Forecasting the Palm Oil Market: A Comparative Study of LSTM and Bi-LSTM Models for Price Prediction

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ABSTRACT

This study underscores the critical need for accurate palm oil price predictions amid market volatility, driven by factors like demand shifts and supply disruptions. Employing advanced neural network models, specifically Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM), the research spans May 2007 to December 2022 using Market Insider data. Evaluation metrics, including RMSE (0.0000833) and MAPE (0.76%), highlight Bi-LSTM's superior predictive prowess. Beyond immediate benefits for decision-making, the study emphasizes broader impacts on market stability, reducing volatility and fostering sustainability in the palm oil industry. Overall, this paper showcases the efficacy of Bi-LSTM in enhancing palm oil price prediction accuracy, offering practical insights and contributing to industry sustainability.

1. INTRODUCTION

Palm Oil, as one of the versatile resources, is an important ingredient for a variety of products, it has extreme health benefits and provides vitality and is utilized as a raw material for a variety of sectors, including both food and non-food businesses. It is a high economic value plantation commodity that has a significant role in the economic activities in worldwide (Salman et al., 2018). In production, according to the Food and Agriculture Organization of the United Nations (FAO) about “Oil Palm” in 2020, palm oil is the most produced and consumed vegetable oil globally, accounting for approximately 65% of all vegetable oil traded internationally. Meanwhile, in 2021 The United States Department of Agriculture (USDA) from “Oilseeds: World Markets and Trade” shows reports about the palm oil exportation. Said that in 2020, Indonesia and Malaysia, the top two palm oil producing countries, accounted for 80% of the world's palm oil exports. About the de-mands of palm oil, a report also shown by USDA from “Oilseeds: World Markets and Trade” in 2021, states that the demand for palm oil has increased significantly in the last few decades, driven by the growing population, increasing urbanization, and rising incomes in developing countries. Malaysia, as one of the top palm oil producers, has Malaysian Palm Oil Council (MPOC) that reports about the versatility of palm oil in 2021 from article “Palm Oil”. In addition, A study by the Oil World Trade Report from “Palm Oil Production and Trade” in 2021, states that the oil palm tree, which is the primary source of palm oil, has a high yield per hectare compared to other oilseed crops, making it an economical option for farmers and countries that rely on its production for income.

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Taking data from "Our World in Data", Fig. 1 and Fig. 2 supports data points provided above. Fig. 1 pictures the vegetable oil productions value worldwide starting 1961 until 2019. The graph shows that palm oil has the highest production value every year from 1961 among other vegetable oil and reached over 74.58 million T in 2019, and also it is important to notice that it has quite sharp fluctuations like in year 2015-2016-2017. Where Fig. 2 described the information about the land used for vegetable oil crops worldwide. From 4 million to 29 million hectares in 2020, the amount of area used to grow palm has more than septuplet since 1961. The interesting fact is, reflecting on the pro-duction shows in Fig. 1, palm oil has the highest oil production, but it accounts for only 6% of the land used in total, which is small when we consider that it produces 36% of the oil.

