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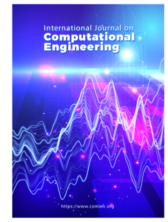


# Modelling The Number of Road Accident Casualities in Southwestern States in Nigeria

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***Abstract*—Road traffic accidents pose a serious public health challenge worldwide, particularly in developing countries where road infrastructure, traffic law enforcement, and safety awareness are often inadequate. This study focuses on traffic fatalities in Nigeria's southwest region—comprising Lagos, Ogun, Oyo, Ondo, Osun, and Ekiti states—which accounts for a substantial proportion of the country's vehicular movement and accident burden. Using quarterly traffic accident data from 2013 to 2023 obtained from the Federal Road Safety Corps website, the study applies descriptive analysis, unit root testing, the ARIMA model, and the neural network autoregressive (NNETAR) model to evaluate predictive performance. Model comparison is based on Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results indicate that the NNETAR model outperforms the other approaches by producing the lowest prediction errors across the training datasets, demonstrating its effectiveness in forecasting road traffic casualties in southwest Nigeria. These findings support the use of autoregressive neural network models for traffic accident forecasting and provide valuable insights for improving road safety strategies, while future research may further explore the impact of policy and intervention measures.***

***Keywords*—Road accident; road causalities; Autoregressive Integrated Moving Average; neutral network auto regression.**

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## I. Introduction

Traffic incidents on the roads are significant global health of humanity hazard, especially in building nations where public safety knowledge, road infrastructure, and traffic law enforcement may be lacking. In Nigeria, the south-western region is a notable area of interest due to its dense population, economic activities, and extensive road networks. This region includes states such as Lagos, Ogun, Oyo, Ondo, Osun, and Ekiti, which collectively account for a significant proportion of Nigeria's vehicular movement and traffic incidents.

During the colonial period and early post-independence years, road infrastructure in south-western Nigeria was limited. The British colonial administration built roads primarily to connect major economic hubs like Lagos, Ibadan, and Abeokuta. Traffic accidents were relatively low, and accidents were not as frequent as in later decades because of limited quantity of automobiles on the road. As the region developed and urbanized, the quantity of automobiles increased, leading to an increase in road traffic accidents. Lagos-Ibadan Expressway, commissioned in 1978, became a critical artery but also a hotspot for fatal accidents.

In the 1980s and 1990s, the south-western region of Nigeria saw a significant increase in road traffic accidents. This period was marked by rapid urbanization and industrialization, which triggered an upsurge in the quantity of vehicles on the highways. Poor road infrastructure, lack of traffic management, and inadequate enforcement of traffic laws contributed to the rise in accidents. The early 2000s saw a continued increase in road traffic accidents. The Federal Highway Safety Agency Corps (FRSC) launched in 1988 to address issue of highway security in Nigeria. Despite their efforts, the number of accidents remained high due to factors like bad road conditions, careless driving, and excessive speeding. There has been a determined attempt in recent years to reduce road traffic accidents in south-western Nigeria. Various measures have been implemented, including road safety initiatives, better road construction, and more stringent traffic law enforcement. However, challenges such as overloading, poor vehicle maintenance, and human error continue to contribute to road traffic accidents [1], [2], [3].

In 2020, the United Nations' Ten Years of Highway Security Action aimed in stabilize and decrease fatal accidents in traffic by 50%. Despite these efforts, Nigeria continues to face challenges in achieving these targets due to under-reporting of accidents and inadequate road safety measures. Between 2020 and 2022, road casualties in Nigeria continued to draw attention, highlighting the need for effective interventions. The Federal Road Safety Corps (FRSC) and the National Bureau of Statistics (NBS) report that, road accidents in south-western region are influenced by factors such as negligent driving, bad road conditions, and insufficient traffic law enforcement. In 2020 alone, FRSC reported over 5,000 accidents nationwide, with a considerable portion occurring in south-western states, underscoring the urgency to model and mitigate this public health issue [4],[5].

