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Modeling Nigerian Crude Oil Prices: Comparative Evaluation of Linear, Volatility, and Deep Learning Approaches

Onyenze Kevin Ikeokwu[1]; Godson Chioma Abugwu[2];
Emmanuel Chigozie Umeh[3*]; Nwachukwu Adaku Chinyere[4]

[1]Department of Economics, IAUE, Rivers State, Nigeria.
[2]Department of Project Management, University of Portsmouth, United Kingdom.
[3]Department of Statistics, Federal University of Technology Owerri, Nigeria.
[4]Department of Economics, IAUE, Port Harcourt Rivers State.

Corresponding Author: Emmanuel Chigozie Umeh[3*]

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Abstract: The study focuses on determining the prediction performance of autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) and long short-term memory (LSTM) models of Nigerian crude oil prices. The comparisons among traditional linear models, volatility-based models, and deep learning approaches were done using monthly data from January 1946 to June 2025. Based on the outcomes, the ARIMA (1,1,0) model produces a fairly good linear fit for the data. However, it has relatively high prediction errors, with an MSE equal to 590.87, RMSE equal to 24.31 and MAPE equal to 28.27%. The GARCH (1,1) models exhibit successful volatility clustering capturing, with the t-distribution variant outperforming the normal specification while still yielding higher prediction error than deep learning.

The MSE for the LSTM model was 112.74 with a RMSE of 10.62 and a MAPE of 15.06% which closely followed the actual price movement. The LSTM model was the best model overall in predicting the Nigerian crude oil prices. This finding was evidence that markets characterised by volatility and nonlinear dynamics are best modeled using deep learning nonlinear approaches rather than the traditional econometric models.

Keywords: *Crude Oil Price Prediction; ARIMA; GARCH; LSTM; Deep Learning; Nigeria.*

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I. INTRODUCTION

Crude oil is the mainstay of the economy of Nigeria as it is responsible for over 80% of the export earnings of the country and a considerable proportion of government revenue (CBN, 2025). As a result, fluctuations in crude oil prices have a significant impact on the stability of the fiscal, performance of exchange rate and economic growth (Adeniyi, Oyinlola, & Omisakin,2011)). Nevertheless, due to demand shocks, geopolitical risks and supply-side issues, crude oil prices are volatile, thereby, making it difficult to forecast but essential (Hamilton, 2009; Kilian & Zhou, 2020).

For a long time, Researchers, policy makers and market participants are interested in predicting crude oil prices. Traditional econometric models like the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976) make good use of this property. In the same way, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models is used to model oil markets to account for heteroskedasticity and clustering volatility (Bollerslev, 1986; Alquist & Kilian, 2010). Even though the methods are useful, they have limited capacity to effectively capture the nonlinear and long-term dependencies that crude oil price dynamics exhibit (Zhang et al., 2019).

AI and deep learning approaches have emerged as potential alternatives for time-series forecasting in the recent year. Long Short-Term Memory (LSTM) neural networks are a variant of recurrent neural networks (RNNs) have recently

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achieved notoriety for their ability to model non-linear relationships and memory of long-term dependencies (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 201 8). According to empirical evidence (data), performance of LSTM is usually superior (better) than that of classical econometric models when predicting financial and energy market time series (Yu et al., 2019; Qian et al., 2021).

- *Several Researchers Have Studied Crude Oil Price Prediction and Their Findings are Review as Follows:*

Due to its performances in classic time series models, the autoregressive integrated moving average (ARIMA) model remains a benchmark for time series prediction. Box and Jenkins (1976) set the theoretical underpinnings of ARIMA. Later studies such as Baumeister & Kilian (2016) and Narayan & Narayan (2007) use ARIMA in energy prices. ARIMA has an easy estimation and is interpretable. The model's main drawback, however, is its incapacity to model the nonlinearities and volatility clustering of prices of crude oils. A recent report information showed ARIMA performs very well for short-term predictions but performs very poorly under volatility (Wang et al., 2018). So, ARIMA serve as a baseline model, after comparison with the actual series, ARIMA cannot actually valid model for oil market that contains huge structural breaks and non-linear dynamic.

Engle (1982) and Bollerslev's (1986) GARCH Models Extend ARIMA by Thinking about a Model of the Conditional Variance. GARCH models are useful to model volatility persistence and clustering in crude oil prices. Several studies (Ewing & Malik, 2013; Fattouh, 2010) show that they are useful for risk management and pricing of derivatives. The EGARCH, TGARCH and GJR-GARCH variants account for asymmetries and leverage effects. Nonetheless, some authors stated that GARCH models are mainly volatility models and not very good at predicting price levels (Salisu & Fasanya, 2013). In addition, using parametric error distributions does not provide flexibility to capture extreme events. GARCH, although better than ARIMA in capturing volatility dynamics, is only moderately accurate in predicting the price of crude oil.

Deep learning can beat econometric models. This has an implication for effectiveness. The Long short-term memory (LSTM) networks were proposed by Hochreiter and Schmidhuber in 1997 and are useful in capturing nonlinear dependencies and long-term memory in time series. According to various studies (Yu et al., 2015; Hewamalage et al, 2021; Ahmed et al., 2020) the LSTM model performs better than the ARIMA and GARCH models. LSTMs do not impose the strong stationarity assumptions of linear models making them flexible to learn complex patterns. Although effective, it has a "black box" nature, which raises questions about their interpretability. Training requires significant computational power (Goodfellow et. al, 2016). Although there are some limitations, LSTM has become the most prominent model for predicting crude oil prices in situations where there is nonlinearity and volatility clustering.

Despite extensive research, several gaps exists. Usually, most studies on crude oil prediction focus on global benchmarks (Brent, WTI) with scant attention devoted to Nigerian crude oil, despite the greater marginal importance of Nigeria in the global energy market. Second, there is limited research comparing ARIMA, GARCH and LSTM directly on the same dataset. Existing works often study third classes of models making the benchmark of their relative performance hard. In a developing country setting, few studies examine critically how the two methods perform together or out perform each other especially GARCH capture the volatility and LSTM accuracy.

