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NON-SEASONAL ARIMA MODELING OF STROKE INCIDENCE

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ABSTRACT

This study employs the ARIMA Box-Jenkins methodology to model monthly stroke incidence data from January 2011 to December 2021. A non-seasonal ARIMA (p,d,q) model is fitted, with ARIMA (1,1,1) identified as the optimal model based on its lowest BIC (=781.5278) and AIC (=772.9022) values compared to alternative models. The Ljung-Box statistic (19.931, df = 22, p = 0.5885 > 0.05) affirms the model's suitability. Projections derived from the fitted model indicate a discernible trend towards increasing stroke incidence. Given the anticipated socioeconomic implications, particularly regarding employment loss, income reduction, and social network disruption among stroke survivors, urgent action from governmental and health authorities is imperative to address the projected challenges effectively.

KEYWORDS: Time Series Analysis, Box-Jenkins, ARIMA Model, Stroke Incidence.

INTRODUCTION

Stroke is a very troubling and debilitating illness as it does not only disable its victim but also kills most of them instantaneously. It leaves its victim and family in a situation of great economic concern, particularly in the developing countries of the world, where poverty and malnutrition also coexist (Donkor *et al*., 2014; Birabi *et al*., 2012). It used to be regarded as a disease of affluent countries, but it's now increasing at an alarming rate in poor countries (Lopez *et al*., 2001). Stroke occurs when the blood supply to part of the brain is interrupted or reduced, preventing brain tissue from getting oxygen and nutrients. Brain cells begin to die in minutes. A stroke is a medical emergency, and prompt treatment is crucial. Early action can reduce brain damage and other complications. Effective treatments can also help prevent disability from stroke.

There are two main causes of stroke, namely; a blocked artery (ischemic stroke) or the leaking/bursting of a blood vessel (hemorrhagic stroke). Some people may have only a temporary disruption of blood flow to the brain, known as a transient ischemic attack (TIA), that doesn't cause lasting symptoms. According to the World Stroke Organisation (WSO), 90% of strokes are associated with 10 risk factors that can easily be identified: hypertension, physical inactivity, diet, weight, smoking, alcohol, cholesterol, diabetes, depression and stress, and atrial fibrillation (AF, or AFib). Stroke is one of the many debilitating diseases in today's society and a leading cause of death and disability worldwide with a prevalence of 1.14 per 1000 (Ekeng, 2020). Reckoning with the prediction of the World Health Organization (WHO) that by the year 2030, approximately 80 per cent of all strokes will occur among people residing in low- and middle-income countries (Mathers, 2002), and with such certainty that 85 per cent of global deaths from stroke were in developing countries which Nigeria is one of them (Feigin *et al*., 2003; Datal and Bahattacharjee, 2007).

According to WHO (2022), stroke is the leading cause of disability worldwide and the second leading cause of death. The Global Stroke Factsheet released in 2022 reveals that the lifetime risk of developing a stroke has increased by 50% over the last 17 years, and now 1 in 4 people is estimated to have a stroke in their lifetime. From 1990 to 2019, there has been a 70% increase in stroke incidence, a 43% increase in deaths due to stroke, a 102% increase in stroke prevalence, and a 143% increase in disability-adjusted life years (DALY). The most striking feature is that the bulk of the global stroke burden (86% of deaths due to stroke and 89% of DALYs) occurs in lower and lower-middle-income countries. This disproportionate burden experienced by lower and lower-middle-income countries has posed an unprecedented problem for families with fewer resources. It is extremely important to pay particular attention to management of stroke, as the signs and symptoms of stroke begin to manifest. Prompt clinical interventions are necessary to avert stroke and its complications.

Among the authors who have incorporated a non-seasonal ARIMA modelling structure in their studies are Inyang *et al*. (2023) and (2024), Etuk *et al*. (2022), Inyang *et al*. (2022), Moffat and Inyang (2022), Shittu and Inyang (2019), and Clement (2014 a and b). Several attempts have been made by various researchers to model stroke prevalence. A few cases include: Lee *et al*. (2008) examined the seasonal variation in ischemic stroke incidence and association with climate with application to a six-year population-based study in Taiwan. It was revealed that the seasonality of ischemic stroke does not exist in Taiwan and that ischemic stroke incidence is, however, significantly related to atmospheric pressure. Fujii *et al.* (2022) investigated the seasonal variation in the incidence of stroke in a general population of 1.4 million Japanese. Results revealed that seasonal variation was more pronounced in intracerebral hemorrhage than in ischemic stroke. Also, incidence rates of stroke were highest in winter and lowest in summer in current Japan.