The modeling of road casualties serves as a critical tool for identifying patterns, predicting future incidents, and devising strategies to reduce accidents and fatalities. By employing statistical techniques, machine learning, and data-driven approaches, researchers can uncover insights into the relationship between various factors—such as road quality, traffic density, weather conditions, and human behaviour on road casualties. Various statistical and predictive models have been employed to analyse road traffic accident data, identify key determinants, and forecast future trends. For instance, studies have utilized regression models to predict outcomes, such the Negative Binomial regression model on road fatalities and identify significant factors like over-speeding, brake failure, and poor weather conditions. This paper also seeks to build upon existing literature and data, such as the works of [6], which examined spatial patterns of road accidents along Lagos/Abeokuta State, and other studies that have highlighted the socioeconomic and infrastructural dynamics influencing road safety in Nigeria. There are several models that the researchers had used to measure and predict the number of road accident casualties in south-western Nigeria. Applying Bayesian belief with fault tree analysis (FTA) networks, [7] determined the risks of traffic accidents and created a model that forecasted their occurrence. According to Bayesian diagnostic inference, loss of control contributed the least to the occurrence of traffic accidents, whereas lack of focus contributed the most. Beta and negative binomial models were used by [8] to monitor the trends in data on traffic accidents. found that the effectiveness of the Negative Binomial model was higher. The findings indicated that the quantity of deaths from traffic mishaps progressively rises over time, with more individuals dying in traffic accidents as the years pass. The most significant factor influencing the frequency of traffic accidents was found to be the kind of car that was involved in the collision and speeding. Road traffic accidents and city size were discovered to be highly correlated favourably ($r = 0.97$; $p = 0.001$) by [9], who also found that males were more likely than females to participate in RTA at a 3:1 ratio and that the incidence of these accidents was higher compared to other occupational categories, among traders (27.6%) and civil servants (38.2%). They concluded that incidence of traffic accidents varies over time and space, as well as between genders and occupational divisions, and that the safety measures in place have no discernible effect on preventing them in their study area. In addition to bolstering the institutional structure in charge of transportation safety, it was suggested that road users should be encouraged to adopt a safety culture. [10] used Geographic Information Systems (GIS) to forecast the temporal and spatial dimensions of road traffic crash hotspots and the corresponding number of fatalities and injuries at several sites. To more precisely forecast RTC hotspots, a variety of models can be incorporated into GIS built on techniques of statistical analysis in landscape [11] and to enhance financial allocation strategy for better monitoring of road crashes and associated injuries. A predictive model for road traffic accidents involvement in the regions of Ekiti State, Osun State, and Oyo state was created by [12] in 2024. The results showed a substantial association between the number of incidents of mishaps and the quantity of individuals actively engaged, both minor and fata mishaps with the biggest consequences. Accident data was collected from relevant agencies over a ten-year period (2014–2023). In addition to providing insights into predictive trends that could guide road safety improvements, the model explained 75.5% of the variations in collision consequences To lower the frequency and severity of accidents in the target area, they suggested tougher highway regulation enforcers, better road maintenance, and safety education programs. They also emphasised the significance of data-driven strategies in reducing road traffic accidents and improving highway hazard administration in order to gather information about the obligatory responsibilities of federal road safety commission in Nigeria, [13] used a straightforward random sample technique with well-structured questionnaires. Descriptive data analysis techniques were used to process the collected data. Only seven of the FRSC's twenty-two statutory responsibilities were judged to be adequately carried out. [14] examined the elements that contributed to traffic accidents used the zero-truncated poison regression model (ztprm), which revealed that a significant percentage of traffic accidents were caused by human error. There was a statistically significant and positive correlation between vehicle factors and traffic accidents. To predict road fatalities with the least amount of error, a zero-truncated negative binomial regression model was applied identified main factors that contributed to traffic fatalities as weariness, poor weather, signal light violations, brake failure, loss of control, and over speeding. Nigerian road accidents and their prevention were examined by [15]. in 2019. The Federal Road Safety Corps in Nigeria stipulated the details regarding the trend of traffic accidents between 1960 and 2017. The test known as Augmented Dickey Fuller (ADF) was employed. to ensure stationary patterns in the data and Johansen's methodology was used to perform the co-integration. The empirical analysis used the Least Square estimate. The findings demonstrated that the whole quantity of fatalities, total number of minor accidents, and total number of wounded in Nigeria had a long-term equilibrium connection. According to the findings, the overall number of casualties was positively and significantly correlated with fatal and severe cases, while the total number of casualties was negatively and significantly correlated with minor instances. When choosing a time series model, [16] took into account types of models that were suited to the Nigerian accident cases count. The Autoregressive (AR), Autoregressive Integrated Moving Average (ARIMA), and Moving Average (MA) models were among the candidate models that were taken into consideration, each with different parameter specifications. The findings indicated that, based on the Mean Square Error (MSE) and Akaike Information

