade[2*]

[1] Department of Mathematics and Statistics, Polytechnic of Ibadan, Nigeria
[2*] Department of Statistics, University of Ibadan, Nigeria

Corresponding Author: Tayo P. Ogundunmade[2*]

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Abstract: Nigeria's criminal scene is characterized by violence, terrorism, alienation of citizens, and political instability. The Global Peace Index has listed Nigeria as one of the nations with the least amount of peace in the globe as of late. It is the nineteenth least tranquil condition. Nigeria is also ranked as the ninth most terrorist-affected country in the world by the Global Terrorism Index. The potential for genocide, or mass murder, is another grave hazard facing Nigeria. Nigeria was the fifth-highest risk country in Africa and the twelfth-highest risk country globally as of the end of 2023. As a result, it is necessary to analyze Nigeria's crime data and create suitable modeling for projections in the future. This work examines the various crime data between 2013 to 2023 as reported by the Nigeria Police Force in Oyo State. Murder, rape, indecent assault, armed robbery, theft, burglary, assault, and kidnapping are crimes considered. To examine the connections between crimes and ascertain their distributions, correlation analysis was employed. In the thirty-three (33) local government areas of Oyo State, big crimes are predicted using machine learning techniques including Autoregressive Integrated Moving Average (ARIMA), Autoregressive Fractional Integrated Moving Average (ARFIMA), and Long Sensory Term Memory (LSTM) models. The result shows that, LSTM produced better performance in modelling crime data compared to ARIMA and ARFIMA models with lowest AIC values. Through this approach, the government and security services would be able to plan appropriately for the likelihood of future crimes in Oyo State.

Keywords: *Crime Modelling, Terrorism, Armed Robbery, Time Series Forecasting, Predictive Modelling.*

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I. INTRODUCTION

According to the National Bureau of Statistics (NBS), there were an expected 51.887 million crime incidences in Nigerian households in 2024. According to the Crime Experience and Security Perception Survey (CESPS), the Southeast had the fewest incidences, while the North-West had the most. Additionally, it was discovered that rural areas were more impacted than metropolitan ones. The Africa organized Crime Index 2023 has ranked Nigeria second, the report says criminality across Africa has steadily increased and shows no sign of slowing down (Geroge, *et al* 2022). Crime is an act that brings offences and it is punishable under the law, its consequences extend beyond individual victims, negatively impacting society, communities, and state at large. Debts, arson, assaults, treason, sedition, kidnapping, smuggling, immigration, theft, robbery, armed robbery, offences against Indian hemp, contempt of court offences, unlawful possession of firearms, offences against Native law and customs, unlawful possession of property, economic sabotage, human trafficking, criminal lunatic, cultist/ritual, breach of peace, and other offences are examples of offences that result in conviction.

Nigeria's crime rate is among the highest in the world. Rich Nigerians reside in high-security compounds, murder frequently occurs alongside petty break-ins, and police in certain states have the authority to apprehend violent offenders upon sight (Kpedekpo and Arya, 1981).

Particularly in Lagos and other metropolitan areas marked by rapid expansion and change, serious crime increased to almost epidemic proportions in the 1980s (Louis et al, 1981). According to crime statistics, there were 134,663 reported offenses in 2017. With 50.975 instances (37.0%), Lagos State has the largest percentage of all cases reported. With 12,408 (9.2%) and 7,150 (5.3%) cases reported, respectively, Abia and Delta State came in second and third (Rencher, 2002).

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The police in Nigeria classify crimes according to the laws that are prescribed. Crimes are divided into the following categories: crimes against people (such as manslaughter, murder, attempted murder, assault, rape, child theft, and serious injury and wounding), crimes involving property (such as armed robbery, retail and home invasions, theft, etc.), crimes against legitimate authority (such as currency note fraud, gambling, disturbances of the peace, bribery, and corruption), violations of local laws (such as infractions involving alcohol or transportation).

