Hybridized LSTM-GRU model for forecasting the Prices of Crude oil

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ORIGINAL RESEARCH

Abstract— Fluctuation in crude oil price doesn't only affect production or transportation but has secondary effect on all ways of life, as increased cost of production would surely lead to increase in the price of produce and increased in cost of transportation, which would in turn increase cost of living, increase poverty and hunger. Owing to this, accurate forecasting of crude oil price through the application of effective and technological driven approach would help the policy makers, industrial decision makers and investors to make informed and strategic policies that would help the government and stakeholders to prevent unplanned economic risk and damage. Conventionally, crude oil price forecasting is being done using traditional methods like Liner regression, generalized autoregressive conditional heteroskedasticity (GARCH) and autoregressive integrated moving average (ARIMA) models, this model most time struggles with the non-linearity and fluctuating nature of the crude oil price. Moreover, this models require additional manual feature selection and extraction which might be time consuming and computationally exhausting. The acceptance and proven accurate performance of deep learning techniques prompted this study to comparatively employ the major variants of Recurrent Neural Networks (RNN) namely Long-short term memory (LSTM) and Gated Recurrent Units (GRU) for forecasting of crude oil price owing to their strengths. The famous Brent crude oil price dataset was used for forecasting of crude oil price, while this dataset went through series of preprocessing like data and time conversion, data windowing, transformation, variable selection after which LSTM-GRU model was used for forecasting, this hybridized model gave a better performance when evaluated with Mean Absolute Error of 0.014 which outperformed LSTM and GRU and when compared with existing studies. This shows that hybridized LSTM-GRU is a good model for forecasting of crude oil price as the model leverage the strength of LSTM and GRU on sequential data.

Keywords— Crude oil price, Deep Learning, Forecasting, LSTM, GRU, Time series,

1 INTRODUCTION

The adoption of renewable energy has gotten much attention for the past few decades due to its assumed economic advantage and low financial implication. However, crude oil is still a major source of energy in industrial production and even transportation. Resulting from its undiluted importance and relevance in the oil and gas sector, fluctuation in its price plays a major role in the production process and the nation's economy at large including economic activities and financial market in general (Hasan *et al.*, 2024). Fluctuation in crude oil price does not only affect production or transportation but has secondary effect on all ways of life, as increase cost of production would surely lead to increase in the price of produce and increased in transportation fare of moving farm produce from the farmland to the market greater determine the selling price of this produce in the market. This would therefore increase cost of living, increase poverty and hunger (Zhang and Hong, 2022).
This shows the great impact increase or swift increase in crude oil price can cause the nation, its effect was felt in Nigerian in the recent fuel price increase that hit the country after the total subsidy removal in late 2023 and the fuel scarcity resulting from this in the first quarter of 2024 leading to high cost of living and difficulties faced by the people to sustain themselves and family resulting from unplanned increased in crude oil price due to lack of well forecasted crude oil price.
Accurate forecasting of crude oil price through the application of effective and technological drive approach would help the policy makers, industrial decision makers and investors to make the right, informed and strategic policies and plans that would help the government and stakeholders to prevent unplanned economic risk and damage. Fluctuation in crude oil price poses a great economic damages to countries like Nigeria that depends so much on oil which affects the cost of living, exchange rate, economic stability, and cost of production among others (Deng, Ma and Zeng, 2021). With the volatility and complexity attached to the crude oil market, there is a need to consider design and development of a sophisticated models that can effectively capture this fluctuation and efficiently predict the price.
Conventionally, crude oil price forecasting is being done using traditional methods like Liner regression, generalized autoregressive conditional heteroskedasticity (GARCH) and autoregressive integrated moving average (ARIMA) models, this model most time struggles with the non-linearity and fluctuating nature of the crude oil price. Moreover, these models require additional manual feature selection and extraction which might be time

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consuming and computationally exhausting (Cheng, Chu and Hsu, 2021). The advancement of technology and need for complex models to capture the intricate nature of crude oil price made researchers to explore other approaches like deep learning techniques by leveraging the strength of this approach. The acceptance and proven accurate performance of deep learning techniques prompted this study to comparatively employ the major variants of Recurrent Neural Networks (RNN) namely Long-short term memory (LSTM) and Gated Recurrent Units (GRU) for forecasting of crude oil price owing to their strengths as they can easily learn pattern and representation from raw time series data without the need for manual feature engineering.

To bridge the gap in the literature, this study employed stacked LSTM-GRU model so that the former can enjoy the strength of the latter and improve the forecasting of crude oil price using the famous Yahoo crude oil price dataset. This study contributed to the body of knowledge mainly in the following ways:

i. Stacking LSTM and GRU together as a hybrid model for forecasting of crude oil price to provide a more complex and sophisticating tool for the players in the oil and gas industry.
ii. Explanation of some concepts related to time series forecasting like windowing and its importance.

The rest of this manuscript is organized as follows: Section 2 present the review of related work on forecasting of crude oil price and the literature gap this study filled. Section 3 discuss the methodology employed in this study ranging from the dataset, preprocessing and description of the models used for forecasting, while Section 4 presents the results and discussions of these experimental results. Lastly Section 5 houses the conclusion and recommendation for future works to be conducted by researchers in this field

2 RELATED WORKS

The importance of early and accurate forecasting of crude oil price using historical crude oil price flow would help as earlier discussed in rightful planning of the nation's economic development and ensure smooth running of various industry. Owing to this, a lot of studies have been conducted using machine learning techniques for forecasting of crude oil price, this section would give a brief review of related works conducted in this field, so as to show the state-of-the-art and obvious research gap this study aimed to fill.