Criteria (AIC), respectively, the ARIMA (3,1,1) and MA (0,1,2) models had been the most helpful in explaining the incidents of accidents in Nigeria. [17] used secondary data gathered from the command's record section between 2006 and 2012 to construct a model using Time Series statistical tools and analyse the seasonality pattern of the number of vehicle collision cases reported according to the Osun Sector command of the Federal Road Safety Commission, Osun Sector command. A decrease in the number of cases reported was seen by the Autoregressive Integrated Moving Average (ARIMA). The Least Squares trend, which showed a quarterly drop in six (6) car accident cases, supported the outcome. The fourth quarter (October, November, and December) was clearly shown by the seasonal trend to have the highest frequency of motor vehicle accidents. The possible relationship between ember months and seasons with regard to crash rates was investigated by [18]. The two distinct variables are the wet/dry seasons and the ember months were used to arrange the 96-month crash rate data (January 2014 till December 2021) that had been taken from the Headquarters Office of the Federal Road Safety Corps (FRSC), Abuja. To determine how the two components were interacting with each other, a two-way analysis of variance (ANOVA) was used to evaluate their main effects. There was no discernible connection between the seasons and ember months with respect to the regularity of collisions in traffic, according to the two-way ANOVA data. It was determined that whereas ember months do not significantly affect crash rates, season has a statistically significant effect. Although the ember months don't seem to have a big impact on the number of crashes, [19] looked into the trends within the sequence of Belgrade traffic accidents. Exploratory data analysis, analysis of regression, and the seasonal autoregressive integrated moving average model (SARIMA) developed by Box-Jenkins have all been used to define and comprehend time series. The time series was found to have a strong seasonal component. It was able to unravel the mean absolute percentage error (MAPE) of the model of 5.22% as an indication that the outlook was fairly correct. In relation to the amount of traffic accidents, forecasting may be a tactic to accomplish many objectives, including campaigns for traffic safety, strategies for traffic safety, and plans of action to achieve the objectives listed in traffic safety strategies. A multivariate regression model was created by [20] to describe countermeasures for traffic accidents. According to the model, every countermeasure increased the overall degree of road traffic crash control. With a positive regression value of 1.0610, road network maintenance was the main factor in the study area's overall decrease in traffic crashes. And concluded that Ogun State's roads need greater attention and should be maintained and renovated. [21] employed mean, ANOVA and Pearson correlation in identifying the frequency as well as causes contributing to traffic accidents in the state of Lagos. The findings showed that there was a significant prevalence (68%)of road accident among commercial drivers and age was one of the demographic main contributor. Furthermore, the state's road traffic incidents are brought on by combination of environmental factor, vehicle, and driver factors. It was determined that 58% of traffic accidents were caused by drivers. [22] employed a moving using Exponential Weight Average (EWMA) as well as two-factor analysis of variance to analyse secondary information derived from the Statistical Digest for the Federal Road Safety Corps for the years from 2004 to 2020. By altering the weighted parameter (0.25, 0.50, and 0.75), the EWMA control chart method was compared. It was found that the control chart for EWMA sensitive in identifying a slight change in the procedure, but more weights are given to recent statistics on traffic fatalities. supported integrating more compared to light weights; therefore, EWMA values for the datasets are better when the weights are higher. Additionally, it showed that the North-Central, South-West, and North-West regions had higher average reported rates of traffic fatalities. Greater weights for the parameters were suggested to have been utilised in view of. these findings since they produced more consistent EWMA values' trend that could be utilised in predicting. [23] carried out research to determine correlation among the frequency, severity of traffic accidents and the features of two-lane highway traffic and road design. Negative binomial regression and Poisson regression (NB), as well as ZINB, or zero-inflated negative binomial regression were models of statistics utilised in traffic accident modelling. The models' independent variables included variables related to road shape and traffic flow. According to accident statistics collected from the FRSC, the Federal Road Safety Commission during the four-year observation period between 2012 and 2015, accident prediction models were created for the South West Nigerian route between Ilesha, Akure, and Owo. The identified effective factors on the probability of crashes were factors such as access road (CHAR), shoulder factor (SF), lane width (LW), curve radius (CR), parentage heavy good vehicle (HGV), average annual daily traffic (AADT), and traffic sign posted (TSP). Lastly a comparison between the three created models demonstrated how well ZINB models perform in comparison to traditional Poisson and NB models. This paper focuses on modelling techniques to analyse the number of road casualties in the south-western states of Nigeria, aiming to provide actionable insights for policymakers and stakeholders. The objectives are to explore the road casualties of south-western states in Nigeria and compare the performances of the models on the data. By integrating recent data and advanced modeling approaches, with the aim of contributing to the expanding corpus of research on traffic safety and provide useful advice in reducing road casualties in south-western Nigeria.

