Crude Oil Price Forecasting: A Comparative Analysis of ARIMA, GRU, and LSTM Models

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***Abstract* — Since 2020, the world hasn't been able to recover fully from the economic crisis that is caused by the pandemic and the ongoing war between Russia and Ukraine. Crude oil is one of the key ingredients that shapes the world's economy as of today. This research paper is aimed to predict uncertainty and volatility of crude oil's prices with time series approaches. To predict crude oil prices, we need to implement Machine Learning and Deep Learning models such as RNN models (LSTM, Bi-LSTM, GRU, and Multi-LSTM) and ARIMA models. To improve the accuracy of the models, we need to preprocess certain data. Picking a variable to be processed is also necessary, in this case we used opening price and date to determine crude oil prices going forward. Data scaling is necessary to maintain numeric data and Ad fuller Test is a must to acknowledge data stationarity. After preprocessing and fitting the data into models, we can see that LSTM and ARIMA stood out within other models, LSTM has an RMSE score of 6.62 and MAE of 4.96 whilst ARIMA has an RMSE score of 6.5 and MAE of 5.03. All the models used are good in predicting crude oil prices, because the R2-Score is ideal, not overfitting and underfitting. This approach on predicting crude oil prices will certainly be impactful in the global economy and avoiding panic bull and bear markets of the crude oil price.**

Keywords — Autoregressive Integrated Moving Average, LSTM, GRU, Vector Auto Regression, Crude Oil prices, uncertainty.

I. INTRODUCTION

Energy is one of the lifelines that keeps the world growing. Energy sources can come from renewable sources and non-renewable ones, with the non-renewable being the more valuable ones. Energy sources such as crude oil, natural gas, and coal being the most valuable out of other sources. Crude oil is a type of raw resource that is extracted from the depths of the earth. Crude oil is an extremely valuable resource because it is the key ingredient in making gasoline, electricity, and petroleum. So far, crude oil is the world's leading fuel source, with one third of fuel coming from crude oil [1]. About 95 million gallons are used daily. So, its supply and demand could make the global economy ripple. The United States, Saudi Arabia, and Russia are the three leaders in producing crude oil all around the world. Recent conflict between Ukraine and Russia sparked hikes in crude oil prices. Global oil prices soared more than $120 when Russia first invaded Ukraine in early 2022 [2]. These recent changes make it important in predicting the future crude oil prices, so that sudden changes will not damage the broad economy.

From our understanding, ARIMA, LSTM, and GRU models have a small error percentage in processing uncertain data so the usage of ARIMA, LSTM, and GRU models is yet to be tested on crude oil price in post-invasion situations. Compared to the research earlier, this research will have three main lines. (1) Using different epochs and layers of ARIMA, LSTM, and GRU will make different predictions on different situations of the world's politics and economy. (2) The result can determine the best method between machine learning and deep learning on crude oil prices. (3) Predicting several outcomes such as global recession, oil demands and others can make damage control more sustainable. In this research, we compare the use of ARIMA, GRU, and multiple LSTM models which are bi-directional LSTM, single LSTM, and stacked LSTM with the use of crude oil price dataset which has never been done before. The comparison results will indicate the best model that can be used for forecasting crude oil effectively and accurately.

The result of this paper will be shown as an article with the following models being the basis parameters of the article itself. The following parts of this paper will show related works in part 2, the method of this research in part 3, the result of comparison in part 4 and conclusion in part 5.

A. Related Works

Crude oil is one of the most valuable commodities in the world. With recent changes in the world's economy, crude oil prices may vary due to global macroeconomics. Therefore, price forecasting of crude oil is essential [1,3,4,5]. Prediction of crude oil price was done by using many models, such as LSTM [1], Artificial Neural Network (ANN) [3,4], and Deep

Learning [5]. In addition, stock prices also carry a huge impact on forecasting crude oil prices [6,7,8,9]. Models frequently used for forecasting stock price are ARIMAX - TARCH [6], Random Forest [7,8], ANN [7], SVR [8], and Multilayer Perceptron [9]. Other than the topics that are mentioned above, forecasting gold price [10,11] and Bitcoin [11] prices have also been carried out. Those topics used ARIMA - Box Jenkins [10] and RNN-based LSTM as their models.