This research fills what the other studies missed by comparing ARIMA, GARCH, and LSTM modelling for Nigerian crude oil price prediction using a long-time data set. The present systematic investigation of error metrics (MSE, RMSE, MAPE) and volatility diagnosis provides new evidence on the relative strengths and weaknesses of traditional time series and deep learning methods. This study, unlike earlier works focusing on global benchmarks, zeroes in on Nigeria's oil market, offering academic and policy-relevant insights.

- *The Main Objective of this Research is to Conduct a Comparative Analysis of Nigerian Crude oil Prices Using ARIMA, GARCH, and LSTM Models. Specifically, the Study Seeks to:*

- Examine the performance of ARIMA, GARCH, and LSTM models in modelling Nigerian crude oil prices.
- Compare the strengths and limitations of traditional econometric models versus modern deep learning approaches.
- Provide policy and investment insights for managing risks associated with oil price volatility in Nigeria.

This study matters for developing a method and gathering information for the interest of a policy. In terms of methods, it compares classical proficiency and modern sophisticated deep learning methods and provides evidence on their respective accuracy with data. From a policy point of view, the findings will be useful in fiscal planning, risk management and energy market regulation in Nigeria. Since accurate oil price forecasts are critical for sustainable economic management in Nigeria.

II. MATERIALS AND METHODS

This section contains the data collection method, the descriptions of Box and Jenkins (1976) model, GARCH model, and LSTM.

- *Method of Data Collection*

This study employs monthly Nigerian crude oil price data covering the period January 1946 to June 2025, obtained from the Central Bank of Nigeria (CBN) statistical database. The series represents the Bonny Light crude oil benchmark, expressed in U.S. dollars per barrel.

The data were collected in their nominal form, without adjustment for inflation, to maintain consistency with the official CBN reports and to reflect real market pricing

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conditions during the period. Each observation corresponds to the monthly average of daily crude oil prices published by the CBN.

Any missing monthly values were interpolated linearly, and beyond this adjustment, no other data were smoothed or replaced.

To ensure stationarity, the series were differenced for the econometric models (ARIMA and GARCH).

To transform the data to the range from [0, 1] for the deep learning model (LSTM), MinMaxScaler has been used, wherein fit was done on training set only. We reported all results and evaluation metrics in the original price scale (USD) to ensure interpretability.

➢ *ARIMA (P, D, Q) Model for Nigeria Crude Oil Price*

The ARIMA class of models uses its own lags and lagged prediction errors to describe a given time series in order to anticipate future values. Any non-seasonal time series having a pattern other than random white noise can be simulated using ARIMA models (Selva 2021). The word ARIMA stands for autoregressive integrated moving average, according to Adhikari and Agarwal (2013). The integrating process, which turns a non-stationary time series variable into a stationary one, is combined with the autoregressive (AR) and moving average (MA) models. A three-step method for selecting the optimal ARIMA model was developed by Box and Jenkins (1976), and it is essential to the selection process. Identification, estimation, and diagnostic testing are the three phases. To identify the best model, repeat these three stages multiple times (Box and Jenkins 1970). The concept of parsimony is essential for choosing the best ARIMA model to prevent overfitting. According to Chigozie et al. (2023), "d" denotes the number of times the data is differenced to make it stationary, "p" denotes the number of lags in the Partial Autocorrelation Function (PACF) plot that cross the significant limit, and "q" denotes the number of lags in the Autocorrelation Function (ACF) plot that do so.

According to Nwigwe et al. (2023), given the Nigeria crude oil price x_t, the ARIMA (p,d,q) model is given as in equation (1):

$$\phi(B)\,(1-B)^d\,X_t = \theta(B)\,Z_t \tag{1}$$

Where:

$\phi(B)$ is the characteristic polynomial of order "p" for the autoregressive component of the model.

$\theta(B)$ is the characteristic polynomial of order "q" for the moving average component of the model.

$(1-B)^d$ is the differencing of order "d" of the data.

X_t is the observed value at time t

Z_t is the random error associated with observation at time t

- *Stationarity Test Using Augmented Dickey Fuller Test*

Stationarity of the serieas will be checked using Augmented Dickey Fuller test on the series. This test considers different assumptions such as under constancy, alongside no drift or along a trend and a drift term. If the series is not stationary, then the first or second difference is likely to be stationary.

✓ *The hypothesis is Given in (Dickey & Fuller, 1979) as:*

❖ $H_0 : |\phi_1| = 1,$ that is: the process contains a unit root and therefore it is non-stationary.

❖ $H_1 : |\phi_1| < 1,$ that is: the process does not contain a unit root and is stationary.

✓ Decision: If the p-value < 0.05, we reject the null hypothesis. This means that there is stationarity in the stock data.

- *Model Estimation*

Once stationarity is attained, next thing is to fit different values of p and q, and then estimate the parameters of ARIMA model. We use iterative methods to select the best model based on the following measurement criteria: AIC (Alkaike information criteria) and BIC (Bayesian information criteria) and log likelihood.

$$\text{Akaike's Information Criteria (AIC)} = -2 * Log(L) + 2(p+q+k+1) \tag{2}$$

where

L is the likelihood of the series

$k = 1,$ if $c \neq 0$ and $k = 0,$ if $c = 0$

$$\text{Bayesian Information Criteria (BIC)} = AIC + [Log(T) - 2] * (p+q+k+1) \tag{3}$$

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where

T is the maximum likelihood estimation limit

- ✓ log likelihood of the data: This is the logarithm of the probability of the observed data coming from the estimated model. The larger the log likelihood, the better the model.
- ✓ Note: smaller values of AIC, BIC with maximum log likelihood indicate a better model.