The nature of crimes varies significantly across different states. Since 2003, certain crimes have become distinctive to specific regions. For example, the Northern part of Nigeria, encompassing states like Borno, Adamawa, Kano, and Yobe, has experienced incidents of bombing, terrorism, suicide bombing, religious wars, and killings, as well as vandalism. On the other hand, the Niger-Delta region grapples with prevalent crimes such as kidnapping, pipeline vandalism, armed robbery, and oil theft. Further diversification is observed in the South-West and Eastern parts of Nigeria, where ritual killings, theft, kidnapping, assaults, wounding, and armed robbery are reported with alarming frequency. (Richard and Dean, 2001). The crime statistics of Oyo State in 2017 for offences was 1,058, offences against properties were 1,865 and against lawful authority was 47 bringing to a total of 2,969 (National Bureau of Statistics). The variations in criminal patterns necessitate targeted and context-specific approaches to address the root causes and mitigate the impact of these crimes on individuals and society. To lessen the threat of crime in Oyo state, numerous preventative and regulating measures have been implemented and are currently being implemented. However, a number of intricate issues plagued crime prevention and control. An offender faces a variety of alternative forms of displacement when their opportunity to commit a crime is denied (Maritz, 2010). This work explores the use of machine learning to characterize and predict crime pattern in Oyo State.

The economic landscape of Nigeria plays a crucial role in the proliferation of criminal activities. Danbazau (2017) identifies the degradation of Nigeria's economy as a significant determinant of the high rate of crime occurrences. Most citizens perceive theft, armed robbery, stealing, and rituals as viable solutions to their economic and social status problems, as reported in the Nigeria Police Report of November 2017. The escalating urban crime rate in Nigeria emerges as a major social problem, inhibiting economic growth, political and social progress, and contributing significantly to underdevelopment. According to Nossiter (2011), criminal activity deters both domestic and foreign investment, lowers the standard of living for states and residents, and threatens democracy, the rule of law, and the nation's capacity to advance peace and sustainable development.

The economic implications of crime to every state cannot be overemphasized. The perception of major crimes as solutions to economic and social status problems, as reported in the Nigeria Police Report of November 2017, poses significant challenges to the socio-economic fabric of Oyo state. Therefore, understanding these challenges is essential for formulating targeted interventions that can address the root causes and mitigate the impact of crime on the state's overall development. The aim of the research is to analyze the crime data reported between 2010 to 2023 in the thirty-three local Government Area of Oyo State using Machine Learning

II. LITERATURE REVIEW

Ahmed (2022) investigated the causes of insecurity and crime rate in Niger State, Nigeria, utilizing Principal Component Analysis (PCA). The research aimed to evaluate the factors contributing to insecurity, and the PCA analysis revealed three principal components Population, Population Density, and Sex Ratio accounting for 76.74% of the total variation in the data.

The multivariate study of some GDP variables and crime statistics in Nigeria was examined by Eze-Emmanuel et al. (2022). The study used multivariate Principal Components Analysis (PCA) and component analysis techniques to examine quarterly Nigerian Gross Domestic Product data from 1981Q1 to 2019Q1 and annual crime data from 2012 to 2020. Crop production, livestock, and forestry were found to be three significant economic variables that explained a significant amount of variance. When the sample size was large, seven crime figures variables—homicide, offenses against morality, other offenses against persons, robbery, breakings, theft of stock, and stealing accounted for a significant amount of variance, while when the sample size was small, four variables homicide, other offenses against persons, breakings, and stealing—accounted for a significant amount of variance.

Boungou and Yatie (2022) determined crime patterns in Kaduna State using Principal Component Analysis and Multidimensional Scaling. The researchers utilized secondary data collected from the 23 Divisional Police Headquarters (DPHs) covering all 23 Local Government Areas (LGA) within Kaduna State. Employing multivariate techniques, the study revealed that three components were retained, collectively explaining about 85% of the total variability in the data. The first, second, and third Principal Components individually accounted for 42.4%, 25.5%, and 16.9% of the total variability in the data, respectively.