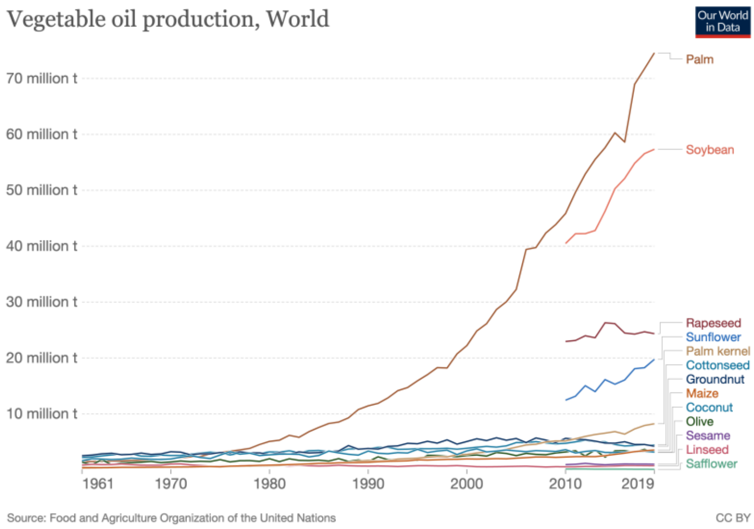

Figure 1. Vegetable Oil Production worldwide

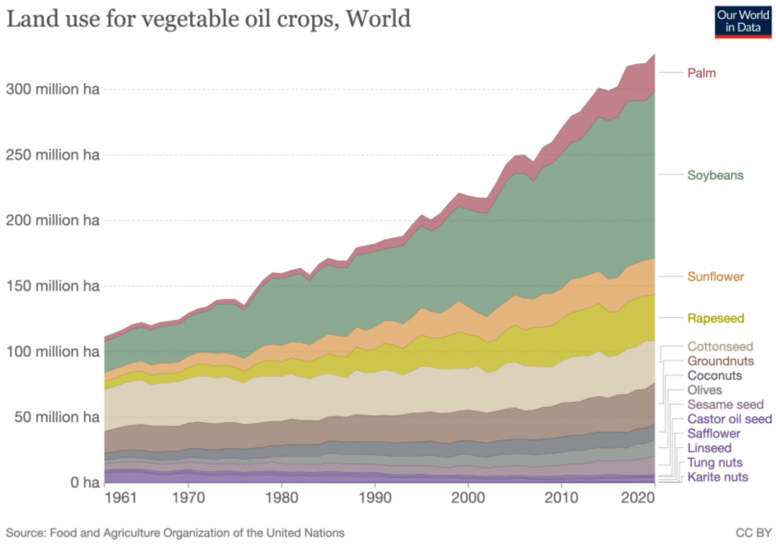

Figure 2. Land used for vegetable oil crops worldwide

Because of the profound effect it had on a wide range of macroeconomic indices, factors such as price increases, GDP growth, the value of the currency, and the international trade balance, and more, it is widely regarded as crucial ingredients. Like other agricultural products, palm oil is prone to severe price swings, various degrees of fluctuation generated by macroeconomic and financial markets (Zhang et al., 2008), which entails a significant risk for all parties involved—

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farmers, producers, traders, consumers, etc. In order to overcome the obstacles and enhance sustainable enterprises, one of the things that both farmers and businesses can do is understanding the commodity value by having data processing support and predictions (Salman et al., 2018). Ignorance of the dynamics' commodity value will have an adverse economic impact, especially for the domestic (Kwas and Rubaszek, 2021), high oil prices frequently cause an increase in inflation, which hurts the economy of oil-importing nations. Conversely, since oil exporting countries' economies can experience poor development, low oil prices might lead to an economic slowdown and political turmoil in such countries (Zhang et al., 2008).

Using Machine Learning to predict prices instead of a commodity expert is one of the viable approaches. Machine Learning can identify significant trends in commodity prices and utilize those trends to forecast future prices. This process is known as Time Series Forecasting (TSF), it entails analyzing past data to estimate future values of a given sequence (Sagheer and Kotb, 2019). Several earlier experiments on price prediction using machine learning techniques have been conducted for predicting price and movement and have supplied some insightful information and results regarding price behavior. In 2020, for stock price prediction,(Istiake Sunny et al., 2020) used two well-known Recurrent Neural Network (RNN) models: the Long Short-Term Memory (LSTM) model and the Bi-Directional Long Short-Term Memory (Bi-LSTM) model. By changing different parameters and measuring RMSE, LSTM and Bi-LSTM models were conducted, and their results were compared. The study collects Google Stock market data from Yahoo Finance starting August 2004 to October 2019. The data includes the stock's Opening, High, Low, and Close (OHLC) value for each day, which can be used to forecast future data. There are 4170 days of data in total. The study looked at how the RMSE changed when different layers, different units in the hidden layers and dense layers, and different times were used to predict the output. After LSTM model and Bi-LSTM model were analyzed with the right hyper-parameter tuning, the research reports that the Bi-LSTM model is superior to the LSTM model with the lowest RMSE, recorded 0.0002421. The model worked best with two hidden layers, each with 64 units, and two dense layers.