- *Model Diagnosis*

The conformity of white noise residual of the model fit will be judged by plotting the ACF and the PACF of the residual to see whether it does not have any pattern, when steps 1-3 are achieved, we go ahead and fit the model

- *Generalized Autoregressive Conditional Heteroscedastic: GARCH (p, q) Model*

The Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model is a statistical model used to analyze time series data that have conditional heteroskedasticity, which is the phenomenon where the variance of the errors in a time series vary over time. In other words, the GARCH model can be used to estimate time-varying volatility in a time series. The model has been widely used in financial econometrics to estimate risk, volatility, and asset returns since Robert Engle first presented it in the 1980s. The GARCH model is based on the Autoregressive Conditional Heteroskedasticity (ARCH) model, which asserts that the variance of a time series is a function of its previous values. The GARCH model extends this concept by allowing the variance to depend on the squared errors of the time series as well as its historical values.

According to Nwigwe et al. (2023), the GARCH model uses the previous variance and past squared observation value to model the variance at time t. The conditional variance is allowed to depend on previous lags in the model. The models project how today's volatility shock will affect volatility over the ensuing years. It calculates how quickly this impact has waned over time. The definition of the GARCH (1, 1) model is given by equation (4).

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (4)$$

➢ *Methods of Estimation of GARCH Models*

- *Maximum Likelihood Function (MLF)*

The maximum likelihood estimator is the technique used to estimate the GARCH model. The technique is used to determine the parameter value that is most likely given the actual series. The GARCH model is estimated in the following two phases.

- ✓ Specify the mean and variance equation, example AR (1) in equation (5) and GARCH(l,1) in equation (6)

$$y_t = \mu + \theta(y_{t-1}) + \mu_t; \quad \mu \sim (0, \sigma_t^2) \qquad (5)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (6)$$

- ✓ Estimate the likelihood function to maximise the normality assumption of disturbance terms given in equation (7)

$$\log L = -\frac{\tau}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{\tau}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{\tau}\frac{\mu_t^2}{\sigma_t^2} \qquad (7)$$

➢ *Long Short-Time Memory Recurrent Neural Network (LSTM-RNN)*

The LSTM-RNN (Recurrent Neural Network) is a soft computing method for encoding sequential data. It is made up of several self-connected LSTM cells that record the networks' temporal state using input, output, and forget gates. The challenging problem of predicting the price of crude oil can be represented by machine learning and artificial neural networks (Nwigwe, Batholomew, Chigozie et al., 2023).

An RNN (Recurrent Neural Network) is a type of neural network that is particularly good at processing time series and other sequential data (Hewamalage, Bergmeir, & Bandara 2021). The LSTM-RNN, a kind of recurrent neural network composed of several self-connected LSTM cells, uses three gates—input, output, and forget—to capture the network's temporal state.

Neural networks are computer systems designed to mimic the natural neural networks seen in human brains. The simplicity of the neurons in the brain served as the inspiration for this network of interconnected nodes. Artificial neurons are made up of a network of interconnected parts, or nodes, that are generally modeled after the neurons found in the human brain. Each connection may send, process, and communicate with the neurons that are connected to it, just like synapses do in the human brain (Haykin 2008). In a recurrent neural network (RNN), the output of the previous step serves as the input for the next step.

III. RESULTS AND DISCUSSIONS

The empirical analysis was carried out using monthly Nigerian crude oil price data from January 1946 to June 2025. The study applied ARIMA, GARCH, and recurrent neural networks (LSTM) models to examine the forecasting performance of linear, volatility-based, and nonlinear deep learning approaches.

➢ *Preliminary Analysis*

The time series plot (Figure 1) of Nigerian crude oil prices shows non-constant variance and volatility clustering. Stationarity of the time series data was tested using the Augmented Dickey -Fuller (ADF) which checks the null hypothesis that the series is not stationary. The result of the ADF showed that the series was non-stationary (ADF = -1.73, p = 0.41), sine the p-value > 0.05.

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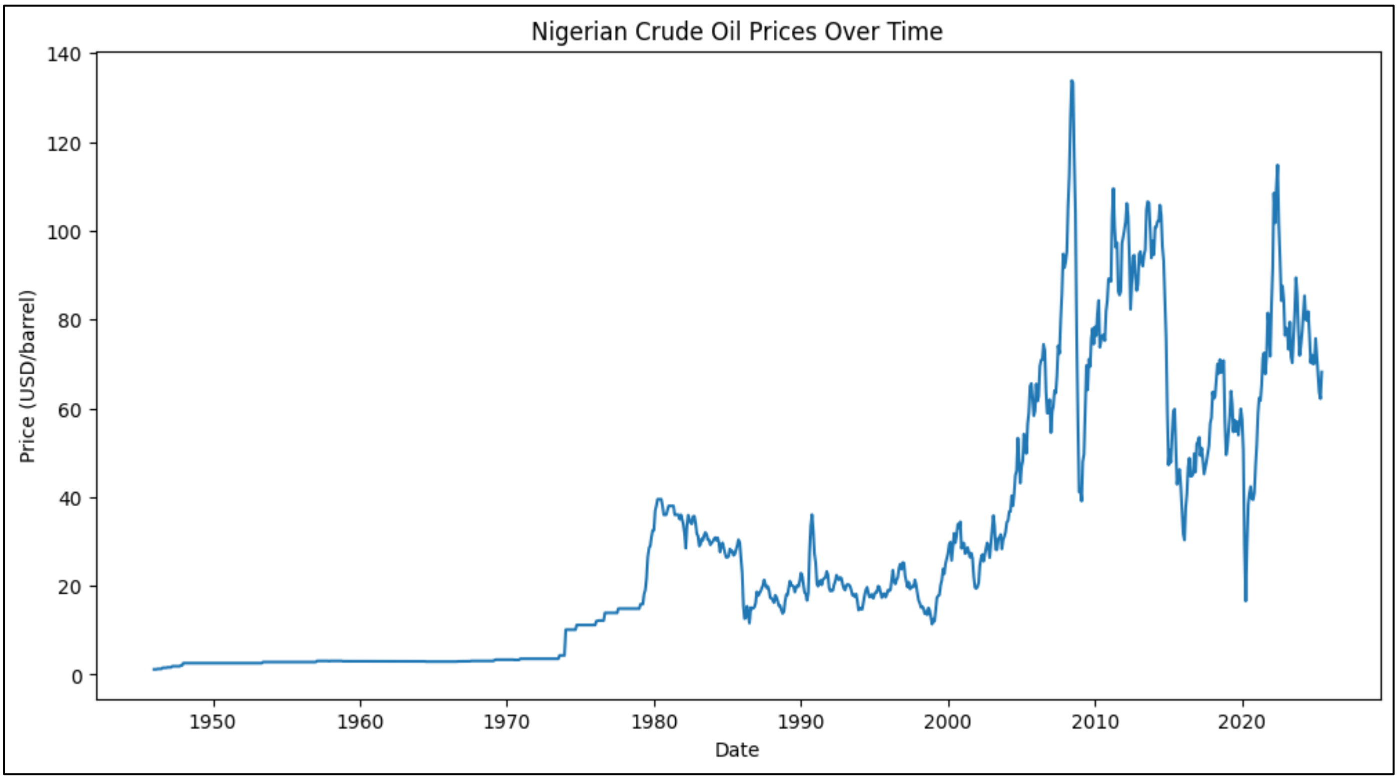