Ugoh *et al.* (2022) studied a dynamic regression model of the prevalence of stroke in the south-east of Nigeria. Their findings revealed that the prevalence of stroke in southeast Nigeria is high and will still rise in the future. Takashima *et al*. (2022) studied the 21-year trend of stroke incidence in a

general Japanese population, and the results proved that there was a significant reduction in stroke incidence from 1990 to 2010. Arabambi *et al*. (2021) investigated the pattern, risk factors, in-hospital outcomes, and stroke mortality cases at the Lagos State University Teaching Hospital (LASUTH) over one year with a total of 230 patient records. Results revealed that the hospital incidence of intracerebral haemorrhage (ICH) was close to that of ischemic stroke (IS), with intracerebral haemorrhage having a proportion of 44.8 percent while ischemic stroke was 52.2 percent.
Katz *et al.* (2016) examined a time series analysis of the relationship between the unemployment rate and hospital admission for acute myocardial infarction and stroke in Brazil over more than a decade. Results revealed that hospital admissions for acute myocardial infarction (AMI) and stroke increased, whereas the unemployment rate decreased. Then, the fitted ARIMA model clearly showed a positive association between the unemployment rate and admission due to AMI but not for stroke. Ekeh *et al*. (2015) examined the mortality of stroke and its predictors in a northern Nigerian teaching hospital. The result of their study revealed that stroke mortality was quite high and that mortality predictors were the indices of severity and the presence of co-morbid conditions. Hence, this work seeks to investigate the trend pattern of stroke incidence and provide a framework for determining stroke incidence by fitting an appropriate time series model to the stroke dataset over the years under study.

METHODOLOGY

ARIMA Modelling

Box-Jenkins ARIMA modelling that we use can only be applied to time series that are stationary. The first step in the analysis is therefore to make our series stationary. Once the stationarity form of the series is attained then, look at the ACF and PACF plots to determine the form of the ARIMA(p,d,q) model for the series.

Autoregressive Moving Average Process

An autoregressive moving average process of order p and q denoted by ARMA(p,q) is written as

$$X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + +\theta_q \epsilon_{t-q} \quad (1)$$

Applying the backward shift operator B, (1) reduces to

$$\Phi(B)X_t = \Theta(B)\epsilon_t \quad (2)$$

Where

$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ and $\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$

X_t=The observed stroke cases at time t., ϕ = Non-seasonal autoregressive parameter

θ = Non-seasonal moving average parameter., B= backshift operator. , ε_t = white noise

For non-stationary time series $\{X_t\}$, Box *et al* (1994) proposed that differencing up to a sufficient order could make it stationary. That is ($\nabla^d X_t$) is stationary, for d is the least order of differencing for which the series is stationary, d=1. Otherwise difference the series again such that d=2, if confirmed to be stationary, and so on. But often, d<3.

Differencing

$$\nabla^d X_t = (1 - B)^d X_t \quad (3)$$

$$\nabla X_t = X_t - X_{t-1} = (1 - B)X_t \quad (4)$$

Where d is the order of non-seasonal differencing.

Autoregressive Integrated Moving Average Process

The autoregressive integrated moving average process is an integrated series which is composed of the autoregressive process and the moving average process. Given an ARMA model with parameters ARMA(p,q) and the differencing operator $\nabla^d X_t$ (3), the resulting model is given as ARIMA(p,d,q), written using the backward shift operator B as:

$$\Phi(B)\nabla^d X_t = \Theta(B) \in_t \quad (5)$$

$$\Phi(B)(1 - B)^d X_t = \Theta(B)\epsilon_t \quad (6)$$

$$\Phi(B)(1 - B)X_t = \Theta(B)\epsilon_t \quad (7)$$

Unit Root Test

To check for stationarity, the Augmented Dickey Fuller (ADF) Test (Dickey and Fuller, 1979) is used.
As a prerequisite for any further analysis in time series modelling, it is pertinent to formally diagnose the characteristics of the series that are used in the study.
The ADF test is based on the regression equation

$$X_t = \phi X_{t-1} + \sum_{j=1}^{p-1} \emptyset_j \Delta X_{t-j} + \epsilon_t \quad (8)$$

Where X_t is the series being tested and p is the number of lagged differenced terms included to capture any autocorrelation.