An examination of Nigeria's crime statistics on eight significant offenses that were reported to the police in 2017 was carried out by Atanu (2019). Robbery, theft, housebreaking, serious hurt and injuring, murder, rape, and assault were among the offenses that were investigated. Principal Component Analysis (PCA) was the analytical method used in the study, and a correlation matrix was specifically used to clarify the connections between the various offenses. Armed robbery, theft, and grievous harm and wounding were found to be significantly correlated. According to the report, crime rates vary by state, with Lagos state having the highest overall crime rate in the nation and Kebbi state having the lowest. Certain states were found to have higher rates of particular crimes, like as armed robbery

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in Rivers state, kidnapping and assault in Abia state, rape, murder, severe hurt and wounding, housebreaking, and theft in Lagos state. The PCA results suggested keeping two components, which accounted for about 85.166 percent of the dataset's overall variability.

In their work titled the application of Principal Component Analysis to Crime Data, Case work: Mathare Slums, Nairobi County in Kenya, Arfaoui and Naoui (2022) looked at the reasons behind crimes in Mathare eslums, Nairobi County, Kenya. The study made use of information gathered in April 2018 via questionnaires. Principal Component Analysis (PCA) was used to lower the dimensionality of the datasets, and correlation analysis was used to investigate relationships between various crime causes. There is a reasonably high positive correlation between unemployment and drug and substance usage, according to the correlation analysis. According to the PCA analysis, three Principal Components drug and substance abuse, unemployment, and parental neglect—account for roughly 52.6% of the variation in the causes of crimes against individuals. Furthermore, it was proposed to keep two Principal Components that account for approximately 42.2% of the overall variation in the causes of crimes against property: drugs and substance misuse and unemployment. A case study of Ekiti and Osun State was used by Markoulis (2022) to examine the Principal Component Analysis of Nigeria's Crime Rate. The study's statistical analysis determined that the following crimes are frequently perpetrated in Ekiti State: stealing, stealing, causing severe hurt, breaking into a house, assault, and occult harm. Arson, assault, armed robbery, receiving stolen property, house breaking, and severe hurt and wounding were found to be the most frequent and serious crimes in Osun State. To lessen the complexity of the crime rate data, the researchers used Principal Component Analysis (PCA). About 82.14% of the overall variation in crime rates for both Ekiti and Osun States could be explained by the first five principle components, according to the PCA results.

Using correlation analysis and principal component analysis (PCA) to ascertain the relationships between various crimes and their distribution across the three Area Councils under the Gwagwalada Area Command, Song et al. (2017) examined the Principal Component Analysis of crime data in Gwagwalada Area Command, Abuja, concentrating on the averages of twenty major crimes reported to the police between 1995 and 2014. The result showed correlation among various crimes, including robbery and rape, grievous hurt and wound (GHW), theft, assault, murder, and unlawful escape. According to the data, the Area Command's highest overall crime rate is found in the Gwagwalada Area Council. Furthermore, it was found that rape was more common in Kwali Area Council, whereas illegal possession and escape were more common in Kuje Area Council.

Principal Component Analysis (PCA) was used by Adegbola and Okunloye (2022) to analyze the distribution of crimes in Oyo State, Nigeria. There were eighteen significant crimes that were reported to the police, including robbery, kidnapping, house and store breakings, theft, serious hurt and wounding, murder, rape, and assault. The study included crime statistics from 1996 to 2014. Principal Component Analysis (PCA) and correlation analysis were used to investigate the connections between various crimes and ascertain how they were distributed throughout the state. In Oyo State, theft/theft was the most common crime, with assaults ranking high among other offenses. Six components were recommended for retention by the PCA analysis, which explained roughly 83.79 percent of the dataset's overall variability. In their study, Uddin et al. (2014) used a stratified multistage random selection process in conjunction with a face-to-face personal interview method. The spatial distribution of criminal victimization in the 11 Local Government Areas of the Kastina Senatorial Zone was examined using Principal Component Analysis (PCA). They discovered that Rimi has the lowest average victimization in the zone, while Batsari has the greatest total average victimization.