## II. Material and Method

### A. Data description

The National Bureau of Statistics of Nigeria provided the quarterly data on the number of road fatalities in the southwest states, which was used in this study. The data covered the period from 2013 to 2023.

### B. Methods

The techniques to be used in the data analysis are described in this section. The frequency of road fatalities in the southwest states of Nigeria is examined using a variety of unit roots tests and time series models, including the ARIMA model and the Neural Network Auto regression model (NNETAR).

*C. Neural Autoregressive Network*

A computer model that is fully based on the structure and functionality of a biologically neutral network is called a neural network (ANN). Nonlinear statistical information modelling tools, or ANNs, are used to identify patterns or simulate intricate interactions between inputs and outputs. An ANN is also known as a neutral network. Three layers, which may or may not be linked, make up an ANN. Neurones comprise the first layer. To help in transmitting the output neutrons to the third layer and a few hidden layers between the input and output layers, the second layer receives data straight from the first neurones [24,25,26].

The mathematical representation of the ANN model is given as:

$$y = \emptyset_0[\alpha + \sum_{h=1}^{H} w_h\, \emptyset_h[\emptyset_h \ + \sum_{j=1}^{J} w_{jh}\, y_{i-1}]] \qquad (1)$$

*D. The ARIMA Model*

An ARIMA model is characterised 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 $B^k\, Y_t = Y_{t-k,}$

$\epsilon_t$ 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 [24,25].

*E. Model Performance Measures.*

Four widely accepted criteria are utilised in this study to evaluate the model's excellence and robustness from a variety of angles. Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are the prediction selection criteria employed in this work [24,25].

*1) Mean Squared Error (MSE*

The Mean Squared Error (MSE) is a frequently used statistic for evaluating regression models. Unlike the Mean Absolute Error (MAE), the MSE accentuates larger errors by squaring the variances between the actual and expected values. This feature makes MSE particularly useful in scenarios where large errors are undesirable since it imposes a heavier penalty on models that produce noticeable discrepancies in their predictions.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \qquad (2)$$

where;

$y_i$ is the actual value,

$\hat{y}_i$ is the predicted value,

$n$ is the number of data points?

*2) Mean Absolute Error (MAE)*

MAE stands for mean absolute error, which is the difference between two continuous variables. Accuracy for continuous variables is measured using MAE. It is used to calculate the average magnitude of mistakes in a series of forecasts. The direction of the magnitude is not taken into account [24,25]

$$MAE = \frac{1}{T}\sum_{t=1}^{T} \left| X_t - \hat{X}_t \right|. \qquad (3)$$

*3) Root Mean Square Error (RMSE)*

The discrepancy in values is measured by the Root Mean Square Error (RMSE). These are the values that the model and the actual values both anticipated. Residuals are any deviance as determined by RMSE. Root Mean Square Deviation (RMSD) is another name for this technique. RMSD is utilised for prediction purposes in order to aggregate the magnitude of the errors [24,25]. The Root Mean Square Error can be computed mathematically as

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(X_t - \hat{X}_t\right)^2} \qquad (4)$$

*4) Mean Absolute Percentage Error(MAPE).*

The accuracy of a forecasting method's prediction is gauged by the mean absolute percentage error, or MAPE. It uses a percentage to represent precision. The mean absolute percentage deviation (MAPD) is another name for it.

$$\text{MAPE} = 100 \text{ X } \frac{1}{T}\sum_{t=1}^{T}\left|\frac{X_t - \hat{X}_t}{X_t}\right| \qquad (5)$$

Note: T is the data length, $X_t$ is the real data, and $\hat{X}_t$ is the predicted data.