The null hypothesis is stated as followings

$H_0 : \beta = 0$ (series has unit root) (9)

$H_1 : \beta \neq 0$ (10)

Test statistic:

$$T = \frac{\hat{\beta}}{S.E(\hat{\beta})} \equiv \frac{\hat{\varphi}}{S.E.(\hat{\varphi})} \sim t_\alpha(n) \text{ at } \alpha \text{ level of significance} \quad (11)$$

Note: If the null hypothesis is rejected, we conclude that the series contains no unit root.

Akaike Information Criterion (AIC)

The AIC (Akaike, 1974), is formulated as

$$\text{AIC} = M_T \left[1 + \frac{2P}{T-P}\right] \quad (12)$$

Where:

M_T = Index related to production error (known as residual sum of squares)

p = No of parameters in the model, T= No. of data points.

Bayesian Information Criterion (BIC)

A criterion for selecting a model from a limited number of models is the BIC (Schwarz, 1978). The model that comes up with the smallest BIC score among two or more estimated models should be chosen. It is provided by:

$$\text{BIC} = n \ln \hat{\sigma}_e^2 + k \ln(n) \quad (13)$$

Where $\hat{\sigma}_e^2$ is the estimated error variance defined by
$\hat{\sigma}_e^2 = \frac{1}{T}\sum_i^T(\curlywedge_i - \bar{\curlywedge})^2$
$\curlywedge =$ Observed data, $T =$Number of observations, $k =$ Number of free parameters to be estimated.

Data Source
The data used for this study are the monthly Stroke Cases spanning from January 2011 - December 2021, were collected from the Record unit of St Luke's hospital in Uyo, Akwa Ibom State. The statistical package used for the analysis of this work is the R language (R-4.1.2-win).

RESULTS AND DISCUSSION

Exploratory Data Analysis
A comprehensive examination of the stroke dataset spanning from January 2011 to December 2021 was conducted to elucidate underlying patterns and trends. Initial analysis encompassed basic summary statistics coupled with graphical representations, facilitating a nuanced understanding of the dataset. Figure 1 illustrates the time series plot, which, notably, does not exhibit any discernible pattern, oscillating seemingly at random. This erratic behaviour suggests potential complexities in the mechanisms governing the dataset generation.

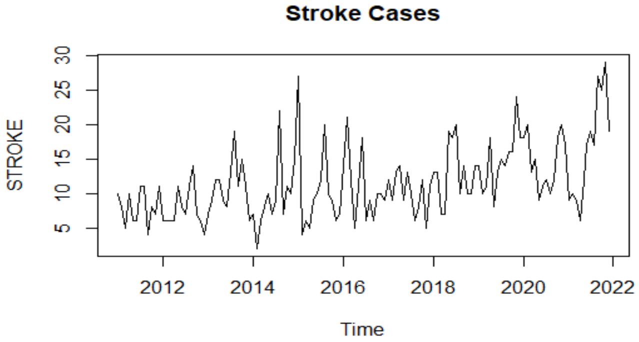

Fig. 1: Time Series Plot of Stroke Cases

Gender-specific analyses unveiled distinct patterns in monthly and yearly stroke incidences. Notably, the incidence of stroke among females surpassed that of males consistently throughout the study period. Figure 6 illustrates this divergence, with males experiencing heightened stroke cases in August, while females exhibited peaks in December. Moreover, yearly trends indicated a similar disparity, with males recording a surge in cases in 2021, while female incidence remained relatively stable in 2019 and 2020 (Figure 7).

Delving deeper into gender-specific statistics, specific observations emerged. For instance, certain months exhibited zero male cases, such as September 2011, March 2012, and February 2014, while January 2015 recorded the highest male incidence at 13 cases. Conversely, female cases ranged from a minimum of 2 to a maximum of 22, with November 2021 marking the peak incidence. The dataset reveals that 545 cases of stroke were documented among males, while 974 cases were reported among females. Consequently, the incidence of stroke appears to be notably higher among females compared to males, as depicted in Figure 8. These findings underscore the heightened vulnerability of females to stroke, warranting further investigation into underlying factors contributing to this gender disparity.