Xian *et al.* (2020) forecasted crude oil price using West Texas Intermediate (WTI) crude oil spot price data acquired from the Energy Information Administration (EIA) website for experimentation. The authors normalized the dataset using MinMax normalization technique. The normalized data was further used for crude oil forecasting using Empirical mode decomposition with support vector machine. This decomposition method is to decompose the time series data into an intrinsic mode function employing the Hilbert-Huang transform which was implemented in R language. The authors further compared the experimental results obtained from this hybridized EMD-SVM with individually implemented ANN and SVM and the result of the hybrid model surpass that obtained from the individual models. Similarly, WTI and Brent crude oil price covering February 10, 1986 to May 17, 2021 were employed by Zhang and Hong (2022) for crude oil price forecasting. The study further compared the performance of LSTM, ANN and ARIMA models for forecasting of crude oil price. The study further considered the fitting and forecasting effects of the models using the short, medium and long term forecasting of the price. The LSTM model gave the best forecasting model among the compared models as mentioned earlier. Compared to earlier study, this study employed only WTI data but they both compared their studies with ANN as a forecasting models and ANN underperformed in the two studies, this might imply that ANN is not a good model for forecasting of crude oil price, based on the fact the dataset employed are time series dataset, which might not be a good suitor for ANN model compared to using structured data.

Another study on forecasting of crude oil price using univariate forecasting methods was conducted by Cheng, Chu and Hsu (2021), as oppose the earlier study, this study focused on using six (6) different univariate forecasting methods namely: Grey Forecast, the hybrid grey model, the multiplicative decomposition model, the trigonometric regression model, the regression model with seasonal dummy variables and the seasonal autoregressive integrated moving average (SARIMA), so as to compare the performance of these methods on short term forecasting. The study employed a primarily acquired crude oil price between January 2015 and December 2019, this data was further split into in and out sample data for estimation and prediction respectively. Implementing these univariate methods, Grey forecast gave the best performance among the methods compared in this study. Bayesian symbolic regression (BSR) was employed for forecasting of crude oil spot price by Drachal (2023) as a novel approach compared to the conventional approach of symbolic regression that is based on genetic programming. The study analyzed the monthly crude oil spot price data between January 1986 and April 2021 to forecast crude oil price, this method was benchmarked with other methods used for crude oil price forecasting like dynamic model averaging, ridge regressions, LASSO, Naïve Bayes, ARIMA and Bayesian model averaging. BSR was experimented with varying values of the linear component k (for 1-13). Its best MAE, MAPE and MASE was obtained at k=9 and RMSE at k=7 when these metrics were used as the evaluation metrics. However, the proposed novel BSR doesn't not give a better performance than the compared model, as

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symbolic regression gave a better accuracy then it in the event of a month ahead crude oil price forecasting.

Deep transfer learning techniques was also used for forecasting of Shanghai Crude Oil by Deng, Ma and Zeng (2021). This crude oil was listed in March, 2018, due to this short and recent listing of this product, there is no enough price data that would be enough to training any model for price forecasting. The authors thought outside the box by employing LSTM with transfer learning for impactful learning. Due to a level of similarities that exist between the Shanghai and Brent oil, this study employed the Brent oil price as the source domain data considering only 871 observations through transfer learning to train the model and this was then transferred to the Shanghai data to solve its data insufficient problem. The T-LSTM model was further compared with other models like LSTM and ARIMA, the transfer learning approach gave a better performance when evaluated. The Brent crude oil price over the period of January 2008 to December 2022 was used to forecast crude oil price by Fauzi, Wijaya and Utami (2023) in their study. The dataset was sourced as a secondary dataset from an online website, this dataset was further normalized for better performance and cascaded forward neural network was used for the forecasting. The model was evaluated using MAPE the result obtained was <10%, showing a good performance of the model for Brent crude oil price forecasting.

For accurate Crude oil price forecasting, the core influencing factors needs to be identified before forecasting would be done. This was presented by Lu *et al.* (2021), where they firstly select the crude oil price forecasting significant variables using elastic-net regularized generalized linear Model (GLMNET), spike-slab lasso method, and Bayesian model average (BMA). The study used 30 initial variables and the monthly West Texas Intermediate (WTI) crude oil price was used as the dependent variable. LSTM was then used for forecasting and is results was compared with average models (ARMA), random walk (RW), elman neural Networks (ENN), , Walvet Neural Networks (WNN) and generalized regression neural network (GRNN), autoregressive integrated moving, ELM Neural Networks (EL). These models were evaluated using RMSE, MAPE and DS as the evaluation metrics. The study performed different evaluation with and without variable selection using the 8 models aforementioned, and employing the Bayesian model average (BMA) variable selection with LSTM as the forecasting model was found to give the best forecasting result. Compared to other studies this study happened to be first result that have considered using different feature/variable selection methods with different forecasting models to compare their performance. Ensemble learning approach is another popularly used machine learning techniques to improve the performance of the weak models, this approach was used by Hassan *et al.* (2023) in their study for forecasting of crude oil price using both WTI and Brent crude oil price data. These dataset were preprocessing for normalization, missing values and mode conversion, so that the daily data were converted to weekly and monthly data so that they can be suitable for short- to medium-term forecasts. Blending ensemble method was used in this study that comprised of k-nearest neighbor (KNN) regression, SVR, linear regression, decision tree regression and ridge regression. The methods gave a good performance for crude oil price forecasting but only univariate variables were considered in the study.

Brent crude oil price was similarly used by Daneshvar *et al.* (2022) for forecasting of crude oil price, this data was normalized using MinMax normalization method, while the appropriate signal interval was selected as a period of 6 years (from January 2015 to March 2021) for the model. Different deep neural network models Recursive neural tensor networks (RNTNs) including long short-term memory (LSTM) and bidirectional long-short term memory (Bi-LSTM) were used for the forecasting. When the models were evaluated using various evaluation metrics LSTM gave the best performance over other two methods compared.