In a study conducted by Maulana, et al the usage of different hidden layers influences the change of accuracy [1]. The use of an early stopping method helps the algorithm to find the epochs that are needed to find the best result of the LSTM method, but no improvement doesn't mean that is the time to stop training. There are two-time frames in this research, daily and weekly, the addition of more LSTM units and look back are proven to make RMSE and MAE achieve a higher accuracy. In this research, the best result conducted for the daily timeframe has RMSE and MAE of 1.27055 and 0.92827. This result was achieved by using 50 LSTM units, 2 look backs, 104 batch size, and 0.05 dropout as hyperparameters. On the other hand, the best result for the weekly timeframe has RMSE and MAE of 3.37817 and 2.60603. The result was achieved using a single (1) LSTM layer, 10 LSTM units, 2 looks back, 104 batch size, and 0.05 dropout as hyperparameters. So, it can be concluded that the daily timeframe has a higher accuracy than the weekly timeframe in forecasting crude oil prices.

Gupta, *et al* has concluded that determining or choosing the data plays an important role on the performance of the model [3]. If there are many unpredictable or random events, the model would not be able to predict such things accurately in the real case scenario. ANN model is proven to be suitable for crude oil price prediction in short term forecasting.

Vochozka, et al. attempted to predict the Brent oil price using Neural Network with a LSTM layer inserted [4]. The paper aims to predict 157 future trading days based on 3 scenarios of the world economy. The dataset used are prices of Brent oil from 1990-2020. The model used 11 layers, including 1 input and output layers and 9 hidden layers. The NN20 is a Neural Network model with a 20 day delay, it was proven to be the best model in identifying crude oil prices in a downward trend economy. The NN30 was used to predict positive development in the economy in scenario 2 and NN10 was used to predict the recovering economy state in scenario 3. The prices of oil in scenario 1 was about 30-33 USD per barrel, in scenario 2 the price was about 70 USD per barrel, and in scenario 3 the price was about 120 USD per barrel.

One notable study is the work of Amir Daneshvar et al, who used deep neural networks to predict the price of Brent crude oil [5]. Their study found that the complex dynamics of price signals and lack of accurate information can be addressed using this method. In this research, it was proven that the best model was the two Layer LSTM with a SGDM solver, why? Because the RMSE of this model was lower than any other models used in this research.

ARIMAX-TARCH is a modified model that has shown promising results as stated in a paper conducted by Fauziyah, *et al* [6]. After trying many ARIMA models, it was stated that for predicting stock prices, ARIMAX (1,1,0), TARCH (1,2) is the most suitable because of its high accuracy which is 86% with a 0.14138% MAPE.

In another study, Vijh, *et al* made a model that can predict stock prices with different approaches [7]. It was stated that the number of variables is crucial for higher accuracy, with insufficient features, the models would not perform at its highest. ANN was shown to be better than RF, with a 0.42 RMSE, 0.77 MAPE, 0.013 MBE.

Eka Patriya conducted research in predicting the movement of the Indonesia Composite Index stock using the Support Vector Machine method [8]. Determining the optimal hyper parameter was done using the Grid Search method generating C = 1000000, epsilon = 1, and gamma = 0.0001 with Mean Squared Error (MSE) of 240.03. Error rate of prediction results has been successfully calculated using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) which produce RMSE training and testing of 14,334 and 20,281, as well as MAPE training and testing of 0.211% and 0.251%. There is no significant difference between the error rate of training and testing data, indicating the prediction model has good predictive and generalisation abilities at data training and testing.