A case study of Katsina State was conducted by Omenma et al. (2020) to examine the use of Principal Component Analysis in the analysis of crime data. The averages of eight major crimes—robbery, auto theft, home and store breakings, theft, grievous hurt and wounding, murder, rape, and assault—that were reported to the police between 2006 and 2008 were the subject of the study. To ascertain the correlations between these crimes and their distribution throughout the state's local government areas, the study used Principal Component Analysis (PCA) and correlation analysis. Four components were recommended for retention by the PCA analysis, which explained roughly 78.94 percent of the dataset's overall variability. George et al. (2012) used Principal Component Analysis (PCA) to study the crime rate in Sokoto State. Seven variables that were acquired from the Sokoto State Police Headquarters' Criminal Investigation Department in Sokoto were the main focus of the study. The PCA technique was used in the analysis, and NCSS and GESS 2007 software were used to analyze the data. Based on the Scree and Loading plots, the results showed that three principal components were kept. This suggests that in Sokoto State, crimes against people and crimes against property are related.

III. MATERIAL AND METHODS

➢ *Data*

The 33 local governments of Oyo state were included in this study. The crime statistics for Oyo State's 33 Local Government Areas (LGAs) from 2010 to 2023. The information was formally gathered from the Nigeria Police Force's Oyo State Command's Statistics (F) Department records. The 33 LGAs were divided into groups based on the current Area Commands for the purpose of simple statistical analysis and interpretation. The information includes important offenses that were reported to the police between 2013 and 2023.

➢ *Machine Learning Models*

Since our data set has high level of dimensionality, we utilize the PCA as input features for our ML models;

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- *ARIMA*

An ARIMA model is characterized by three parameters: (p, d, q), where:

p is the order of the autoregressive part (AR),

d is the degree of differencing (I),

q is the order of the moving average part (MA)

Thus, the general ARIMA model is given by:

$$(1-\emptyset_1 B-\emptyset_2 B^2-\cdots-\emptyset_p B^p)(1-B)^d Y_t$$
$$=\in_t+(\theta_1 B+\theta_1\ B^2+\cdots+\theta_1 B^p)\in_t$$

Where:

B is the backshift operator, such that $B^k\ Y_t=Y_{t-k,}$

ϵ_t is the white noise error term.

The relationship between the present value of the series Y_t and previous values, prior errors, and differenced values is expressed by this equation (Ogundunamde *et al*, 2025).

- *Autoregressive fractional Integrated Moving Average (ARFIMA)Model.*

An ARFIMA model is defined as an ARIMA (p, d, q) model in which the difference parameter is limited to a fractional value, for example, (0 < d < 0.5).

$$\boldsymbol{\alpha}\ (\boldsymbol{L})\Delta^d \boldsymbol{x}_t\ =\boldsymbol{\varpi}+\boldsymbol{\beta}(\boldsymbol{L})\in_t$$

L

xL

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WhereΔ^d =$(1-L)^d$, $\alpha\ (L)$ *and* $\beta(L)$are p-and q-order lag polynomials respectively. $\in_t$ is a white noise,$corr(\in_{t,}\in_s)=0$,t≠ s and $E[\in_t]=\mu$.The stochastic process x_t is both stationary and invertible if all roots of $\alpha\ (L)$ *and* $\beta(L)$ lie outside the unit circle and $|d|<$ 0.5.When $d_\in$ (-0.5,0.5) and d≠ 0, then ACF of ARFIMA process decays hyperbolically to zero as $i\to\infty$. This decay rate is significantly slower than the exponential decay of a stationary ARMA process (i.e., d=0).

- *Long Short-Term Memory (LSTM)*

Dependency relationships that persist are frequently difficult for traditional recurrent neural networks (RNNs) to represent because of problems including vanishing or expanding gradients during training (Ayansola *et al*, 2022). To address this challenge, the Long Short-Term Memory (LSTM) network was introduced, featuring a more advanced architecture that maintains long-term memory and allows for controlled forgetting and updating of information as necessary.