Fig 1 Time Series Plot of the Nigerian Crude Oil Monthly Prices (1945 - 2025)

The series was then subjected to transformation in order to achieve stationarity given that the outcome of the ADF test and the time series plot showed that the time series data is non-stationary. The first differencing of the series was conducted and the ADF test rechecked. The result of the ADF test (ADF = -7.89, p =0.01) after the first differencing showed that the series is now stationary at 5% level of significance (α).

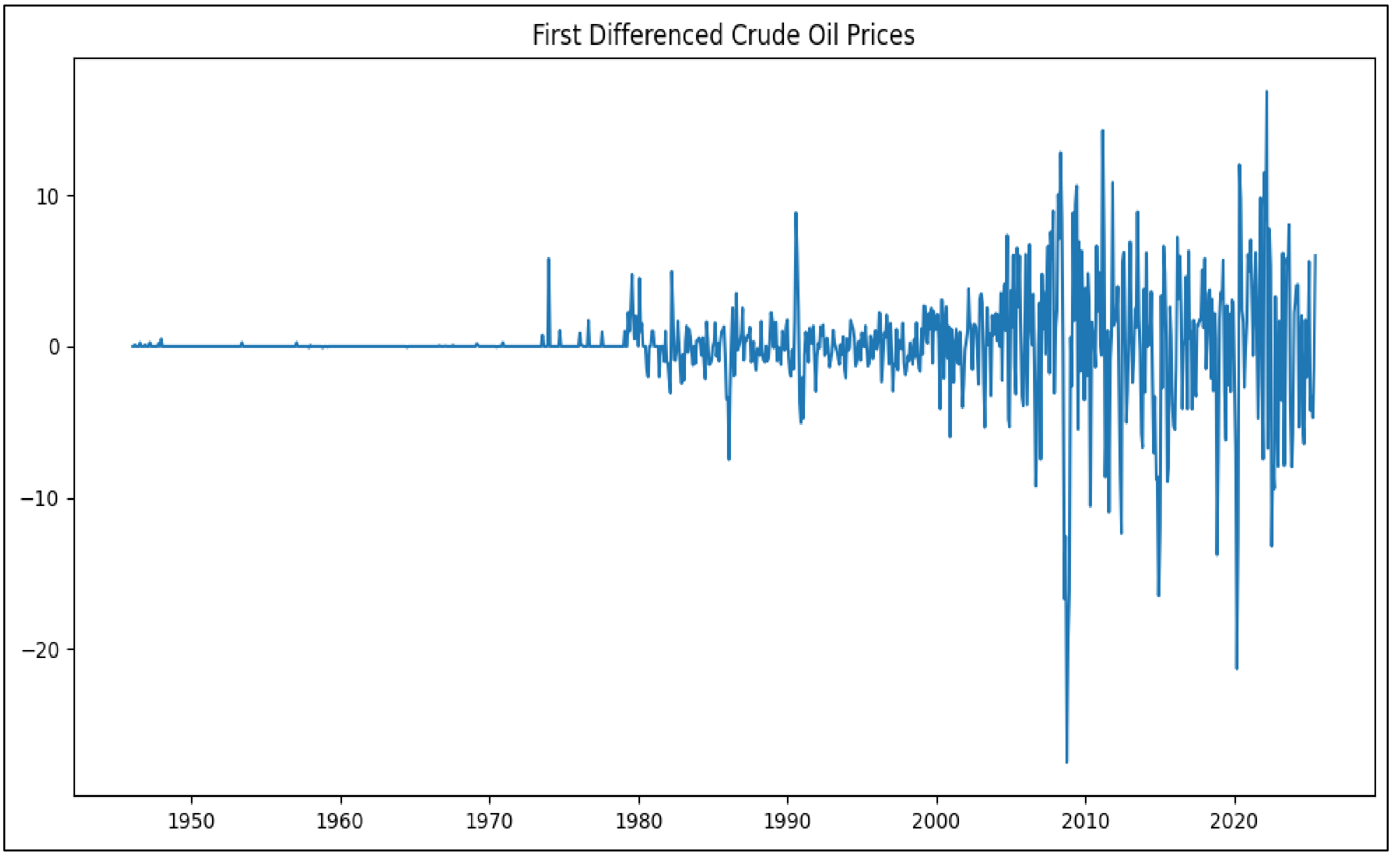

Fig 2 First Differencing of the Time Series Plot

The first differencing time series plot (figure 2) shows there is no pattern in the differenced series which confirms that the stationarity has been achieved after the first differencing.