The essentiality of crude oil in industrial production and economic growth as earlier discussed prompted researcher to conduct many cutting edge research on predicting its volatile and fluctuating price so as to ensure stability in economic growth and finance. The reported works majorly used both WTI and Brent crude oil price for forecasting of crude oil price and most of these studies used LSTM either as a deep learning method or as transfer learning neglecting other variants of RNN that are suitable for forecasting time series variables. As a result of that, this study aimed to diver into the application of other variant and most popular which is Gated recurrent unit (GRU) and hybridization of LSTM and GRU for possible better crude oil price forecasting performance outcome.

3 METHODOLOGY

Recurrent Neural Network (RNN) and its variant are the mostly employed methods for forecasting of time series variable. RNN is use to handle time series and sequential data, which makes it more applicable when solving temporal problems like speech recognition and image captioning such that if a new word/ class/price or disease outcome is to be predicted the previous ones must be known or required to understand the pattern which is where the memory of RNN architectures come into effectiveness. RNN differs from other traditional Neural Networks because of their memory, which allows them to take information from the previous input to effect the current input and output, this information is in RNN cycle in form of loop between the hidden layers. The methodology employed in this study is a comparative deep learning techniques approach and the overview data acquisition, preprocessing, forecasting, evaluation

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and comparison of different evaluate models. This is represented in Figure 1 for simplification and clarity.

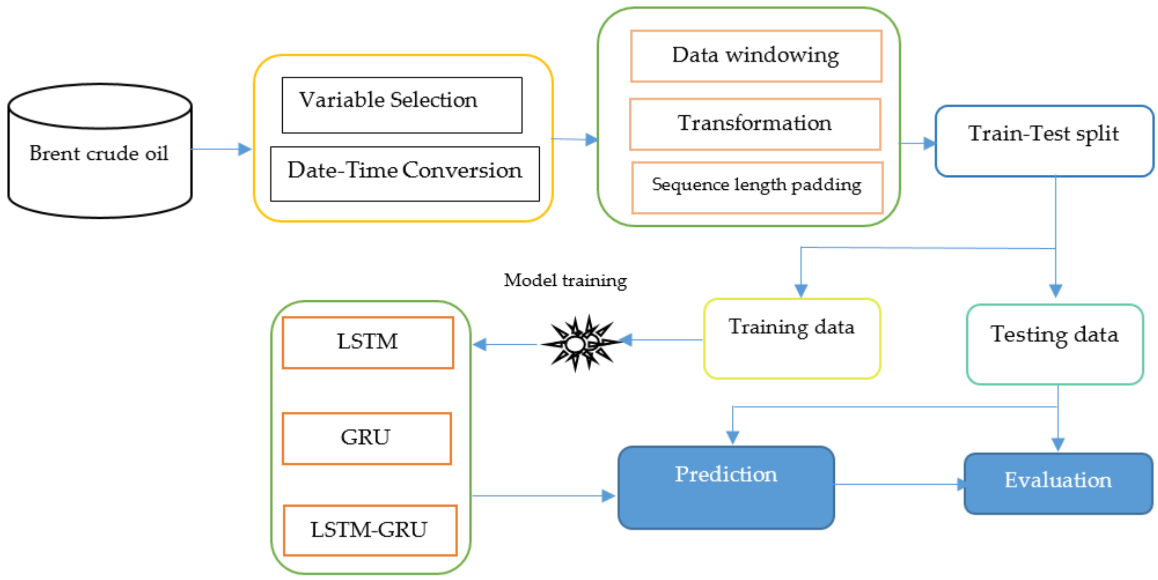

Figure 1: Overview of Research Methodology

3.1 Data Acquisition

For forecasting of crude oil price, there is need for historical data through which the proposed model would learn from. There are many dataset for crude oil forecasting as used by different researchers in the earlier reported studies, but the most common among them is the Brent crude oil price. This study employed this dataset acquired from Yahoo finance as secondary dataset. The data used spanned through the January 2009 to December 2011 of daily crude oil price amounting to a total of 775 observations. This dataset consist of six variables namely Date, open, close, high, low, volume and an unnamed column. However, a local crude oil dataset would have been employed, but as it is known that Nigerian does not currently have a historical data of crude oil price as the price is being majorly subsidized by the Nigerian government. But with the current development of the floated Naira-Dollar exchange rate and the said removal of crude oil subsidy, there might be availability of such dataset, in the nearest future.

3.2 DATA PREPROCESSING

Acquisition of the dataset does not imply immediate use or feed as input to the proposed machine learning model, a thorough preprocessing needs to be done on it so as to ensure it is in the right format for implementation and better form to ensure improved and accurate performance when implemented and evaluated. This study performed some preprocessing on the acquired dataset such as variables selection, data and time conversion, data windowing and transformation.

i. **Variable selection**: Feature engineering is a major preprocessing techniques in machine learning, as it has a lot of advantages likes adequate use of computational resource, fast execution and improve the performance of the model as irrelevant features would have been dropped that might be wasting computational resource. This would enable us to focus on the attributes with significant effect to the target variable. As earlier mentioned the dataset have seven variables and with review of literatures and consideration of natural phenomenon not all these variables determine the price of the crude oil, as the crude oil price have nothing to do with the highest of lowest price recorded per day. Moreover, the open price and the volume of the crude oil recorded per day would not have significant effect to the crude oil price. Owing to this, the researcher selected only the date and the closing price of the crude oil per day as the major variable needed to predict crude oil price daily.

ii. **Date and Timer Conversion**: The data showing the daily crude oil price as included as one of the major variable for forecasting of crude oil price was in string format. This would not enables the model to perceive the data as a time series dataset but rather as just a structured data and this would not help in accurate forecasting of the crude oil price as necessary. In order to ensure this, the date was converted from string to data and time format for correct implementation. This would enable the researcher to perform necessary time series techniques on the dataset for improve performance.