Another study was done by Andhika Octa Indarso and A. B. Pangaribuan in which Multilayer Perceptron (MLP) was used to predict LQ45 Stock Index price [9]. The level of accuracy of the MLP model reaches 99.8%. However, after entering into the calculation of MSE or Mean Absolute Error, a number of 242.36 came out which is very high compared to the closing number. It can be concluded that the MLP is not the best model to predict the price of LQ45 Stock Index.

John and Latupeirissa predicted the gold price using the ARIMA model with checking by the Box-Jenkins method [10]. In this research, they predicted the gold price for ten months to come. They used the prices of gold starting from 2014 up to 2019 for datasets in the model. The ARIMA model that is used is (1,1,1) according to the PACF and ACF. Independence test was done to determine correlation between lags, because the Ljung Box-Pierce < X (2) (a,d,f) between the 12th lag and 48th lag, that means the residual is independent and ARIMA model (1,1,1) fulfilled the normality test. The results of the test vary throughout months, the first month predicted and actual was close (671,097 for predicted and 690 for actual), but in the following months results start to differ with the prediction. Although the result of the prediction was not that good, we need to consider external conditions such as the COVID-19 pandemic that made gold prices skyrocket.

Yuxiao Duan, *et al* conducted research using RNN-based LSTM model to predict gold and Bitcoin prices [11]. This research aims to find the number of hidden layers and nodes optimal for the LSTM model. The model prediction accuracy of 1, 2, and 3 hidden layers are calculated, with the requirement that each layer have 128 nodes. It has been discovered that the accuracy is at its highest and the impression is at its best when there are two hidden levels. Based on the discovery that there are two hidden layers, adjusting the number of nodes for optimization to 64, 128, and 256 demonstrates that the latter is preferable. As a result, a hidden layer (256,256) shorter memory network model is developed.

There are many insights that can be drawn from several studies [1,3,4,5], the results were different, but all these papers have the same goal, which is to predict oil prices. Several studies [3,4,5] also used the same method, namely neural networks, but in papers [4,5], there was an additional layer in the form of an LSTM layer that caused some changes in the method. In paper [1], there was an early stopping method that made the accuracy better than the others. In paper [11], LSTM was also used to predict gold and bitcoin prices. In this research, the training - testing split which is 4:1 and cross-validation of 50% can be used as a benchmark in making our LSTM model because the results of the prediction were quite accurate. The use of only 2 hidden layers compared to the 10 hidden layers used in paper [4] can also be considered for this research.

II. Research Methodology

The workflow of the research method done is presented in Figure 1. Detailed information about this workflow is explained in this chapter.

Fig. 1. Crude Oil Price Forecasting Workflow

A. Dataset

The dataset with the title "Crude Oil Price" that was collected from Kaggle is used in the suggested crude oil price prediction system [12]. The dataset has 468 rows of data and is monthly from 1983 to the present. This dataset contains columns which contain information regarding the dates, prices, changes, and percent changes of crude oil price. However in this research, only the date and price variable is used. The dataset was then divided into two train and test sets, with 374 and 94 data, respectively.

B. Pre-processing Data

Some modifications were made once the dataset was divided into the train and test sets. By looking at the table's contents, the row with null values was removed or deleted. After that, StandardScaler was used to normalise or standardise the dataset. It scales down each piece of data in a given feature. Additionally, the data is examined to see if it is steady or not. Adfuller was used to demonstrate that the data is stationary, allowing differencing to be used to transform the data into a stationary series.

C. Models

Preprocessed crude oil data will be fitted into several models to predict future outcomes of the data, it will also be scored with several metrics to check the model quality. Models that will be used are as follow:

i. Single-layer LSTM

A special subset of recurrent neural networks are called long short-term memory (LSTM) networks [13]. They are well-liked for using time-series data and other sequential data because they may pick up long-term dependencies. The vanishing gradient issue is dealt with using LSTMs. A vanishing gradient problem results from the gradient being excessively tiny or huge when the time step is considerable. This problem occurs when the optimizer back propagates while the process continues even though the weights effectively do not change at all. The long-short-term memory cell's output gate, forget gate, and input gate are all fundamental multilayer perceptrons. These gates decide whether or not the data can pass depending on its significance. The gates give the network the capacity to decide what data to store, discard, recall, focus on, and output. The cell state and concealed state are used to collect data for processing in the following state. Therefore, the declining gradient can be protected. Figure 2 depicts the LSTM cell's node architecture.