➢ *ARIMA models of Nigeria Crude Oil Prices*

- *Model Identification*

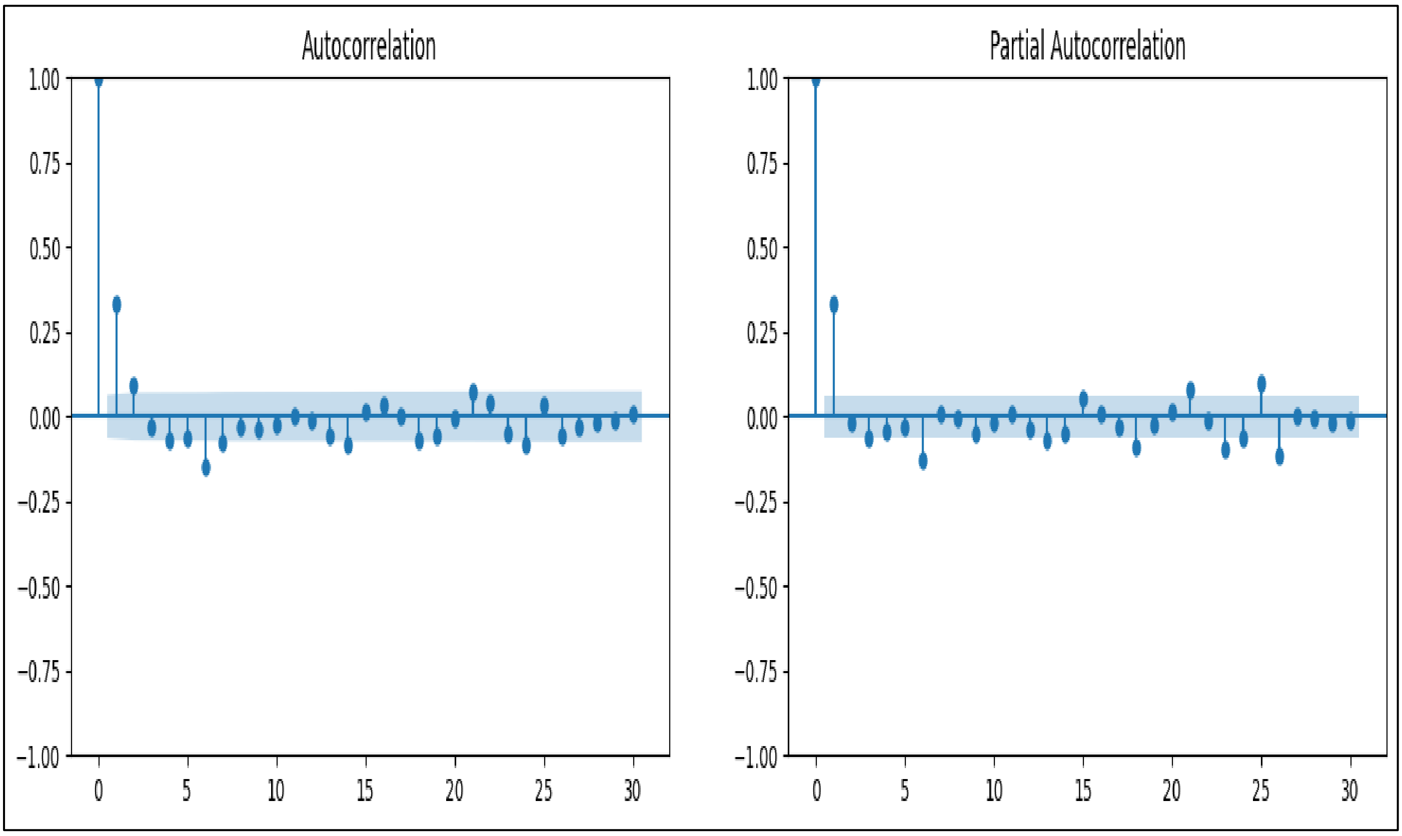

Fig 3 ACF and PACF of the Series After the First Differencing

Autocorrelation (ACF) and partial autocorrelation (PACF) plots (figure 3) showed significant spikes at lag 1 in each case, this suggests the presence of autoregressive and moving average components. Based on the Box-Jenkins methodology (Box & Jenkins, 1976), three ARIMA models were estimated: ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1).

- *Model Estimation*

Table1 The Different ARIMA Models

Models	AIC	HQIC	BIC
ARIMA (1,1,0)	4900.176	4905.730	4914.755
ARIMA (0,1,1)	4910.206	4915.760	4924.785
ARIMA (1,1,1)	4901.869	4907.423	4916.448

ARIMA (1,1,0) provided the best fit because it has the lowest AIC value.

Table 2 The Estimate of the Coefficients of ARIMA (1, 1, 0) Model

Parameter	Coefficient	Std. Error	Z-value	P-value
AR (1)	0.29	0.04	7.62	<0.001
σ^2 (variance	9.97	0.20	51.11	<0.001

Estimate of the ARIMA (1,1,0) showed that autoregressive parameter is statistically significant, suggesting short-term persistence in crude oil price changes.