An exploration of mean values over time shed light on temporal variations in stroke incidence. Monthly and yearly mean calculations, depicted in Figures 9 and 10, revealed fluctuations indicative of non-constant mean functions. Notably, August exhibited the highest monthly mean, while March displayed the lowest. Similarly, 2021 witnessed the highest yearly mean, contrasting starkly with the lowest recorded in 2011 and 2012. These fluctuations underscore the dynamic nature of stroke incidence, suggesting the influence of external factors on dataset distribution.

ARIMA Modelling
The analysis of the time series depicted in Figure 1 of Appendix I revealed characteristics indicative of non-stationarity, with irregular peaks occurring at intervals of unequal length, suggesting the absence of a seasonal trend. Confirmation of these attributes was obtained through examination of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) displayed in Figure 2. The persistence of autocorrelation in both ACF and PACF at high lags further supported the assertion of non-stationarity within the series.

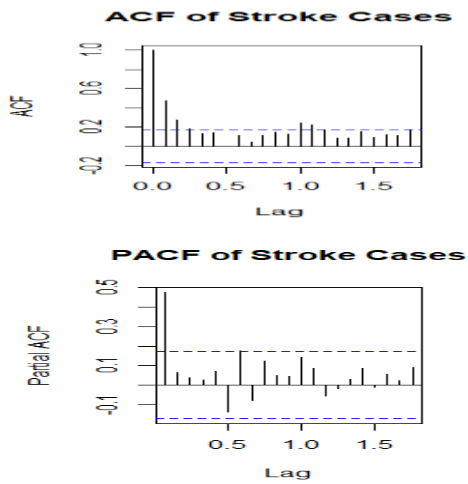

Fig. 2: ACF and PACF Plot of Stroke Cases

To achieve stationarity, the series underwent first-order differencing, as illustrated by the graph of the differenced series in Figure 3.

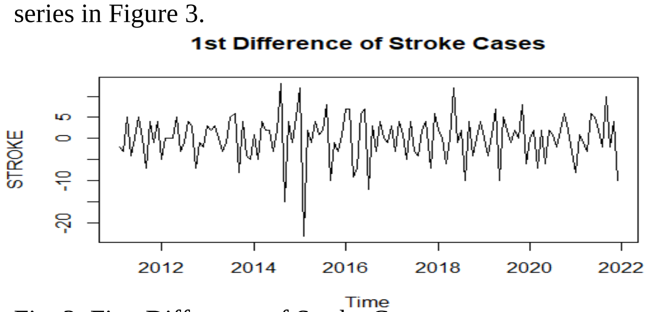

Fig. 3: First Difference of Stroke Cases

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Subsequent verification via the Augmented Dickey-Fuller Test confirmed the attainment of stationarity, with a p-value of 0.0000, signalling rejection of the null hypothesis of a unit root presence, Table 1.

Table 1: Unit Root Test After First Differencing

Test	Augmented Dickey-Fuller
Data	First Difference Series
Dickey-Fuller	-7.5292
Lag order	5
P-value	0.01
Alternative hypothesis	Stationary

Following the Box-Jenkins methodology, four candidate models were identified and estimated, with their respective ARIMA(p,d,q) specifications summarized in Table 2

Table 2: Parameters of the Estimated Models.

Model		Estimate	Std. Error	z value	Prob. Value
(1,1,1)	AR1	0.328202	0.091076	3.6036	0.0003***
	MA1	-0.931980	0.032509	-28.6685	2.2e-16***
(2,1,1)	AR1	0.3289210	0.0929493	3.5387	0.0004021***
	AR2	-0.0036282	0.0929262	-0.0390	0.9688554
	MA1	-0.9316507	0.0337380	-27.6143	2.2e-16***
(1,1,2)	AR1	0.3200111	0.2639101	1.2126	0.225292
	MA1	-0.9228968	0.2742200	-3.3655	0.000764***
	MA2	-0.0082253	0.2462572	-0.0334	0.973355
(2,1,2)	AR1	-0.571696	0.105834	-5.4018	6.597e-08***
	AR2	0.230619	0.100840	2.2870	0.0222*
	MA1	0.012571	0.057709	0.2178	0.8276
	MA2	-0.874250	0.055314	-15.8053	2.2e-16***

Evaluation of model adequacy was performed through diagnostic checks, including assessment of the Normalized Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). Notably, the ARIMA (1,1,1) model emerged as the preferred choice, boasting the lowest BIC and AIC values among the estimated models, as presented in Table 3.