## III. Result and Discussion

The results of the analyses are displayed in this section. It includes the model performance for the machine learning models taken into consideration in this work as well as the exploratory data analysis of the data. The Phillips-Pearson Unit Root Test, the Augmented Dickey Fuller Test, and the training set error set were used to determine whether the time series data was stationary. The Neural Network Autoregressive Model (NNETAR) and the ARIMA model are the machine learning models taken into consideration.

*A. Descriptive Analysis*

This section presents the descriptive figure findings for the variables. The number of traffic accidents in the southwest states of Nigeria, including Oyo, Osun, Ogun, Lagos, and Ondo, is shown in Table 1 along with the mean, standard error, median, standard deviation, sample variance, kurtosis, and skewness, as well as the range of minimum, maximum, and count values.

TABLE I
The Descriptive Analysis for South-Western States in Nigeria

| | EKITI | LAGOS | OGUN | ONDO | OSUN | OYO |
|---|---|---|---|---|---|---|
| Mean | 77.00 | 746.16 | 518.98 | 297.52 | 291.77 | 377.02 |
| Standard Error | 6.34 | 45.20 | 41.47 | 22.66 | 23.13 | 29.76 |
| Median | 66.00 | 710.00 | 621.50 | 302.00 | 279.50 | 402.00 |
| Mode | 50.00 | 1002.00 | 820.00 | 150.00 | 173.00 | 144.00 |
| Standard Deviation | 42.02 | 299.82 | 275.05 | 150.34 | 153.44 | 197.38 |
| Sample Variance | 1765.95 | 89893.90 | 75652.77 | 22601.88 | 23544.51 | 38957.14 |
| Kurtosis | 9.95 | 0.11 | -1.37 | 0.85 | 0.53 | 0.059 |
| Skewness | 2.73 | 0.24 | -0.53 | 0.66 | 0.89 | 0.22 |
| Range | 235.00 | 1385.00 | 825.00 | 649.00 | 630.00 | 842.00 |
| Minimum | 35.00 | 201.00 | 68.00 | 55.00 | 57.00 | 51.00 |

| | EKITI | LAGOS | OGUN | ONDO | OSUN | OYO |
|---|---|---|---|---|---|---|
| Maximum | 270.00 | 1586.00 | 893.00 | 704.00 | 687.00 | 893.00 |
| Sum | 3388.00 | 32831.00 | 22835.00 | 13091.00 | 12838.00 | 16589.00 |
| Count | 44.00 | 44.00 | 44.00 | 44.00 | 44.00 | 44.00 |

The descriptive outcome of the quantity of traffic collisions in Nigeria's southwest states is shown in Table 1. Ekiti's mean, variance, standard deviation, and standard error are 77, 42.02, 1765.95, and 6.34, in that order. The corresponding values for Lagos are 746.16, 299.82, 89893.90, and 45.20. The corresponding values for Ogun are 518.98, 275.05, 75652.77, and 41.47. The corresponding values for Ondo are 297.52, 150.34, 22601.88, and 22.66. The corresponding values for Osun are 291.77, 153.44, 23544.51, and 23.13. The corresponding values for Oyo are 377.02, 197.38, 38957.14, and 29.76. This indicates that from 2013 to 2023, Lagos had the most traffic accidents, followed by its neighbour, Ogun State, and Ekiti, which had the fewest traffic accidents.

### *B. Unit Root Test (Stationarity Test)*

The purpose of the unit root test is to demonstrate the stationarity of our data. The unit root test methods used to check for stationarity in the number of traffic accidents include the Phillips-Pearson unit root test and the Augmented Dickey-Fuller test.