LSTM networks incorporate gates to regulate the flow of data:

- ✓ *Forget gate*: Chooses which data from the cell state should be removed.
- ✓ *Input gate*: Updates the cell state by adding fresh data.
- ✓ *Output gate*: Uses the current cell state to determine the subsequent concealed state.

The equations for LSTM are as follows:

$$\left.\begin{aligned}
f_t &= \sigma(W_f x_t+U_f h_{t-1}+b_f)\\
i_t &= \sigma(W_i x_t+U_i h_{t-1}+b_i)\\
\check{C}_t &= \tanh(W_C x_t+U_C h_{t-1}+b_C)\\
C_t &= f_t C_{t-1}+i_t\check{C}_t\\
o_t &= \sigma(W_o x_t+U_o h_{t-1}+b_o)\\
h_t &= o_t\tanh C_t
\end{aligned}\right\}$$

Where:

f_t, i_t, o_t are the forget, input, and output gates,

σ is the sigmoid activation function,

tanh is the hyperbolic tangent function,

C_t is the cell state at time t,

$\check{C}_t$ is the candidate cell state.

LSTM models excel at capturing long-term dependencies in crime data, rendering them a powerful tool for crime data.

IV. RESULTS AND DISCUSSION

This chapter analyzes crime cases reported from January 2019 to December 2023 for murder, rape and indecent assault, armed robbery, theft/stealing, burglary, assault and kidnapping. The analysis uses two-time series models: ARIMA, ARFIMA and LSTM. First, exploratory data analysis is conducted, including descriptive statistics, time plots, and stationarity tests using Augmented Dickey-Fuller test. Next, the Correlation analysis used to analyse the relationship between crimes and determine their distributions. Machine Learning procedures such as ARIMA, ARFIMA and LSTM were used to predict major crimes in the thirty-three (33) local government areas of Oyo State and the results are presented. Finally, the chapter concludes with forecasts generated from the models.

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➢ *Exploratory Data Analysis*

This section presents an overview of the crime data, including summary statistics and visualizations. We provide descriptive statistics for armed robbery, pick pockets, shoplifting, fraudster, auto theft, house breaking, theft/stealing, grievous hurt, murder, rape and assault to illustrate the patterns in the data over time.

- *Descriptive Statistics*

The descriptive statistics for the factors this study looked at murder, rape and indecent assault, armed robbery, theft, burglary, assault, and kidnapping are summarized in Table 1 below. The mean, standard deviation, minimum, maximum, skewness, and kurtosis are among the important metrics shown in the table.

Table 1 Descriptive Statistics

Descriptive	Murder	Rape & Indecent Assault	Armed Robbery	Theft/ Stealing	Burglary	Assault	Kidnapping
Mean	42.1	94.2	71.3	1061.5	170	478.4	26.2
Standard Error	2.85	3.40	2.95	20.52	7.59	37.32	2.67
Median	43	94.5	73	1062.5	165	458	26.5
Standard Deviation	9.03	10.77	9.33	64.89	24.00	118.03	8.46
Sample Variance	81.65	116.17	87.12	4211.16	576.22	13932.71	71.73
Kurtosis	-1.25	-0.61	-0.75	-1.48	1.17	-0.63	-0.49
Skewness	-0.34	-0.10	-0.14	-0.05	0.98	0.51	-0.03
Range	25	34	29	180	83	355	28
Minimum	28	76	57	970	138	310	12
Maximum	53	110	86	1150	221	665	40
Sum	421	942	713	10615	1700	4784	262
Count	10	10	10	10	10	10	10