Table 3: Model Evaluation

Model	**BIC**	**AIC**	**Ljung-Box Q**		
			Statistics	**DF**	**P-value**
(1,1,1)	781.5278	772.9022	19.913	22	0.5885
(2,1,1)	786.4015	774.9007	20.006	21	0.5209
(1,1,2)	786.4017	774.9009	19.988	21	0.522
(2,1,2)	787.893	773.517	17.146	20	0.6434

Further scrutiny of the ARIMA (1,1,1) model's residuals, as depicted in Figure 5, revealed that all coefficients fell within the significance bounds ($\pm\frac{2}{\sqrt{132}} = \pm 0.1741$), indicative of adequacy. Additionally, validation through Ljung-Box Q Statistics yielded p-values exceeding the alpha threshold of 0.05, signifying the absence of autocorrelation in the model.

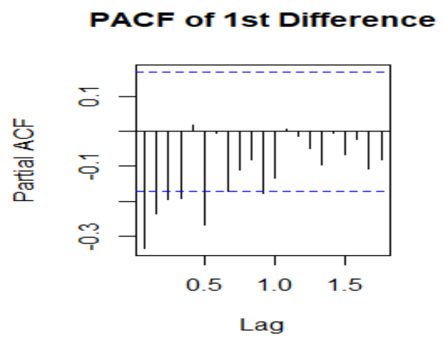
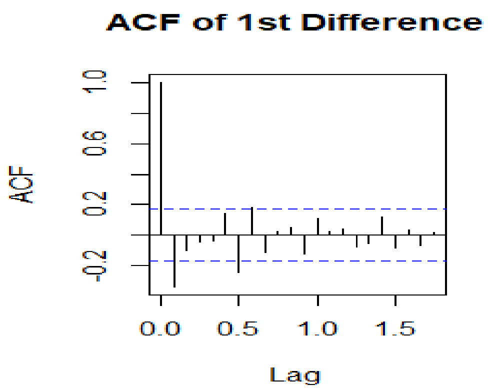


Fig. 4: ACF and PACF of First Difference of Stroke Cases



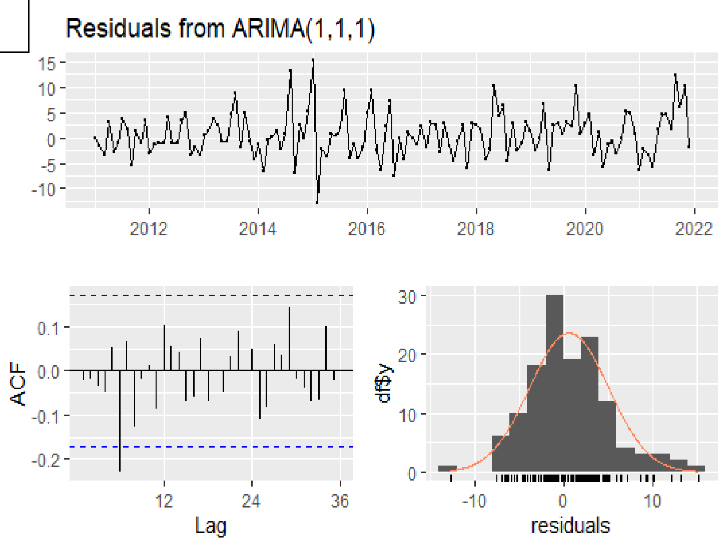


Fig. 5: Plot of Residuals of the Fitted ARIMA(1,1,1)

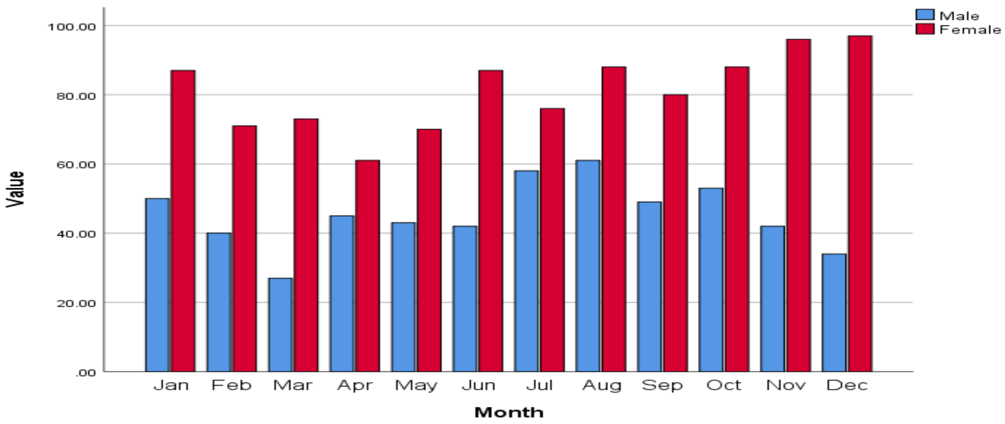


Fig. 6: Monthly Total for Male and Female Stroke Cases.