TABLE II
AUGMENTED DICKEY-FULLER TEST

| | Statistic | Lag | P-Value |
|---|---|---|---|
| OYO | -2.3497 | 0 | 0.4354 |
| | -5.6674 | 1 | 0.01 |
| OSUN | -2.3525 | 0 | 0.4342 |
| | -5.5211, | 1 | 0.01 |
| OGUN | -3.5582, | 0 | 0.0476 |
| | -4.7534, | 1 | 0.01 |
| ONDO | -2.2751, | 0 | 0.4649 |
| | -5.2368, | 1 | 0.01 |
| LAGOS | -4.3324, | 0 | 0.01 |
| EKITI | -2.7936, | 0 | 0.2596 |
| | -5.1545, | 1 | 0.01 |

TABLE III
PHILIP PEARSON UNIT ROOT TEST

| | Statistic | Lag | P-Value |
|---|---|---|---|
| OYO | -20.984 | 0 | 0.03236 |
| | -45.928, | 1 | 0.01 |
| OSUN | -21.558, | 0 | 0.02646 |
| | -43.251, | 1 | 0.01 |
| OGUN | -20.051, | 0 | 0.04195 |
| | -46.68 | 1 | 0.01 |
| ONDO | -14.632, | 0 | 0.2148 |
| | -38.57, | 1 | 0.01 |
| LAGOS | -36.21, | 0 | 0.01 |
| | -51.8, | 1 | 0.01 |
| EKITI | -29.1, | 0 | 0.01 |
| | -43.77, | 1 | 0.01 |

According to Table 2's results, the time series using augmented dickery at lag 0 has a p-value greater than 0.05, which means the null hypothesis cannot be rejected. The time series is non-stationary, with the exception of the Ogun state, while at lag1, all of the states have values less than 0.05, which indicates that the occurrence is stationary. The Phillip Pearson values for the southwest states are displayed in Table 3. At lag 0, all of the states' values are less than 0.05, indicating a significant p-value and a stationary trend, with the exception of Ondo.

### *C. ARIMA results.*

The ARIMA findings for the number of traffic accidents in each of the southwest states of Nigeria are displayed in Tables 4–9.

TABLE IV
ARIMA OUTCOMES FOR EKITI STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,0,2) | 366.4401 |
| ARIMA(0,0,0) | 359.5022 |
| ARIMA(1,0,0) | 358.8723 |
| ARIMA(0,0,1) | 358.4741 |
| ARIMA(0,0,0) | 405.3301 |
| ARIMA(1,0,1) | 361.0154 |
| ARIMA(0,0,2) | 361.0257 |
| ARIMA(1,0,2) | 363.7715 |
| ARIMA(0,0,1) | 387.3899 |

TABLE V
ARIMA OUTCOMES FOR LAGOS STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,0,2) | Inf |
| ARIMA(0,0,0) | 492.5456 |
| ARIMA(1,0,0) | 494.8895 |
| ARIMA(0,0,1) | 494.8574 |
| ARIMA(0,0,0) | 555.4459 |
| with zero mean | |
| ARIMA(1,0,1) | Inf |

TABLE VI
ARIMA OUTCOMES FOR OGUN STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,1,2) | Inf |
| ARIMA(0,1,0) | 438.9584 |
| ARIMA(1,1,0) | 440.6065 |
| ARIMA(0,1,1) | 440.4516 |
| ARIMA(0,1,0) | 437.1494 |
| ARIMA(1,1,1) | Inf |

TABLE VII
ARIMA OUTCOMES FOR ONDO STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,1,2) | Inf |
| ARIMA(0,1,0) | 409.309 |
| ARIMA(1,1,0) | 411.6532 |
| ARIMA(0,1,1) | 411.5734 |
| ARIMA(0,1,0) | 407.2264 |
| ARIMA(1,1,1) | 413.341 |

TABLE VIII
ARIMA OUTCOMES FOR OSUN STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,1,2) | Inf |
| ARIMA(0,1,0) | 430.1673 |
| ARIMA(1,1,0) | 431.2971 |
| ARIMA(0,1,1) | Inf |
| ARIMA(0,1,0) | 427.9737 |
| ARIMA(1,1,1) | Inf |

TABLE IX
ARIMA OUTCOMES FOR OYO STATE

| ARIMA | AIC |
|---|---|
| ARIMA(2,1,2) | Inf |
| ARIMA(0,1,0) | 425.6629 |
| ARIMA(1,1,0) | 426.5075 |
| ARIMA(0,1,1) | Inf |
| ARIMA(0,1,0) | 423.653 |
| ARIMA(1,1,1) | Inf |