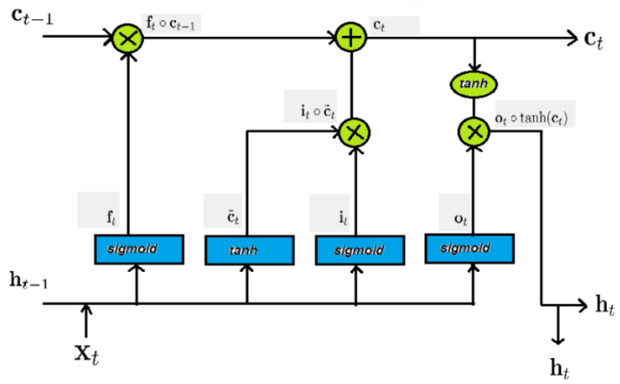

Fig. 2. Diagram of an LSTM cell. This diagram shows that the gates managed input, output, and all the updates of the cell.

ii. Multi-layer LSTM

A single hidden LSTM layer, followed by a typical feedforward output layer, makes up the basic LSTM model [14]. An improvement on this idea is the Stacked LSTM, which has numerous buried LSTM layers with various quantities of memory cells. By stacking LSTM hidden layers, the model grows deeper, more accurately qualifying the term "deep learning technique," as the efficacy of neural networks on a variety of challenging prediction problems is often attributed to their depth.

iii. Bi-LSTM

Bi-LSTM is an RNN-based extension of the LSTM, commonly referred to as Bidirectional Long Short-Term Memory [15]. Both Bi-LSTM and LSTM have unique applications and diverge slightly from one another. The loss of pertinent information from the backward direction is caused by LSTM's exclusive focus on the forward direction. In contrast, Bi-LSTM preserves information in both directions while processing the sequence utilizing two distinct LSTM layers in both the forward and backward orientations. The equation used in Bi-LSTM is shown below.

$$y_t = [h_t^F; h_t^B] \quad (1)$$

Bi-LSTM outputs y which are the outcomes of the LSTM network's forward and backward outputs, h_t^F and h_t^B, respectively.

iv. GRU

The GRU model or Gated Recurrent Unit is an algorithm that is based on a deep learning library in Keras [16]. GRU is a type of a recurrent neural network or RNN that is an enhanced version of the normal RNN. GRU are used to break the limits of simple RNN such as gradient problems and the ability to catch long term dependency. Because GRU is an RNN, there is a formula to calculate it. To find candidate o the hidden state, we can use:

$$\widehat{H} = \tanh(x_t * U_g + (r_t \circ H_{t-1}) * W_g) \quad (2)$$

To update the hidden state, we use the update gate as follow:

$$H_t = u_t \circ H_{t-1} + (1 - u_t) \circ \widehat{H_t} \quad (3)$$

v. *Autoregressive Integrated Moving Average* (ARIMA)

The Autoregressive Integrated Moving Average is a model that forecasts data using only historical values. The preprocessing phase in ARIMA is different from the LSTM model [17]. Data stationarity is a must in an ARIMA model, a dataset is stationer when it passes the ADF (Adfuller Test) and when its properties don't change over time. Mean and variance also has an impact on data stationarity. If a data is non-stationer, we can do data differentiating and transformation to make a data stationer.