The findings of the descriptive statistics for the crime data are displayed in Table 1 above. According to the table, there are 60 observations in the data set for burglary, with a range value of 153. The mean is 61.83, with the lowest and greatest values being 17 and 170, respectively. The variance is 674.21 and the standard deviation is 25.97. A somewhat skewed and peaked distribution is indicated by the skewness and kurtosis values of 1.05 and 3.73, respectively. The table displays 60 observations for Breach of Public Peace, with a range value of 1460. The mean is 557.92, with the lowest and greatest values being 58 and 1518, respectively. The variance is 151482.9 and the standard deviation is 389.21. A moderately skewed and comparatively flat distribution is indicated by the skewness and kurtosis values of 1.26 and 0.47, respectively. The table displays 60 observations for thefts and various forms of theft, with a range value of 1533. The mean is 821.9, with the lowest and maximum values being 39 and 1572, respectively. The variance is 88557.58, and the standard deviation is 297.59. The distribution is comparatively flat and symmetrical, as indicated by the skewness and kurtosis values of -0.30 and 0.72, respectively.

- *Correlation*

This section examines the relationships between the three variables, revealing the extent of correlation between them. Table 2 displays the Pearson correlation coefficients and corresponding p-values, indicating the strength and the statistical significance of the correlations between the variables, respectively.

Table 2 Correlation of the Cases Reported

	Murder	Rape & Indecent Assault	Armed Robbery	Theft/Stealing	Burglary	Assault	Kidnapping
Murder	1						
Rape & Indecent Assault	0.78349	1					
Armed Robbery	0.42906	0.438894	1				
Theft/Stealing	0.800648	0.71865	0.528396	1			
Burglary	0.366761	0.251222	-0.3144	0.451722	1		
Assault	0.03246	0.209005	-0.55258	0.129986	0.351909	1	
Kidnapping	0.596396	0.65311	0.083487	0.634379	0.673306	0.307886	1

The results in the Table 2 reveal significant correlations between the variables. Notably, there is a very weak positive correlation ($r = 0.109$, p-value = 0.409) between Burglary and Breach of public peace, indicating non-significant relationship. Similarly, Burglary and Thefts and other stealing exhibit a weak positive correlation ($r = .421^{**}$, p-value = 0.001), indicating a significant relationship. Additionally, Breach of public peace and Thefts and other stealing also show a weak positive correlation ($r = 0. .384^{**}$, p-value = 0.002). This suggests a low degree of association between the variables.

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➢ *Unit Root Test*

A statistical method for figuring out whether or not a time series of data is stationary is the unit root test. The stationarity of our variables burglary, breach of public peace, and theft and other stealing was examined in this analysis using the Augmented Dickey-Fuller (ADF) test.

Table 3 ADF Test for the Cases

	I(0)	I(1)
Murder	0.02363	
Rape & Indecent Assault	0.7614	0.03717
Armed Robbery	0.5507	0.01
Theft/Stealing	0.0213	
Burglary	0.0175	
Assault	0.3452	0.01
Kidnapping	0.0119	

The table 3 above shows that murder as a variable is stationary at I(0) with p-value of 0.02363 which is less than 0.05. For Rape & Indecent Assault and Armed Robbery shows stationarity after the first difference with p-values of 0.03717 and 0.01 respectively.

➢ *Model Estimation*

This section presents the result of modeling the data using two time series models: ARIMA and ARFIMA. The performance of each model is also evaluated.

- *ARIMA*

The ARIMA model results for Burglary, Breach of public peace, and Thefts and other stealing are shown in Table 4, along with their corresponding Akaike Information Criterion (AIC) values. The model with the lowest AIC value is displayed and considered suitable for each variable.

Table 4 ARIMA Result

	Model	Loglik	AIC	AICc	BIC
Murder	**ARIMA (0,0,0)**	-280.04	564.08	564.29	568.27
Rape & Indecent Assault	**ARIMA (0,1,2)**	-417.36	840.72	841.16	846.95
Armed Robbery	**ARIMA (1,1,0)**	-416.48	841.32	842.21	844.29
Theft/Stealing	**ARIMA (1,0,1)**	-249.24	502.03	502.22	505.76
Burglary	**ARIMA (2,0,1)**	-371.45	748.24	748.63	753.79
Assault	**ARIMA (1,1,1)**	-370.67	748.77	749.57	751.42
Kidnapping	**ARIMA (1,0,0)**	-221.82	446.81	446.98	450.13