Table 4 ARIMA (0,0,1) has the lowest AIC value (358.4741), suggesting that ARIMA (0,0,1) is the most effective model for Ekiti State's traffic accident rate. Table 5 demonstrates that ARIMA (0,0,0) has the lowest AIC value of 492.5456, suggesting that it is the most effective model for the number of traffic accidents in Lagos State. The number of road accidents in Ogun State is best predicted by ARIMA (0,1,0), as Table 6 demonstrates, with the lowest AIC value of 437.1494. Table 7 indicates that ARIMA (0,1,0) has the lowest AIC value (407.2264), indicating that it is the most effective model for the number of traffic accidents in Ondo state. With the lowest AIC value of 427.9737, Table 8's ARIMA (0,1,0) model suggests that it best captures the number of traffic accidents in Osun State. Table 9 indicates that ARIMA (0,1,0) has the lowest AIC value (423.653), indicating that it is the most effective model for Oyo State's traffic accident rate.

#### 1) *Performance Measures using ARIMA*

This section discusses the performance outcomes for the models taken into consideration in this investigation. The values of sigma^2, log likelihood, AIC, AICc, and BIC are displayed in Table 10, and the ME, RMSE, MAE, MPE, MAPE, MASE, and ACF1 for the models' forecast performance are displayed in Table 11.

TABLE X
MODEL PERFORMANCE MEASURES

| | EKITI | LAGOS | OGUN | ONDO | OSUN | OYO |
|---|---|---|---|---|---|---|
| sigma^2 | 1925 | 103733 | 12554 | 31087 | 23541 | 20652 |
| log likelihood | -175.84 | -244.08 | -202.55 | -217.51 | -212.92 | -210.76 |
| AIC | 357.67 | 492.16 | 407.1 | 437.02 | 427.84 | 423.52 |
| AICc | 358.47 | 492.55 | 407.23 | 437.15 | 427.97 | 423.65 |
| BIC | 362.25 | 495.21 | 408.59 | 438.52 | 429.34 | 425.02 |

TABLE XI
TRAINING SET ERROR MEASURES

| | EKITI | LAGOS | OGUN | ONDO | OSUN | OYO |
|---|---|---|---|---|---|---|
| ME | -0.1688055 | 3.410605e-13 | 8.207853 | 7.207559 | 20.17859 | 12.38424 |
| RMSE | 42.56194 | 317.3048 | 110.385 | 151.1582 | 173.7039 | 141.5796 |
| MAE | 29.31745 | 256.6471 | 78.67844 | 92.79579 | 100.2374 | 89.56071 |
| MPE | -21.26477 | -29.48553 | -0.2255946 | -6.620837 | 0.6068748 | 0.9121774 |
| MAPE | 41.61628 | 52.47286 | 23.46217 | 33.17513 | 20.55678 | 21.55696 |
| MASE | 0.9723375 | 0.8689189 | 0.9706125 | 0.9706058 | 0.9706087 | 0.9706086 |
| ACF1 | -0.003616947 | 0.04483699 | 0.05123614 | -0.1988725 | -0.1544108 | -0.2189417 |

Ekiti state has the lowest sigma^2, log likelihood, AIC, AICc, and BIC values of 1925, -175.84, 357.67, 358.47, and 362.25, according to Table 10's model performance measure values. The RMSE, MAE, and MAPE results for Nigeria's southwest states are displayed in Table 11. Ogun has the lowest MAPE values (20.56), whereas Ekiti has the lowest RMSE and MAE values (42.56 and 29.32, respectively).

### D. *The Neural Network Autoregressive Result*

The neural network results for the number of traffic accidents in Nigeria's southwest states are displayed in this section. Table 13 displays the number of heading mirrors of MSE values in the neural network for the states, whereas Table 12 displays the sigma sq. estimated values for models 1, 1, 2(4).