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iii. **Data Windowing:** This is a time series processing technique also known as sliding window used for creating a training instances from time series dataset. For a time series forecast, deep learning model uses input sequence and the price target as the price to forecast, in order to ensure this, this study employed data windowing by creating sequence of input price sequence for the next three days, while the price of the present day, day after and third day serve as the input sequence and fourth day's price being the price to be forecasted. This would enable used to know the future price of the crude oil four days ahead. This method of data windowing would help the stakeholders to make the right decision if there is going to be increase or decrease in the crude oil price. Moreover, it would help in feeding the model with sequence of structured data point to enable the model to learn from it and enhance forecasting of future crude oil price three days ahead using historical observations. The pseudo code used for data windowing is listed in the algorithm 1 for breakdown.

iv. **Data Transformation:** This is also known as reshaping the dataset so as to ensure it fits into the input requirement of the proposed model. LSTM and GRU models are deep learning models designed to handle and accept sequential data, it is essential to reshape the input data into the right format acceptable by the models where each input sample consist of a sequence of data point. This is important as LSTM and GRU models accept input in a specific 3D format namely: *samples, time steps and features*. This transformation makes the preprocessed dataset to be acceptable by the input format of the propose models for forecasting.

Algorithm 1: Pseudo code for data windowing

1. Create a window function
2. Input:
3. Data: first and last date on the data
4. window size (n=3)
5. Initiate X and Y as empty list
6. Output:
7. X: List of input sequence from the close price (2D array using numpy)
8. Y: List of target values
9. Start the target date from the second week
10. For I in range (0,n)
11. Append window data for the 3 days targets to X
12. Append Target to Y
13. Return X and Y for the first and last data within 3 days window size

3.3 Deep Learning models for Crude oil forecasting

This study employed basically the stacked hybridization of LSTM and GRU for improved performance of the models and to enable shared strength of the models.

a) Long short Term Memory (LSTM)

LSTM is a variety of RNN that is able to learn dependencies over a long-term most especially in prediction problems that has to do with sequence or time series where the previous output is needed to help in successful and accurate prediction of the current outcome, with this it is capable of processing an entire sequence of data (like video, voice record or speech) and not just a single data points like drawings or photos. LSTM has the ability to enforce constant error flow through cells which makes it possible for LSTM to bridge small time lags (Choi *et al.* 2021). LSTM is comprises of neural networks and many memory blocks which is known as Cell connected in a chain-like manner. A simple LSTM will structurally contain a cell, and three gates-input, forget and output gate- that manipulate the memory (cell) by controlling the flow of information in and out of the of the cell, while the cell stores information over time.

The input gate will block any value from entering the next layer when the gate generate any value close to 0, the value will just be eliminated from the net input, the forget gate keeps the value till a value greater than 0 is generated by it, and the block omit/ forget the value it keeps when 0 is produced by the forget gate, while the output gate make the decision of when the cell should output what it stores (Dutta *et al.*, 2020). LSTM is sometimes hybridized with CNN (CNN-LSTM) or GRU (LSTM-GRU) for better performance accuracy. The architectural diagram of LSTM is represented in Figure 2

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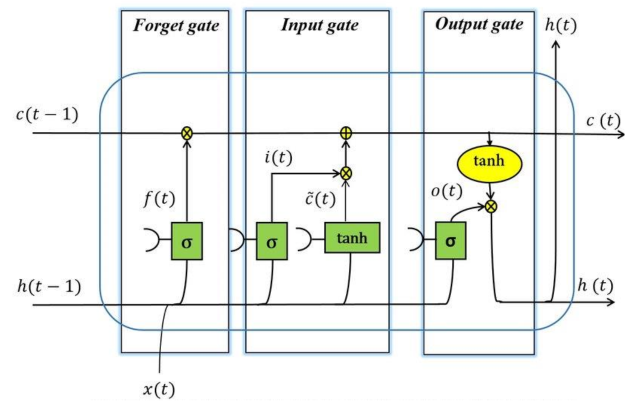

Figure 2: Architectural diagram of LSTM with its gates (Chadha et al., 2020)

a) Gated Recurrent Units

Gated recurrent unit like LSTM was developed to solve the problem of gradient varnishing in conventional RNN, just that GRU have just three gates without any internal cells that keeps information like in the LSTM, the information needed to be stored are incorporated into GRU hidden state. Literatures like Dutta *et al*. (2020) and Kaur *et al*. (2022) considered GRU to outperform LSTM due to faster execution time, fewer gates and better performance accuracy. The schematic diagram of GRU showing its gates and relationship is shown in Figure 3.

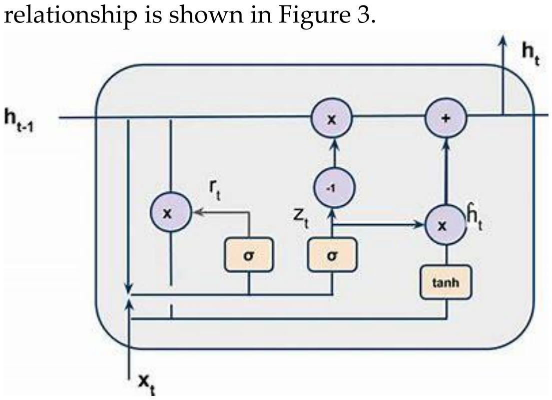

Figure 3: Architectural overview of GRU (Chung *et al.*, 2014)

Update, Reset and Current memory gates are used by GRU to solve the problem of gradient a varnishing problem by determining which information is worth retaining or forget and which information are to be fed into the future for usage. GRU when compared to LSTM is said to be easily modified due to lesser number of block component and to be preferably used with small data series as it gives better performance.