An ARIMA model also concludes two models, Autoregressive (AR) and Moving Average (MA). There is also an integration (I) that defines data transformation iteration to make a dataset stationer. In the Autoregressive part we can predict future values using past data, the equation for AR are as follow:

$$p: xt = \alpha + \sum_{i=1}^{p} \beta i x_{t-1} + \epsilon \quad (4)$$

Then, to calculate the MA part of the ARIMA we can use equation such as:

$$xt = \mu + \sum_{i=1}^{q} \Phi_i \epsilon_{t-1} \quad (5)$$

These parameters combined could determine the ARIMA model parameters. The prediction is done by combining the p,d,q values into an ARIMA model. P,d,q can be obtained by using PACF and ACF graphs.

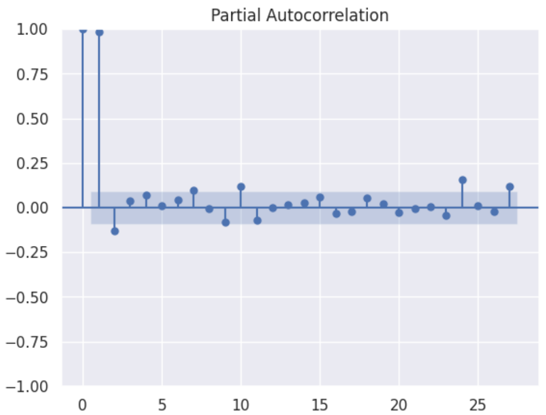

Fig. 3. PACF graph of Crude Oil Price

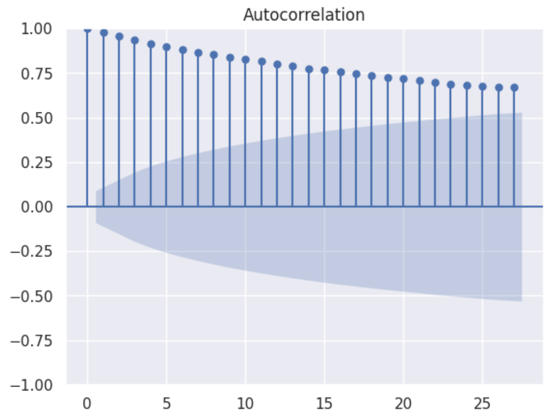

Fig. 4. ACF graph of Crude Oil Price

From figures 3 and 4, we can determine the value of p, d, and q. The p value can be obtained by the edge points in the PACF graph, and the q value can be obtained from the ACF graph. We can also use Auto Arima, which is a library in the ARIMA model. The Auto ARIMA function is used to find the best fit of p,d,q for an ARIMA model using stepwise search such as differencing, grid search and selecting the best models from the AIC,BIC,and AICc.

III. Result and Discussion

Several models were tested using the pre-processed datasets and compared to each other by its metrics scores. The models that were analysed consists of GRU, Bi-LSTM, LSTM, Multi-LSTM and ARIMA. RMSE, MSE, MAE and R2 score were the used metrics as shown in Table 1.

Table 1. Performance metrics of all the models used.

Model	Metrics	Score
GRU	RMSE	7.17
	MSE	51.33909
	MAE	5.49414
	R2 Score	0.84005
Bi-LSTM	RMSE	6.77
	MSE	45.89963
	MAE	5.08197
	R2 Score	0.857
LSTM	RMSE	6.62
	MSE	43.85956
	MAE	**4.96937**
	R2 Score	**0.86335**
Multi-LSTM	RMSE	7.28
	MSE	53.02952
	MAE	5.36143
	R2 Score	0.83479
ARIMA	RMSE	**6.5407**
	MSE	**42.78083**
	MAE	5.03648
	R2 Score	0.8629

As stated in the table, all models on its own have shown great performance by looking at its metrics. However, after analysing and comparing each model, slight differences could be found. Each model was adjusted by its properties, while maintaining the same fundamentals to ensure uniformity and fairness when comparing. For the recurrent neural network models, the look back value was set to 15, which means each model predicts by looking or accounting the previous 15 time steps. Also, all RNN models consist of 20 units on its model layer followed by a dense output layer. GRU, Bi-LSTM, LSTM models use their own layer respectively, while LSTM uses a single layer and Multi-LSTM incorporates three LSTM layers. The models were compiled using MSE loss function and Adam optimizer, and were trained with 20 epochs.