- *Residual Diagnostics of ARIMA (1,1,0)*

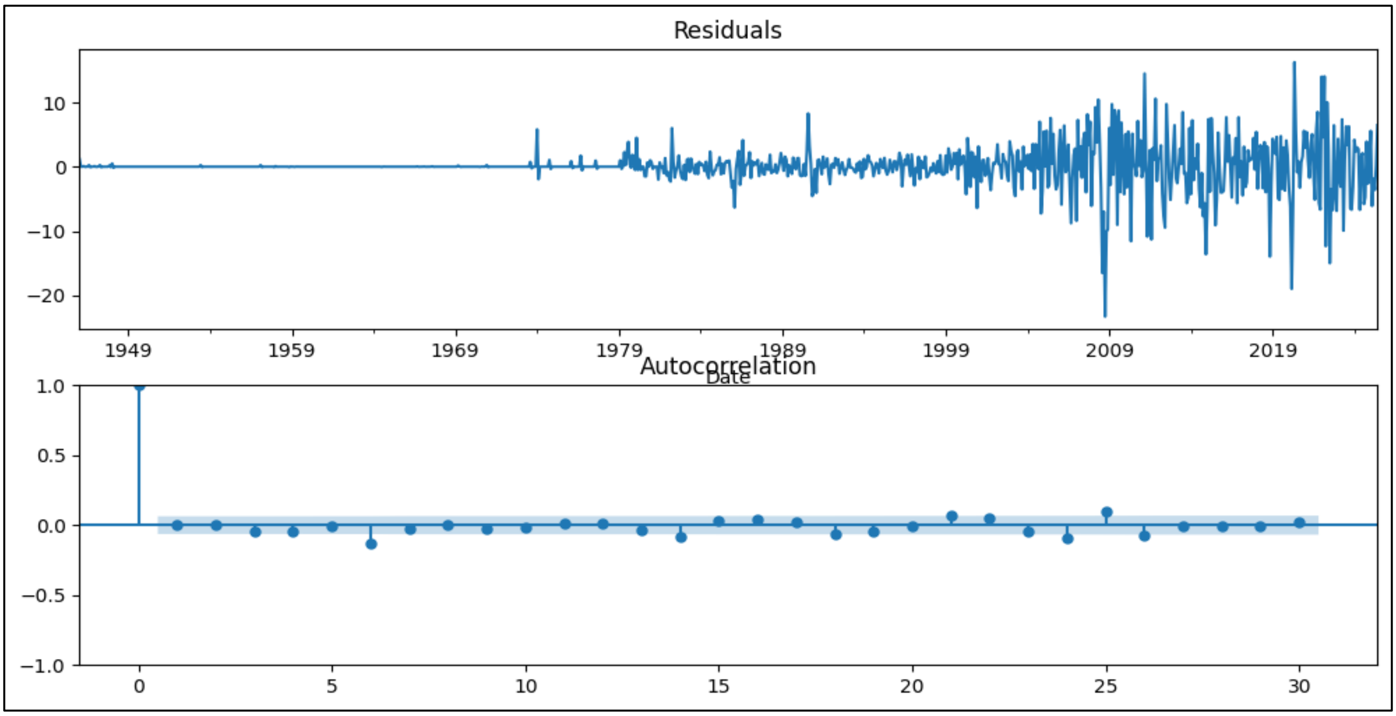

Fig 4 Residual of White Noise

The residula and autocorrelation of arima (1,1,0) are shown in figure 4. The residuals appear to be randomly distributed around zero, with no clear trend or structure. However, it can be seen that volatility increases substantially in later years, consistent with known oil price shocks and market turbulence.

The autocorrelation plot of the residuals shows that most spikes lie within the 95% confidence bounds, indicating that serial correlation has largely been removed. This confirms that the ARIMA (1,1,0) adequately represented the linear dynamics in the Nigerian crude oil price series.

➢ *GARCH Models of Nigeria Crude Oil Prices*

The presence of conditional heteroskedasticity was examined using the ARCH–LM test. The test statistic gave p-values of greater than 0.30 at lags 3, 5 and 7. As these p-values are greater than the 5% significance level, we do not reject the null hypothesis of no ARCH effects. In other words, the unconditional mean model residuals do not exhibit significant conditional heteroskedasticity. GARCH modeling technique was used to capture potential volatility clustering observed in the visual diagnostics of the return series rather than a regression of the statistically significant ARCH-LM outputs.

Table 3 Results of the ARCH LM Test for Nigeria Crude Oil Prices

Lag	LM statistic	*p*-value
3	3.4731	0.3243
5	3.8489	0.5714
7	3.8570	0.7961

Weights Ljung-Box Q-statistics has very small p-values ($p < 0.05$) which implies residual autocorrelation is still present in fitted ARIMA model. This indicates the model does not capture all serial dependencies present in the data, thus justifying the use of higher-order or non-linear models such as GARCH and LSTM for better dynamic representation.

Table 4 Results of the weighted Ljung-Box Test on Standardized Residuals

Lag	Statistic	*p*-value
1	11.5118	0.0007
5	28.6418	0.0000
9	29.8181	0.0005

Table 5 Comparison of the GARCH Models

Model	Log Likelihood	AIC	BIC
sGARCH (1,1) Normal	–3111.34	6230.67	6250.11
sGARCH (1,1) t-distrib.	–1505.23	3020.47	3044.77

The conditional volatility plots (Figure 5) confirmed the persistence of volatility clustering, a key feature of crude oil prices.

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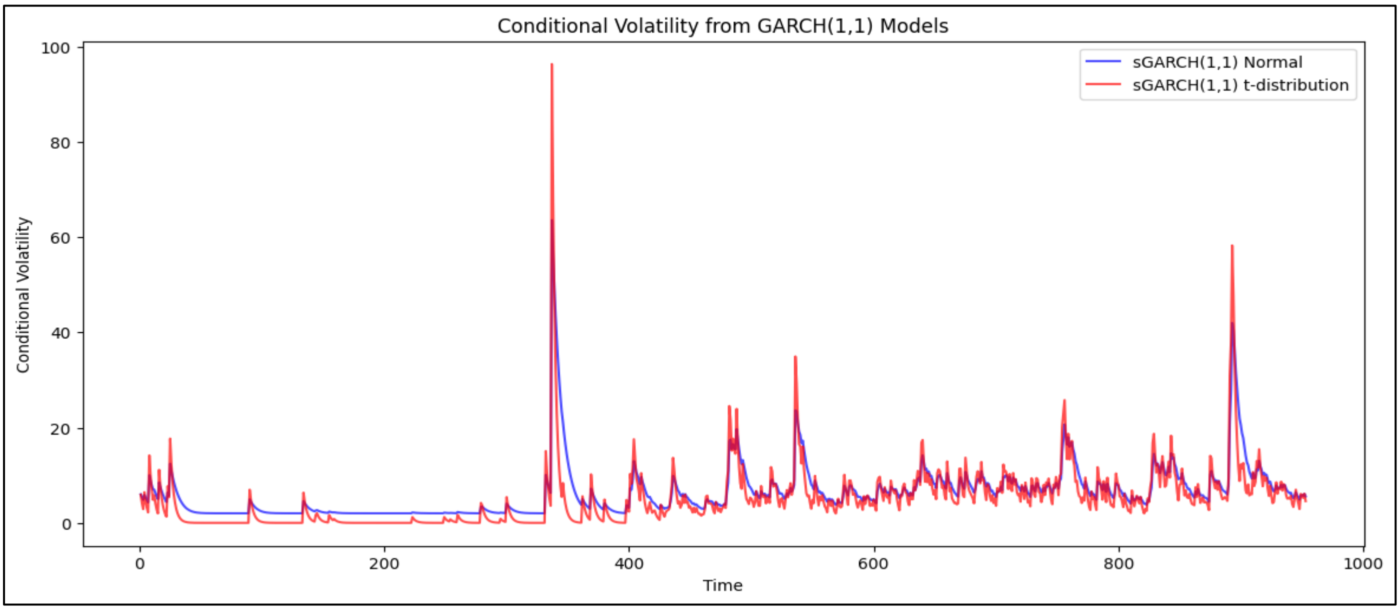