GRU has two inputs at a time, the previous output (h_t) and the input vector (X_t). As shown in Equations 1, 2, 3 and 4, r: reset gate, z: update gate, h_t: output function, $\ddot{h}_t$: candidate activation function, σ_g= sigmoid function, ϕ_h: hyperbolic tangent, b_z, b_h: bias vector, W_r, W_z, U_r, U_z: parameter matrices, X: input vector.

$$r = \sigma_g(W_r X_{(t)} + U_r h_{(t)} + b_r) \quad (1)$$

$$z_{(t)} = \sigma_g(W_z X_{(t)} + U_z h_{t-1} + b_z) \quad (2)$$

$$h_t = (1 - z_t) \odot h_{(t-1)} + z_{(t)} \odot \ddot{h}_{(t)} \quad (3)$$

$$\ddot{h}_t = \phi(W_h X_{(t)} + U_h (r_{(t)} \odot h_{(t-1)} + b_h \quad (4)$$

b) Sequential hybridization of LSTM and GRU

This study combined the LSTM and GRU units in a sequential manner so as to leverage on the advantage of both models. This is done by stacking the LSTM unit followed by the GRU unit for various values of neurons so that this stacked units would be used to forecast the sequesntial preprocessed Brent crude oil price before dense layer was applied for forecasting. This is designed so that the LSTM would process the sequentually processed inputs to capture the long term dependencies of the window data while the GRU would further process the LSTM output to refine and modify the sequence representation. After which the output from the last GRU layer was fed into the dense layer with sigmoid activation function for final forecasting of the crude oil price. The dsign arrangent of the stacked LSTM-GRU units is represented in Figure 6 for clarification. The windowed data were presented as input to the model with LSTM being the first layer with 128 neurons. This hyrbidized model is shown in Figure 4 for simplification

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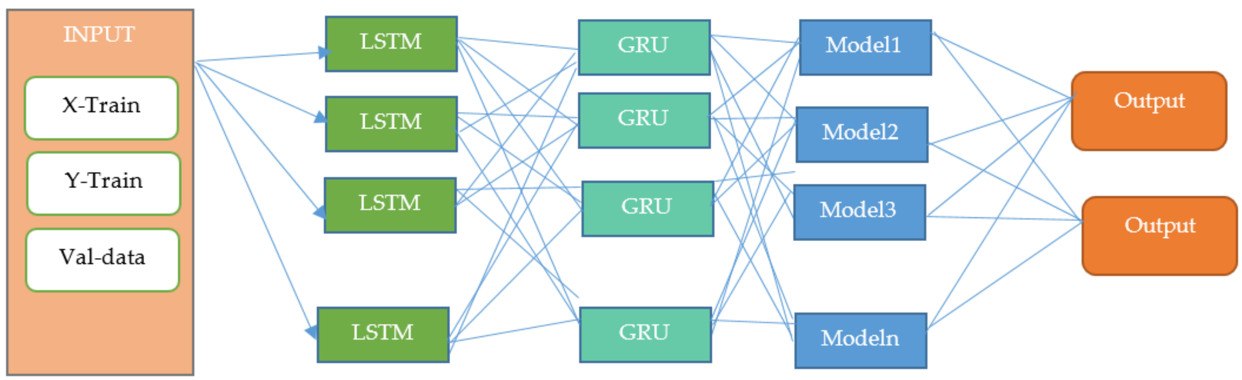

Figure 4: Overview of Stacked LSTM-GRU units

3.4 Performance Evaluation

The crude oil forecasting model have to be evaluated to examine the performance of its forecasting and training of the model. In the course of doing so the study would employ Hold-Out evaluation method with 80% of the dataset for training, 10% for validation and 10% for testing. The data distribution among this split is shown in Figure 5 with the validation and testing portion staring from early 2011 while the testing data was chose from the last 10% of the whole dataset

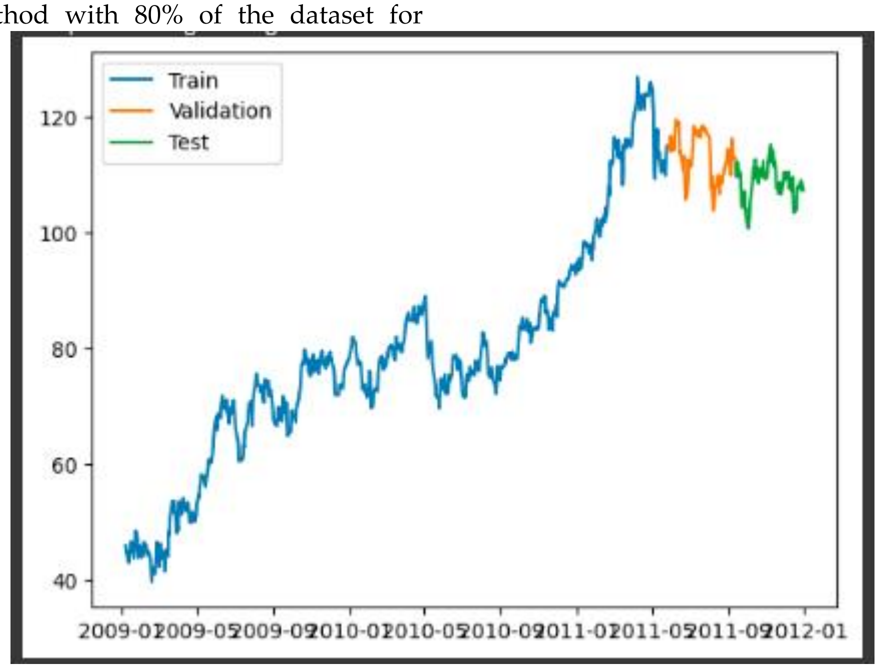

Figure 5: Overview of the Brent crude oil price

Moreover, the model was evaluated using Mean Absolute Error (MAE) as the evaluation metrics. The mean absolute error (MAE) is a statistical metric used for evaluating the average error magnitude for a set of forecasted values with respect to its original values. It is the average of the absolute differences between the forecast and the actual observation in the test sample, with all individual errors assigned with the same weigh, the mathematical expression of MAE is shown in Equation 5

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \qquad (5)$$

$\hat{y}_i$= Forecasted value: y_i= actual observation

4 RESULTS AND DISCUSSION

As earlier mentioned, that the Brent crude oil price data was used for forecasting with the LSTM_GRU model. This dataset span through three years for

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daily crude oil price. The distribution of this price is shown in Figure 6. It would be noticed that the crude oil price was as low as 45 dollars but skyrocket to above 120 US dollars around April of 2011.