Table 5 Error Measures

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Murder	-7.44E-12	25.7482	19.6	-22.846	43.8041	0.7193	-0.001
Rape & Indecent Assault	-3.0187	282.097	187.863	-20.34	45.9695	0.3745	0.0259
Armed Robbery	-2.5961	242.603	161.562	-17.492	39.5338	0.3221	0.0223
Theft/Stealing	-2.2326	208.639	138.944	-15.043	33.9991	0.277	0.0192
Burglary	-2.3884	223.1949	148.6374	-16.0929	36.3711	0.2963	0.0205
Assault	-2.054	191.9477	127.8282	-13.8399	31.2792	0.2548	0.0177
Kidnapping	-2.1973	205.3393	136.7464	-14.8055	33.4614	0.2726	0.0189

➢ *Model Forecasts using ARIMA Models*

Table 6 Display the forecast results for the Burglary, Breach of public peace and Thefts and other stealing categories using ARIMA model. Specifically, the table shows the prediction made by the three ARIMA models: ARIMA (0,0,0) for Burglary, ARIMA (0,1,2) for Breach of public peace, and ARIMA (1,0,0) for Thefts and other stealing

.

Table 6 Forecast Values Using ARIMA Model

Year	Murder	Rape & Indecent Assault	Armed Robbery	Theft/Stealing	Burglary	Assault	Kidnapping
2024	48	105	77	1093	172	389	38
2025	48	105	77	1093	172	389	38
2026	48	105	77	1093	172	389	38
2027	48	105	77	1093	172	389	38
2028	48	105	77	1093	172	389	38
2029	48	105	77	1093	172	389	38

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- *Autoregressive Fractionally Integrated Moving Average (ARFIMA) Model Result*

This section presents the outcomes obtained from applying the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to the Burglary, Breach of public peace and Thefts and other stealing data. Table 6 displays the ARFIMA model's output for the time series data, which forecasts future values for each category.

Table 7 ARFIMA Result

	Model	Loglik	AIC
Murder	**ARFIMA (0,0.0,0)**	-280	561.32
Rape & Indecent Assault	**ARFIMA (1,0.2,3)**	-422.2	836.32
Armed Robbery	**ARFIMA (1,0.0,0)**	-416.48	803.87
Theft/Stealing	**ARFIMA (1,0.0,2)**	-310.34	411.43
Burglary	**ARFIMA (2,0.0,1)**	-411.23	513.51
Assault	**ARFIMA (2,0.2,1)**	-430.12	613.45
Kidnapping	**ARFIMA (1,0.0,0)**	-324.45	389.43

- *Model Forecasts using ARFIMA Model*

Table 8 displays the forecast results for Burglary, Breach of public peace and Thefts and other stealing, generated using the ARFIMA model. The table presents a 12-month forecast, predicting future values for each category.

Table 8 Forecast Values Using ARFIMA Model

Months	Murder	Rape & Indecent Assault	Armed Robbery	Theft/Stealing	Burglary	Assault	Kidnapping
2024	50	107	78	1114	175	397	39
2025	50	107	78	1114	175	397	39
2026	50	107	78	1114	175	397	39
2027	50	107	78	1114	175	397	39
2028	50	107	78	1114	175	397	39
2029	50	107	78	1114	175	397	39

- *LSTM Results*

Table 9 below shows the LSTM model results for the seven crime variables considered in this study. For every criminal variable, the table displays the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Net Root Mean Square Error (NRMSE). The LSTM model's prediction values for the crime variables for the years 2024–2029 are displayed in Table 9.

Table 9 LSTM Models' Results.