Fig 5 Conditional Volatility from GARCH (1,1) Models

➢ *Long Short Time Memory-Recurrent Neural Network (LSTM-RNN)*

For detecting nonlinear relationships and long-term dependencies, a Long Short-Term Memory (LSTM) recurrent neural network was developed using TensorFlow–Keras framework.

The input sequence length was 60 months, corresponding to a 5-year rolling window of lagged observations. The model architecture consisted of:

- Two stacked LSTM layers with 50 and 25 hidden units respectively (first layer with return_sequences=True),
- A dense layer with 25 neurons and ReLU activation,
- An output dense layer with a single neuron for one-step-ahead forecasts.

The Adam optimizer was set to a learning rate of 0.001 and used Mean Squared Error (MSE) loss. The model was then trained for 100 epochs with a batch size of 32. Overfitting was prevented by using a patience value of 10 epochs for early stopping. The data sets were chronologically split into three groups, with the training data running from January 1946 to December 2019, validation from January 2020 to December 2021, and testing from January 2022 to June 2025.

The performnce of the model was evaluated using MSE, RMSE, and MAPE, computed on the test set. All predictions were rescaled back to the original USD values for comparability with the econometric models.

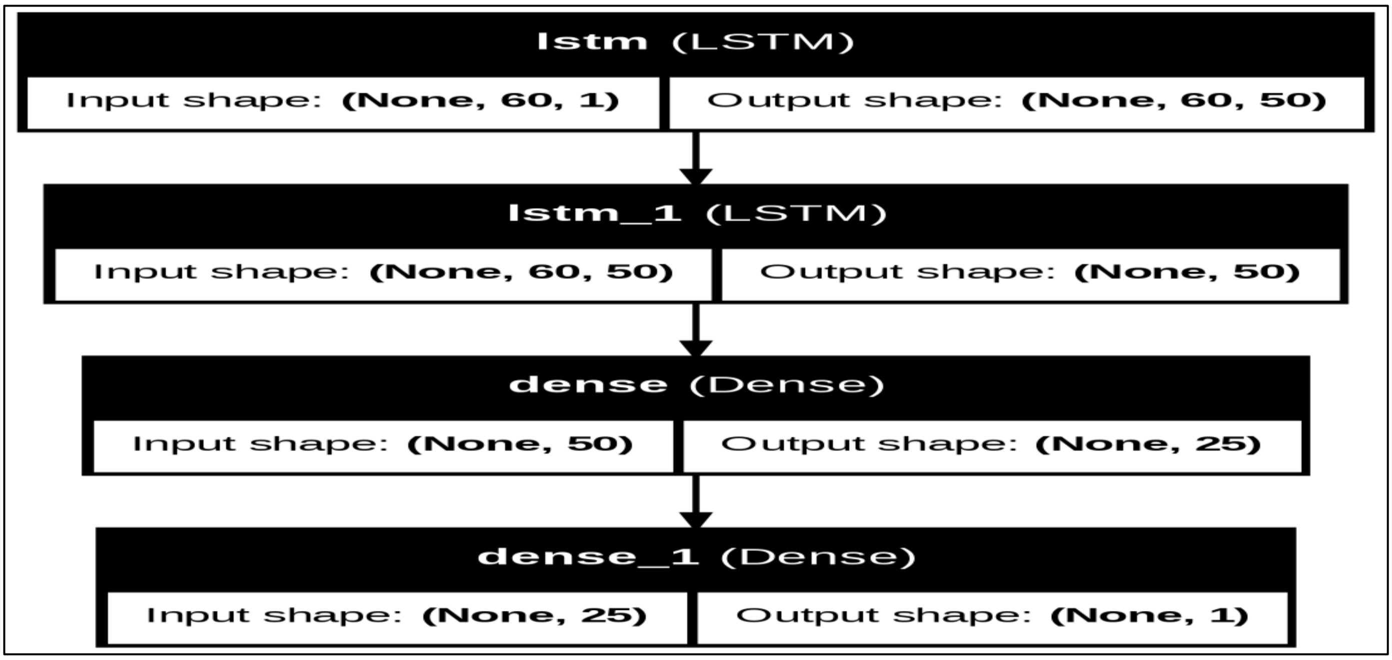

Fig 6 Architecture of the LSTM Model

➢ *Training and Validation Loss of the LSTM Model.*

The loss curves for training and validation are illustrated in Figure 7. For both losses, a sharp drop was seen in the first epochs, and stabilization followed afterward. The training loss and validation loss almost followed the same curve indicating that the model generalizes well.

Fig 7 Training and Validation Loss of the LSTM Model.

➢ *Comparative Performance of ARIMA, GARCH, and LSTM Models Using RMSE, MSE and MAPE.*

Table 6 Comparative Performance of ARIMA, GARCH, and LSTM Models using RMSE, MSE and MAPE.

Models	**MSE**	**RMSE**	**MAPE**
ARIMA (1,1,0)	590.8749	24.3079	28.27%
sGARCH(1,1) Normal	520.3150	22.8150	25.41%
sGARCH(1,1) t-dist	505.2280	22.4700	24.92%
LSTM	112.7414	10.6180	15.06%

The ARIMA (1,1,0) model exhibited the most substantial forecast errors, indicating an incapacity to adequately achieve a projected value due to the failure to capture nonlinearity and clustered volatility. The GARCH models fared better in prediction accuracy than the ARIMA model, with the t-distribution specification yielding slightly lower errors than the normal distribution model. The LSTM model did better than the GARCH models, for all three-error metrics it had a substantially lower value.