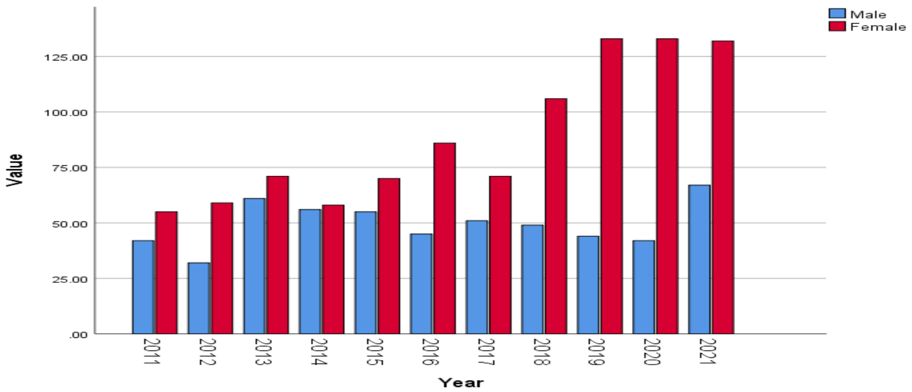


Fig. 7: Yearly Total for Male and Female Stroke Cases.

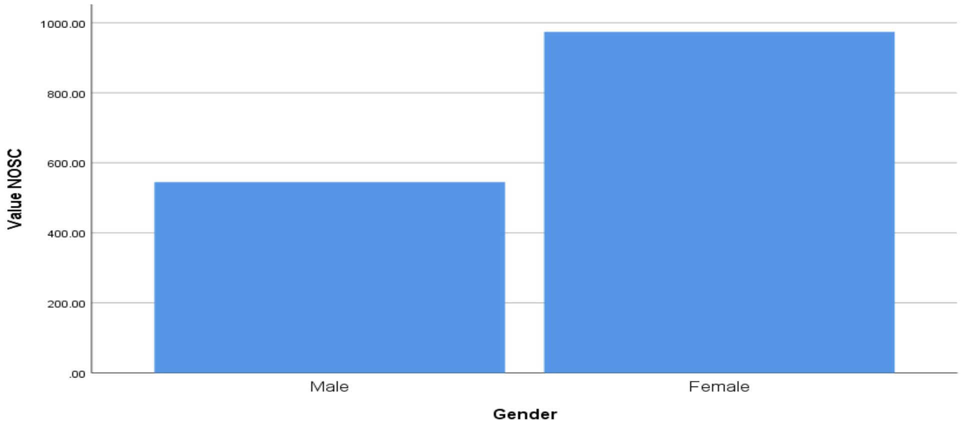


Fig. 8: Total Number of Stroke Cases by Gender

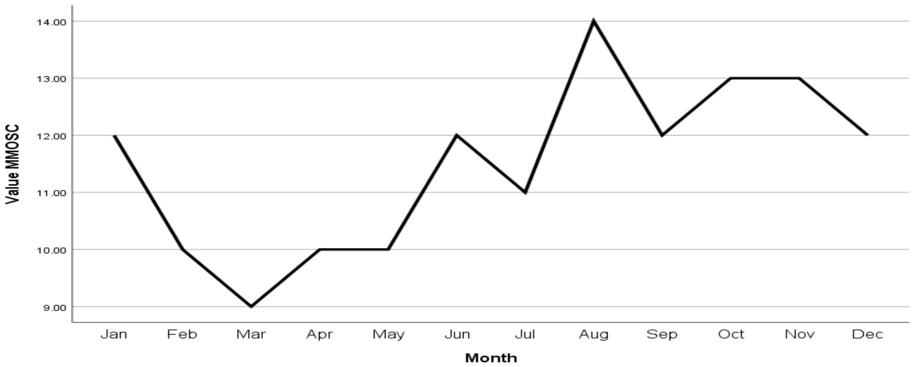


Fig. 9: Plot of Monthly Mean of Stroke Cases against Time

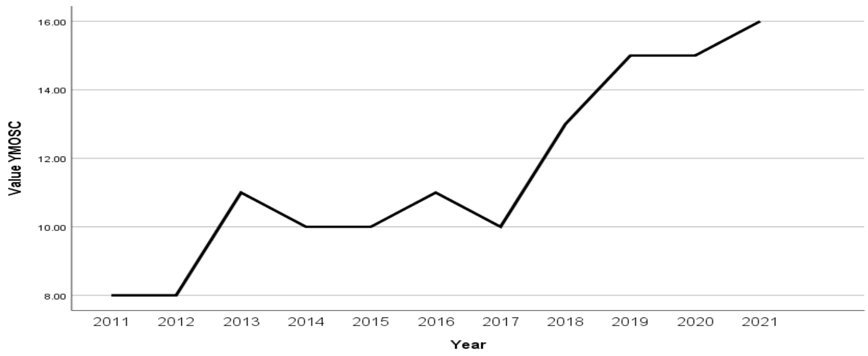


Fig. 10: Plot of Yearly Mean Stroke Cases Against Time

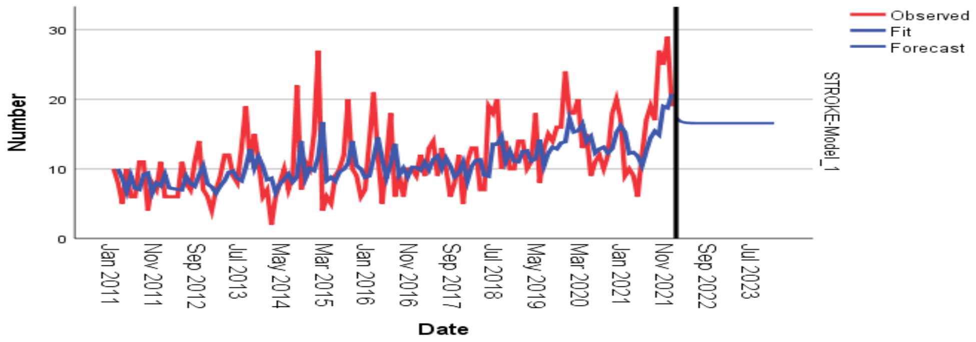


Fig. 11: Forecasting with the Fitted **ARIMA (1,1,1)** Model

In summary, the ARIMA (1,1,1) model emerged as the optimal choice for modelling the stroke dataset, evidenced by its superior performance in terms of BIC and AIC values, as well as the adequacy confirmed through diagnostic assessments. This rigorous approach to model selection and validation highlights the robustness and reliability of the chosen ARIMA framework in capturing the underlying dynamics of the stroke dataset. The mathematical representation of the selected model is delineated as per equation (7).

$$X_t^* = 0.3282X_{t-1} + \epsilon_t - 0.932\epsilon_{t-1} \qquad (14)$$

Where:
$X_t^* = \nabla X_t = X_t - X_{t-1} = (1-B)X_t$

The present study has established a structured framework for predicting stroke incidence by employing a suitable time series model on the dataset. The projections derived from the fitted model indicate a discernible trend towards escalating stroke prevalence. This finding resonates with the conclusions drawn by Ugoh *et al*. (2022) and Feigin *et al*. (2022), which posit that approximately one in four individuals is expected to experience a stroke during their lifetime.

CONCLUSION

The findings indicate a notable and statistically significant increase in stroke incidence within the Uyo region. This upward trajectory in stroke cases is anticipated to exert a substantial adverse impact on the local government and broader state economy. Given that stroke survivors often contend with enduring physical disabilities, leading to compromised work capabilities, income loss, and diminished social connections, urgent measures are warranted. Governmental authorities must prioritize the provision of robust healthcare infrastructure tailored to address the needs of stroke patients. Furthermore, concerted efforts towards regular and comprehensive public awareness campaigns are imperative, emphasizing early symptom recognition, timely detection, and effective treatment interventions for stroke. These initiatives align with the World Health Organization's annual commemoration on October 29th, emphasizing the importance of proactive measures in mitigating the socioeconomic repercussions of stroke within the Uyo region.

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