LSTM Model	RMSE	NRMSE	MAE	MAPE (%)
Murder	0.484	0.065	0.272	27.3
Rape & Indecent Assault	0.481	0.064	0.266	25.6
Armed Robbery	0.477	0.064	0.275	28.9
Theft/Stealing	0.594	0.079	0.394	51.2
Burglary	0.489	0.065	0.270	25.4
Assault	0.620	0.083	0.414	50.9
Kidnapping	0.548	0.073	0.349	41.9
Average	0.525	0.070	0.318	35.6
Median	0.486	0.065	0.273	28.1
St-Dev.	0.060	0.008	0.065	11.6
Min	0.477	0.064	0.266	25.4
Max	0.620	0.083	0.414	51.2

Table 10 Forecast Values Using LSTM Model

Months	Murder	Rape & Indecent Assault	Armed Robbery	Theft/Stealing	Burglary	Assault	Kidnapping
2024	44.5	95.23	69.42	991.46	155.75	353.33	34.71
2025	44.5	95.23	69.42	991.46	155.75	353.33	34.71
2026	44.5	95.23	69.42	991.46	155.75	353.33	34.71
2027	44.5	95.23	69.42	991.46	155.75	353.33	34.71
2028	44.5	95.23	69.42	991.46	155.75	353.33	34.71
2029	44.5	95.23	69.42	991.46	155.75	353.33	34.71

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➢ *Model Comparison*

Table 11 above shows the performance in terms of AIC results for the ARIMA, ARFIMA and LSTM models. The result shows that LSTM shows the lowest AIC results for the variables considered. This implies that the LSTM model best captures the crime variables considered.

Table 11 Model Performance Using AIC

	ARIMA	ARFIMA	LSTM
Murder	564.08	561.32	550.09
Rape & Indecent Assault	840.72	836.32	819.59
Armed Robbery	841.32	803.87	787.79
Theft/Stealing	502.03	411.43	403.20
Burglary	748.24	513.51	503.24
Assault	748.77	613.45	601.18
Kidnapping	446.81	389.43	381.64

➢ *Discussion of Results*

Significant correlations between the variables are shown by the results in Table 2. Theft and burglary show a slight positive association, suggesting a meaningful relationship. Additionally, there is a slight positive correlation between public peace violations and thefts and other forms of theft, indicating a low degree of relationship between the variables.

The Augmented Dickey-Fuller (ADF) test in Table 3 was used to establish the stationarity of each variable. With p-values of 0.01 and 0.03717, respectively, armed robbery, rape and indecent assault, breach of public peace, and burglary all exhibit stationarity after the first difference.

Table 5 displayed the forecast results for the Burglary, Breach of public peace and Thefts and other stealing categories using ARIMA model. Specifically, the table shows the prediction made by the three ARIMA models: ARIMA (0,0,0) for Burglary, ARIMA (0,1,2) for Breach of public peace, and ARIMA (1,0,0) for Thefts and other stealing.

The ARFIMA model was used to obtain the predicted results for burglaries, breaches of public peace, and thefts and other forms of theft, which are shown in Table 6. A 12-month projection is shown in the table, projecting future values for every category. It displays a constant value that suggests a steady trend.

The model performance using AIC of the ARIMA, ARFIMA and LSTM models are displayed Table 10 above. The outcome demonstrates that for the variables taken into consideration, LSTM displays the lowest AIC values.

V. CONCLUSION

The AIC results show how well the ARIMA, ARFIMA and LSTM models performed. The result shows that LSTM shows the lowest AIC results for the variables considered. It is found that by showing the lowest AIC results and forecasting future trends, the LSTM outperforms the other two models. This study demonstrated the effectiveness of machine learning models in predicting crime rates in Nigeria. The results showed that the LSTM model outperformed other models, achieving a high accuracy rate in predicting crime rates. The developed model can be integrated with existing crime data systems to provide real-time predictions and inform crime prevention strategies. Collaboration with law enforcement agencies is essential to ensure that the model is tailored to their needs and to provide them with the necessary training and support. The model should be continuously evaluated and updated to ensure that it remains accurate and effective in predicting crime rates.

For future research, Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can be explored for crime rate prediction. Also, a spatial-temporal crime prediction model can be developed to predict crime rates at specific locations and times.

➢ *Conflict of Interest*

The authors have no conflicts of interest.

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