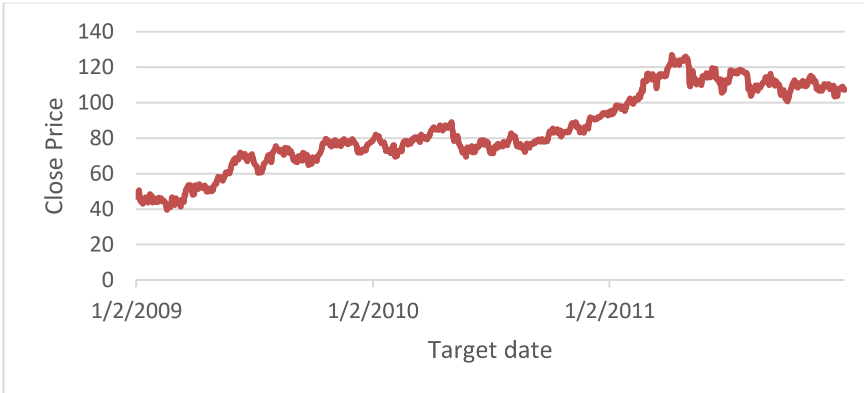

Figure 6: Representation of the Brent crude oil data

4.1 Optimal Parameter Selection

As earlier discussed, this study employed the sequentially stacked hybridized LSTM and GRU model for the forecasting of the crude oil price using the Brent crude oil price dataset. The model as known needs to be in its optimal form with optimal hyper parameters to attain the best forecasting performance. The LSTM-GRU model was designed with the first layer of the model being LSTM unit with 128 unit of neurons with *tanh* as the activation function whose *recurrent activation function* was initiated to be sigmoid function and the *return sequence* was initiated True. This layer was followed with GRU unit with 64 units of neurons, *tanh* activation function and sigmoid *recurrent function*. These 2 layers were followed with 2 dense layers with 32 neurons and an output layer. This design for the stacked hybridized LSTM-GRU gave the best performance for the forecasting. Adam optimizer was used as the optimization algorithm with learning rate of 0.001 trained over an epoch of 100 and Mean Square Error as the loss function.

The study used various Libraries within the Python Programming language such as sci-learn, keras among other. All experimentation was conducted in Google Colab on a stable workstation with 500GB and 6GB storage and RAM with stable internet connection provided through mobile internet network.

4.2 Result of the Crude oil price forecasting using LSTM-GRU model

The designed LSTM-GRU model as discussed for used for the forecasting of the crude oil price with a window slide of three days as earlier discussed. The forecasting performance of this model is graphically represented for the training, validation and testing results respectively. The training prediction and observation is shown in Figure 7 for easier understanding and representation.

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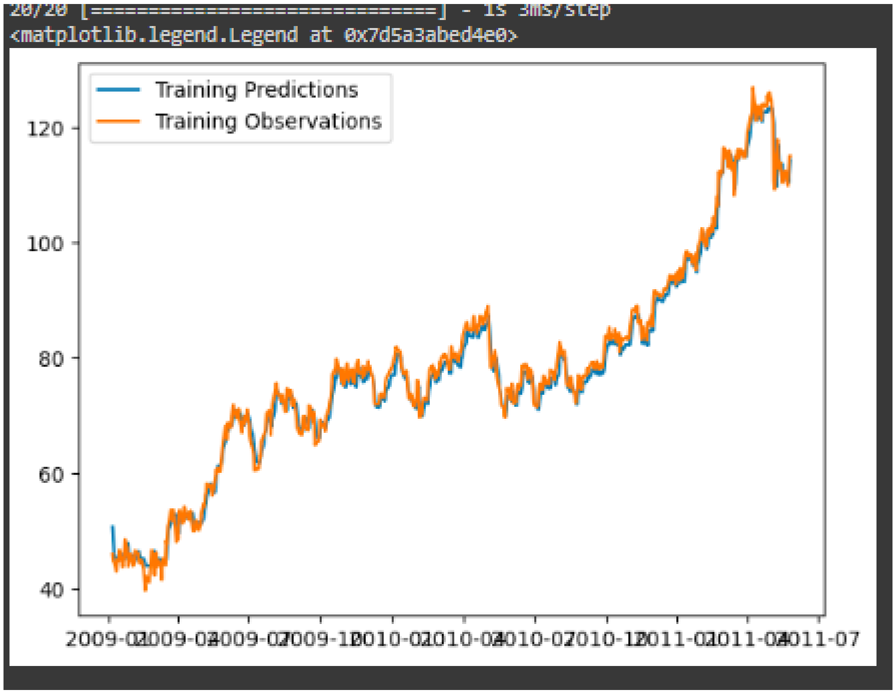

Figure 7:LSTM-GRU Training results

As shown in Figure 7, the training prediction and observation overlap each other, showing an insignificant difference in the two values generated during the training. The model was validated using the 10% validation split so as to evaluate the performance of the model during training and the validation prediction and validations result were represented with Figure 8 as shown.