TABLE XII
NEURAL NETWORK

| | MODEL | SIGMA SQ.ESTIMATED |
|---|---|---|
| OSUN | (1,1,2)[4] | 36.23 |
| EKITI | (1,1,2)[4] | 11.53 |
| LAGOS | (1,1,2)[4] | 86.2 |
| OGUN | (1,1,2)[4] | 37.76 |
| ONDO | (1,1,2)[4] | 20.96 |
| OYO | (1,1,2)[4] | 20.56 |

TABLE XIII
MSE VALUES FOR NEURAL NETWORK

| No of heading mirrors | OSUN | EKITI | LAGOS | OGUN | ONDO | OYO |
|---|---|---|---|---|---|---|
| 1 | 0.1672 | 0.0042 | 0.0906 | 0.0542 | 0.0437 | 0.0248 |
| 2 | 0.1256 | 0.0082 | 0.0906 | 0.0552 | 0.0557 | 0.0252 |
| 3 | 0.1375 | 0.2085 | 0.0906 | 0.0553 | 0.0529 | 0.0253 |
| 4 | 0.1456 | 0.0836 | 0.0907 | 0.0543 | 0.0575 | 0.0256 |
| 5 | 0.1520 | 0.0583 | 0.0929 | 0.0543 | 0.0572 | 0.0260 |
| 6 | 0.1228 | 0.0839 | 0.0929 | 0.0558 | 0.0587 | 0.0257 |
| 7 | 0.1057 | 0.0311 | 0.0977 | 0.0531 | 0.0582 | 0.0258 |
| 8 | 0.1023 | 0.0459 | 0.0991 | 0.0554 | 0.0582 | 0.0265 |
| 9 | 0.0949 | 0.0374 | 0.0983 | 0.0539 | 0.0581 | 0.0254 |
| 10 | 0.1304 | 0.0225 | 0.0986 | 0.0538 | 0.0564 | 0.0267 |

Table 12 compares the model (1,1,2) [4] neural network values for the states in the southwest. The state with the lowest estimated sigma square, 11.53, is Ekiti. The number of heading mirrors in the neural network's MSE values is displayed in Table 13. According to the number of heading mirrors of MSE values for neural networks, Oyo state has the lowest values (0.0253, 0.0256, 0.0260, 0.0257, 0.0258, 0.0265, 0.0254 at heading mirrors of 3,4,5,6,7,8, and 9) and Ekiti state has the lowest values (0.0042, 0.0082, and 0.0225 at headings 1, 2, and 10). This suggests that MSE for neural networks is the most effective model for the frequency of traffic accidents in Oyo and Ekiti states.

### E. *Discussion*

The number of traffic accidents across the six states of southwest Nigeria—Ogun, Ondo, Osun, Oyo, Lagos, and

Ekiti—is basis for this research. Table 1 demonstrates how the number of vehicles grew as the states in this region urbanised and developed, which in turn caused an increase in traffic accidents. The state with the most traffic accidents was Lagos, followed by Ogun, which is the state closest to it. The least amount of traffic accidents was reported in Ekiti.

The outcomes of the unit root test are displayed in Tables 2 and 3. When compared to the augmented Dickery Fuller, the Phillip Pearson test reveals that the p-value for Oyo, Ogun, Lagos, and Osun is less than 0.05 at lag 0. Tables 4-9 show that ARIMA (0,1,0) has the lowest AIC values for Ogun, Osun, Ondo, and Oyo states. This suggests that ARIMA (0,1,0) is the most suitable model for the the number of traffic accidents in this area. Furthermore, table 13 shows that the Oyo and Ekiti states are best modelled by the neural network's MSE in a 7:3 ratio. It demonstrates that Ekiti had the lowest MSE values three times while Oyo state had the lowest seven times.

## IV. Conclusion

In this study, we modelled the quantity of traffic collisions in the southwest state, Nigeria using ARIMA model and the Neural Network Autoregressive Model (NNETAR). We assessed the stationarity of the data using the augmented Dickey Fuller unit root test and the Phillip-Pearson unit root test. The data was initially judged to be stationary using the Phillip-Pearson unit root test. Using the data, a descriptive analysis was performed to quantify the road causalities in the southwest state. While ARIMA uses six training set error measures—mean error, mean absolute error, root mean square error, mean absolute percentage error, and mean percentage error—the Neural Network Autoregressive (NNETAR) model reflects the mean square error.

The Neural Network Autoregressive (NNETAR) model fared better than other model in predicting road causalities in the southwest state of Nigeria since it only generated the mean square error across all training sets analysed. Finally, we suggest employing an autoregressive neural network model to calculate how many traffic accidents that occur in south-western states. Future studies can take into account the analysis of the intervention.

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