After evaluation of RNN based models, LSTM performs better compared to the others. The performance was scored by using evaluation metrics : RMSE value of 6.62, MSE value of 43.85956, MAE of 4.96937 and R2 Score of 0.86335. The performance metrics indicate low errors between the true and predicted values, resulting in a great performing model. It can be further depicted on the graph shown in figure 5, which the predicted values are not far and similar to its baseline.

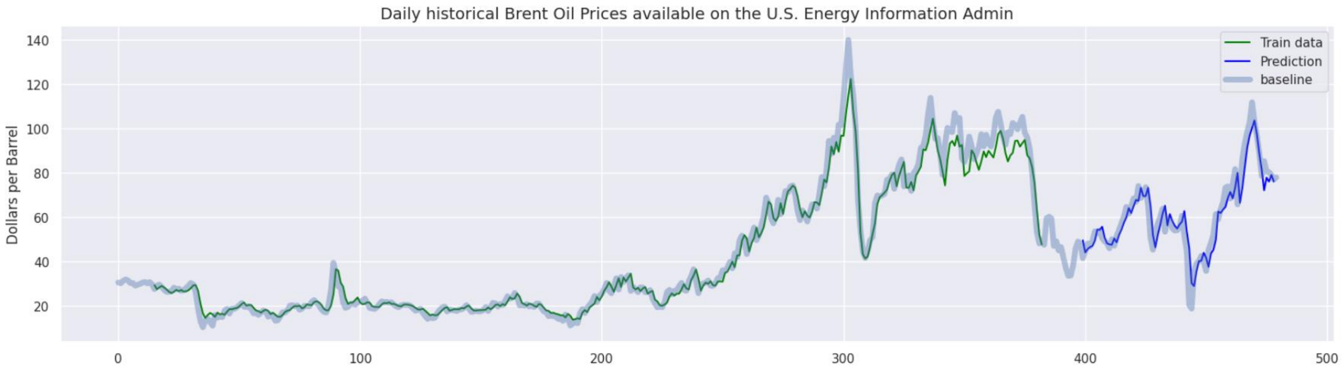

Fig. 5. Predicted Brent Oil Prices using LSTM Plot

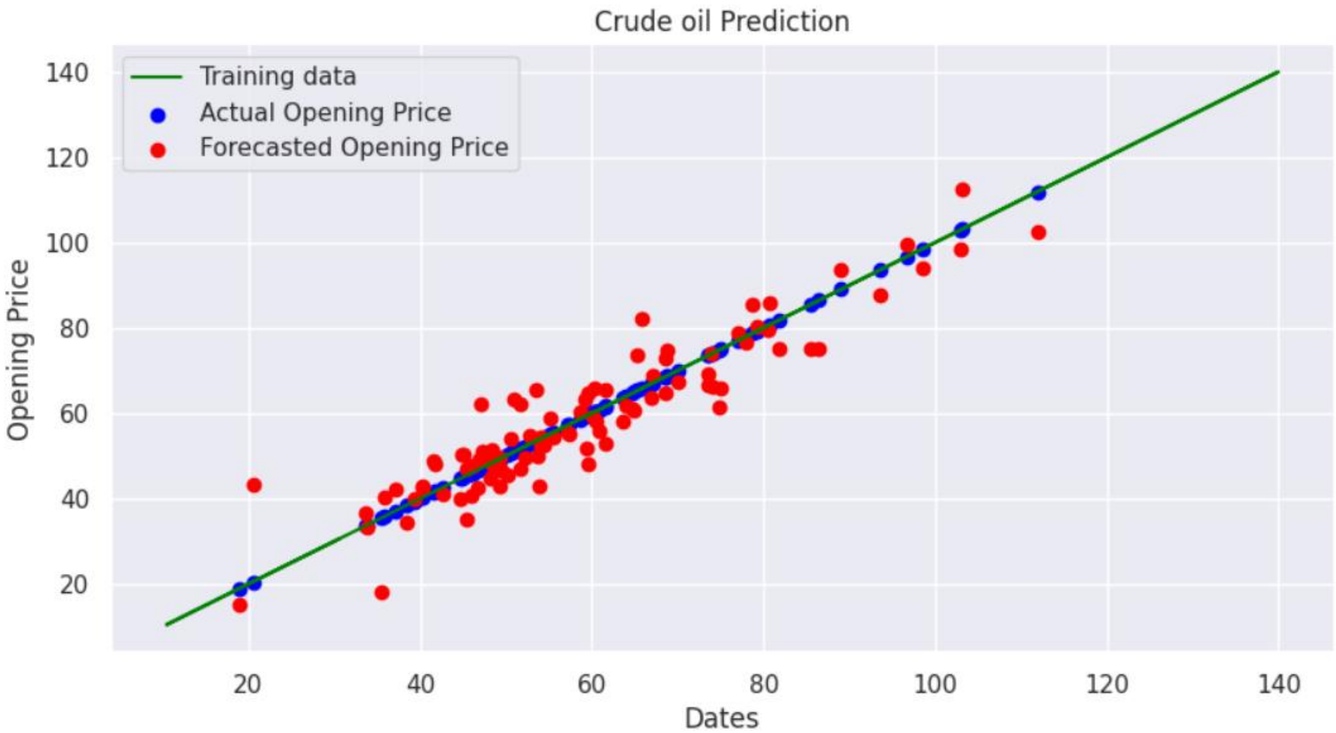

Fig. 6. Predicted Brent Oil Prices using ARIMA Plot (Training data is represented with the green line, forecasted prices are shown as red dots). As we can see, forecasted prices of ARIMA are somewhat different than the training data, so the model is not 100 % accurate.

Other than the RNN-based models that were trained, there is also an ARIMA model in this comparison. The ARIMA model was fitted on the data using (2,1,3) order, which was determined by using auto-ARIMA by looking at its best model based on the lowest AIC score (2215.403). ARIMA model also has great performance with a score that is not far different from LSTM : RMSE of 6.5407, MSE of 42.78083, MAE of 5.03648 and R2 score of 0.8629, this can be proven by looking at the data distribution between the actual and predicted values on figure 6. Even though the RMSE and MSE scores are lower than LSTM, the LSTM model exhibited a higher R2 score, making it a better fit for this case.