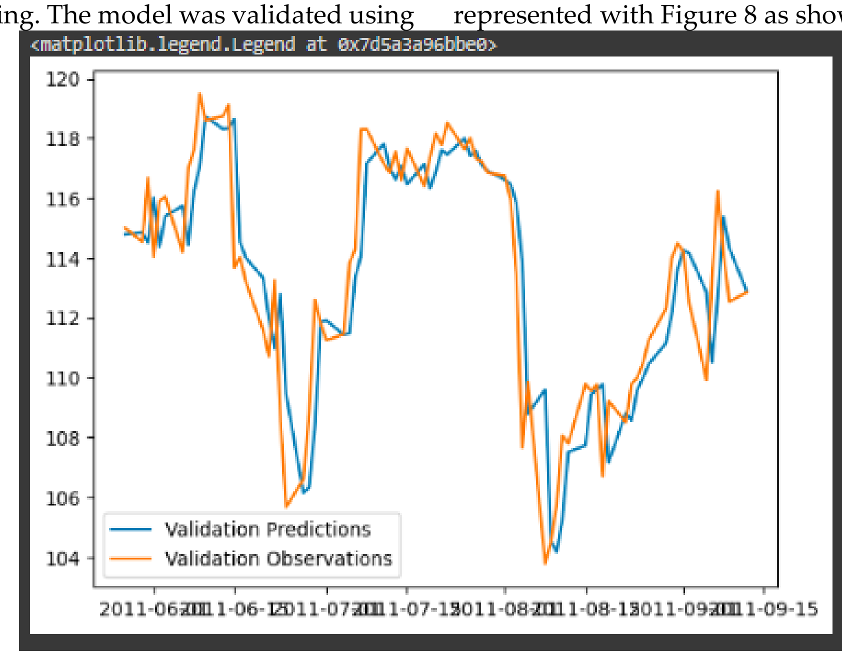

Figure 8: Validation Predictions and observations result

Moreover, the model was further evaluated with the remaining 10% testing split and the testing predictions and observations results were generated as shown in Figure 9

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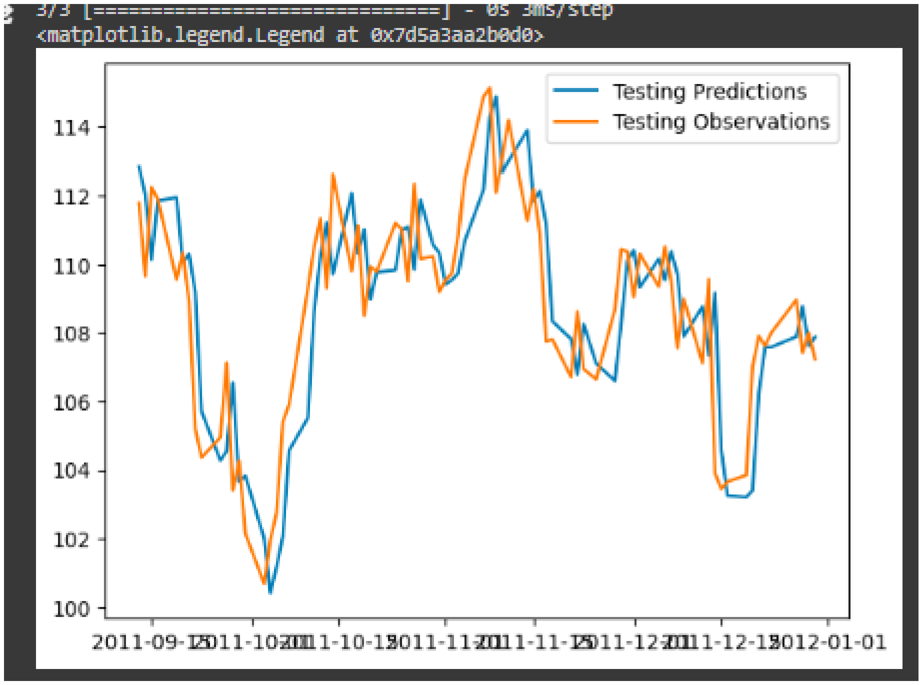

Figure 9: Testing Predictions and observations result

As shown in Figure 11, the testing prediction implies the forecasted prices from the implementation model when testing with the 10% testing split while the Testing observations were the actual price as it is in the Brent crude oil price. The graphical representation showed that there is a close margin between these two prices, indicating the good performance of the model. These three aforepresented graphs were combined as a collective summary of the whole training, validation and testing predictions and validation, which gives a summary of the whole results as shown in Figure 10

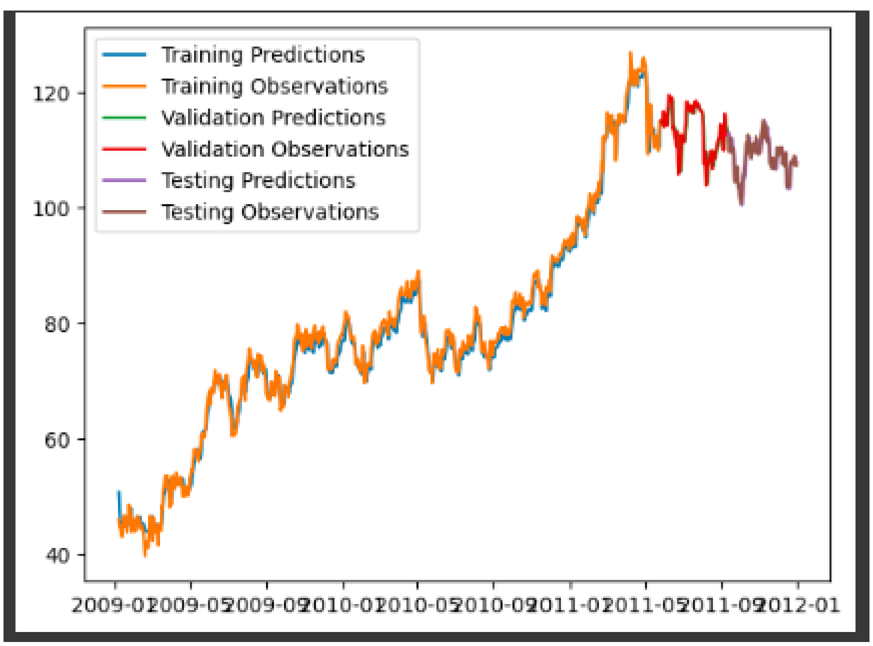

Figure 10: Collective summary of the experimentation results

https://dx.doi.org/10.4314/fuoyejet.v9i2.14 engineering.fuoye.edu.ng/journal

4.3 Comparison of Results

As earlier discussed under the methodology, this study used a stacked hybridized LSTM-GRU, this model was evaluated using Mean Absolute Error. The Experimental results in comparison with that of LSTM and GRU are presented in Table 1

Table 1: Experimental Results

S/N	Model	Evaluation result (MAE)
1	LSTM	0.0289
2	GRU	0.0179
3	LSTM-GRU	0.0144

As shown in Table 1, the least MAE was gotten from the evaluation result of LSTM-GRU implying that it gave the best crude oil forecasting performance as its average difference between the actual and forecasted values is the least. This shows the shared strength of the hybridized model which helped in its improved performance. This results shows that LSTM-GRU was able to effectively forecast the 3 days window slide of crude oil price using Brent crude oil price dataset.