The results show that nonlinear deep learning methods outperform time-series methods in forecasting Nigerian crude oil prices since such methods are unable to capture the complexities of their dynamics.

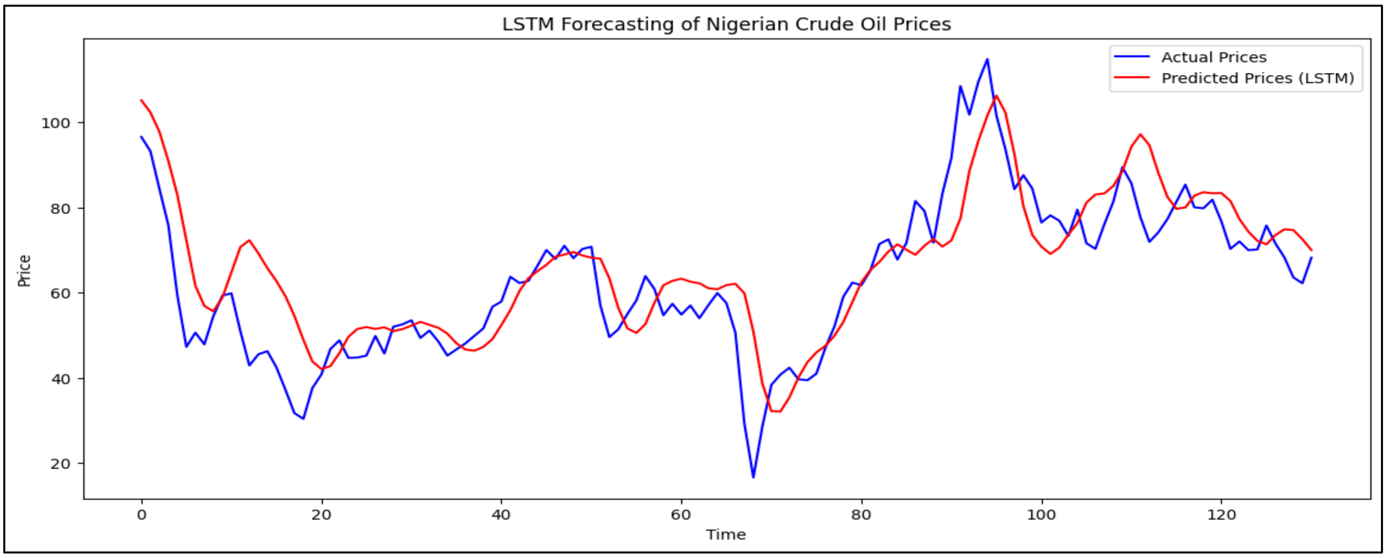

Fig 8 Graph of Nigeria Crude Oil Price Prediction Using LSTM-RNN

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The superiority of the LSTM as shown in Figure 8 compares the actual versus predicted Nigerian crude oil prices. There's not much difference between the predicted series and the actual series data as both are parallel. As a result, moreover, the study confirms the usefulness of deep learning approaches, particularly LSTM networks, to model complex dynamics and volatility of crude oil markets.

- *Summary of Results*

In this paper, the results are summarized as follows:

- The ARIMA models fitted to Nigerian crude oil prices revealed ARIMA (1,1,0) as the best model as it has the least AIC, BIC and HQIC values when compared along with other ARIMA specifications. But the residual diagnostics showed that volatility clustering was present, meaning that there was heteroskedasticity.
- The crude oil price series was further modeled using standard GARCH specifications with both normally distributed and t-distributed errors. The two families of GARCH models were compared, and the sGARCH(1,1) with t-distributed errors provided slightly better performance than the normal distribution model, although both showed persistence in volatility.
- The series was equipped with an LSTM-based recurrent neural network model. This model has the best predictive performance with the least MSE (112.74), RMSE (10.62), and MAPE (15.06%).

After comparing the three approaches, LSTM was the best among ARIMA and GARCH in terms of accuracy of predictions. The ARIMA is the weakest in capturing the nonlinearities. The GARCH explains the volatility dynamics better. The LSTM model captures both trend and volatility. Therefore, LSTM is the most reliable tool for forecasting Nigerian crude oil prices.

IV. CONCLUSION

The aim of this study is to evaluate the various prediction capabilities of ARIMA, GARCH, and LSTM models using Nigerian crude oil prices spanning from January 1946 to June 2025 (Monthly Data). The main task is to compare performance of a linear model, a volatility model, and a non-linear model, in order to identify the best and most effective tool for predicting crude oil prices.

The results indicate that the ARIMA (1,1,0) model was able to provide a reasonable linear fit but it did not capture the volatility clustering that is inherent in the series. The GARCH models have managed to well model the volatility persistence. The t-distribution specification did have slightly better results than the normal distribution.

Nonetheless, the prediction errors obtained from both ARIMA and GARCH were quite high. On the other hand, the LSTM model recorded the least error metrics (MSE = 112.74, RMSE = 10.62, MAPE = 15.06%) and tracking of real crude oil price movements, thus proving considerably better than the traditional models.

Comparing these methods, we find that LSTM gives us the best and most reliable prediction in prices of Nigeria crude oil. GARCH does next best, and ARIMA fares the worst. Machine learning approaches for crude oil price prediction are of great importance in a market exhibiting non-linearities with volatility clustering.

To summarize, the analysis offers convincing proof that deep learning methods, particularly LSTM networks, have a greater ability to forecast crude oil prices in Nigeria. What we learn is useful for policymakers, energy economists, and financial market participants who need accurate predictions of crude oil prices to make decisions and manage risks.

- *Conflict of Interest:*

The authors declare that there is no conflict of interest.

- *Funding:*

This study did not receive any form of funding from any organization.

- *Data Availability:*

https://www.cbn.gov.ng/rates/crudeoil.html

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