From analysing and comparing each model, the results provide great insights for studies while successfully making great performing models. However, there may still be some adjustments or additions to improve the models. Future experiments could set or play around hyperparameter tuning, so that each model could have its preferred configurations that are optimal.

IV. Conclussion

This paper reported the results of LSTM which used the RNN algorithm and ARIMA which used AR (Autoregression), I (Difference), and MA (Moving Average). The paper focuses on searching for the best algorithm with testing in the test data. GRU, Bi-LSTM, Multi LSTM are enhanced versions of the LSTM model. From analyzing other versions of the LSTM model, the natural model is proven to be the best for Crude Oil with 20 hidden layers, 1 dense layer, and 1 LSTM layer with 20 epoch and 1 batch size. RMSE of 6.5407. MSE of 42.78083, MAE of MAE of 5.03648 and R2 score of 0.8629 are gained from test data of the LSTM model. Compared to other models such as GRU, Bi-LSTM, and Multi-LSTM, the LSTM model has a 6.6267% better RMSE score. On the other hand, the ARIMA model is computed using Auto Arima to find the best p,d,q parameters to fit the model. (2,1,3) was found to be the best fit for the ARIMA model which produced results similar to the LSTM method. Through this observation, we can see that LSTM and ARIMA are superior from other enhanced models, if compared one another LSTM still has better accuracy overall. We recommend the use of LSTM in predicting crude oil because LSTM is more flexible with the changing factors such as Russia Ukraine War and COVID-19 pandemic.

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