4.4 Comparison with Existing Studies

In order to confirm the performance of the developed model for forecasting of crude oil price, this study's experimental result was compared with existing studies' result for the forecasting of crude oil price. The comparison results are presented in Table 2 for clearer understanding and presentation. This comparison result show in Table 2 gives the employed LSTM-GRU more significance as the studies selected for 3 different years were all outperformed with the performance gotten from this study. This shows that hybridized LSTM-GRU is obviously the best among the results gotten by different studies that used different methods and similar dataset. The second study happened to be the Xian *et al.* (2020) study which gave MAE of 0.023 with a difference of 0.009. This clear difference showed the great impact this hybridized model would have in the real time forecasting of crude oil price.

Table 2: Comparison of LSTM-GRU Experimental result with existing studies'

S/N	Author	Methodology	Dataset	Evaluation results (MAE)
1	Xian *et al.* (2020)	EMD-SVM	WTI	0.023
2	Deng, Ma and Zeng (2021)	T-LSTM	Brent	0.071
3	Zhang and Hong (2022)	LSTM	Brent and Shanghai	0.088
4	Developed system	LSTM-GRU	Brent	0.014

5 CONCLUSION AND RECOMMENDATION

This study employed stacked hybridization of LSTM and GRU so that this two models can leverage the strength of others so as to help in improving the forecasting performance of the hybridized model. Moreover, this hybridized models were then further individually implemented for evaluation and evaluated. The result obtained showed that the LSTM-GRU hybridized model gave a better performance than just LSTM and GRU. The GRU model was the second best performing model for forecasting as it is known for its fewer cells making it to have shorter computational time and better performance. This hybridization of these two model have not been found to have been used for the forecasting of crude oil price as at the time of conducting this study, making this study to be the first to have employed that hybridization design based on the reviewed literature. This study employed window slide of three days by creating a sequence of data point for the model using the close price of the next three days with the third day being the target price. Future study should employ other dataset like WTI and any available crude oil price dataset to validate the developed hybridized LSTM-GRU model and use long observation so as to capture more historical data and increase the window size from three days to a week or two weeks, so that longer days' price would be captured ahead of time to enhance the decision making of the stakeholder.

REFERENCES

Chadha, G., Panambilly, A., Schwung, A. and Ding, S. (2020) "Bidirectional Deep Recurrent Neural Networks for Process Fault Classification" *ISA Transactions, 106: pp. 330–342*

Cheng, M., Chu, C. and Hsu, H. (2021) "A. study of univariate forecasting methods for crude oil price" *Maritime Business Review, 8(1), pp. 32-47*

Choi, Y, Park,S., Jun, Pyo, C., Cho, K., Lee H. and Yu., J. (2021) "Deep Learning-Based Stroke Disease Prediction System Using Real-Time Bio Signal" *Sensors vol. 21(269)* https://doi.org/10.3390/s21134269

Chung, J.; Gulcehre, C.; Cho, K.; Bengio, Y. (2014). "Empirical evaluation of gated recurrent neural networks on sequence modeling". *arXiv* , arXiv:1412.3555

Daneshvar, A., Ebrahimi, M., Salahi, F., Rahmaty, M. and Homayounfar, M. (2022). "Brent Crude Oil Price Forecast Utilizing Deep Neural Network Architectures" *Computational Intelligence and Neuroscience*

Deng, C.; Ma, L.; Zeng, T. (2021). "Crude Oil Price Forecast Based on Deep Transfer Learning: Shanghai Crude Oil as an Example". *Sustainability* 13, 13770. https:// doi.org/10.3390/su132413770

Drachal, K. (2023). "Forecasting the Crude Oil Spot Price with Bayesian Symbolic Regression". *Energies, 16(4).* https://doi.org/10.3390/ en1601000

Dutta, S., Mandal, J.K., Kim, T.H. and Bandyopadhyay, S.K. (2020) "Breast Cancer Prediction Using Stacked GRU-LSTM-BRNN" *Applied Computer Systems, 25(2), pp. 163–171*

Fauzi, F., Wijaya, D. R. and Utami, T. W. (2023) "Brent Crude Oil Price Forecasting using the Cascade Forward Neural Network" *Journal RESTI (Rekayasa Sistem dan Teknologi Informasi), 7(4), pp. 964-969*

Hasan, M., Abedin, M. Z., Hajek, P., Coussement, K., Sultan, M and Lucey, B. (2024) "A blending ensemble learning model for crude oil price forecasting" *Annals of Operations Research* *https://doi.org/10.1007/s10479-023-05810-8*.

Lu, Q., Sun, S., Duan, H. and Wang, S. (2021) "Analysis and forecasting of crude oil price based on the variable selection-LSTM integrated model" *Energy Informatics, 4(Suppl 2):47*

Xian, L. J., Ismail, S., Mustapha, A., Abd Wahab, M. H., Syed Idrus, S. (2020). "Crude Oil Price Forecasting Using Hybrid Support Vector Machine" *IOP Conference Series: Materials Science and Engineering 917, 012045*

Zhang, H. and Hong, M. (2022). "Forecasting crude oil price using LSTM neural networks". *Data science in Finance and Economics, 2(3), pp. 163-170*