At the same time, (Livieris et al., 2020) suggested that CNN-LSTM method be used to forecast the gold price movement (up or down) and the regression task of forecasting the gold price, using the daily gold price data in US dollars from the Yahoo website from January 2014 to April 2018. The proposed model was utilized in two versions, named CNN-LSTM1 and CNN-LSTM2. The motivation behind using these models to analyze time-series data is driven by knowing that in order to create a more accurate prediction model, CNNs may exclude irrelevant information from the input data and focus on the most important features, while LSTM models can capture sequence pattern information more effectively because of their unique architecture design (Livieris et al., 2020). Then the models were evaluated against LSTM (one and two layer), Support Vector Regression (SVR) and multiple layer Feed-Forward Neural Network (FFNN). The forecasting horizon, which refers to the number of daily prices that are taken into consideration, was used in the study with three distinct values: 4, 6, and 9 days. To measure how well each model performed, the MAE and RMSE were observed. For the binary classification problem, the evaluation criteria that were observed is ACC, AUC, sensitivity, and specificity. As conclusion, CNN-LSTM1 demonstrated the highest predicting performance for the classification task achieving 55.26%, 56.81%, and 55.26% score of accuracy (ACC) for horizon 4,6 and 9 respectively, and 0.533, 0.577, and 0.533 score of AUC for predicting horizon 4,6, and 9 respectively, whilst CNN-LSTM2 demonstrated the best performance for the regression task, achieving the lowest MAE and RMSE score compared to other model, that is 0.0079, 0.0082 and 0.0089 score of MAE for predicting horizon equal to 4, 6 and 9 respectively, and recorded 0.0082, 0.0095, and 0.01 score of RMSE for predicting horizon 4, 6 and 9 respectively.

Notably, research (Mgale et al., 2021) used information from the Government of Tanzania to compare the ARIMA and two-categorized Holt-Winters' Exponential Smoothing models, that is additive and multiplicative, for forecasting the monthly wholesale rice price in Mbeya region of Tanzania starting January in year of 2004 to September in year of 2019, with total 189 samples.

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First, the paper indicated the best ARIMA model were ARIMA(0,1,3)×(2,1,0) for the forecast model of the rice prices studied. Second, the Holt-Winters additive model was indicated as the model that best fits the analyzed price series in the research, which based on the comparison of the fitted values of the models (additive and multiplicative) to the original series, showing additive model performed better than the multiplicative model. The final nine observations in the dataset series are used to compare the estimated price to the actual price as the indicated models are then evaluated against each other using the MAPE parameter. As a result, the Holt-Winters additive model achieve 5.3314 score of MAPE, while ARIMA's ARIMA(0,1,3)×(2,1,0) achieve 5.7512 score of MAPE.

Using information from the data U.S. Research Economic Data, from January 2017 through September 2017, (Lee et al., 2022) analyzes the performance of the Autoregressive Integrated Moving Average (ARIMA) and the Seasonal Autoregressive Integrated Moving Average (SARIMA) in predicting the price of crude oil in the United States and Europe. Three statistical factors were used as evaluation: MAPE, RMSE, and MAE parameters. In this study, the author concludes that SARIMA(2,1,0)(1,1,1,12) and SARIMA(2,1,1)(0,1,1,12) are the most optimal models for forecasting the future price of crude oil in Europe and the United States, respectively with SARIMA, and ARIMA(1,0,1) and ARIMA(1,0,1) as the optimal model with ARIMA for Europe and USA, respectively. As a conclusion, after comparing the ARIMA and SARIMA models, the ARIMA has proven to be more accurate in predicting future crude oil prices in Europe and the United States. In both Europe and USA tests, the ARIMA model performed with the highest degree of accuracy, records MAPE(Europe−ARIMA) = 0.05, and MAPE(USA−ARIMA) = 0.05.

Research (Gao et al., 2022) used many advanced machine learning models, such as Multiple Linear Regression, K-Nearest Neighbor Regression, Random Forest, Catboost, and including eXtreme gradient boosting (XGB) and the Light Gradient Boosting Machine (LGBM), and had them compared to find the best way to predict crude oil price movements with relation to the COVID-19 pandemic and see which model was better for forecasting the crude oil price based on Mean Error (ME), MSE, MAE, MAPE, and RMSE. Using data obtained from West Texas Intermediate (WTI), two categories were created by the author for dividing the dataset, i.e., training samples and validation test samples. The model was trained using the training sample, and the testing sample was used to evaluate the effectiveness of training. In addition, the authors decided to make the in-sample error and out-of-sample error of the models based on the evaluation metrics. So, specifically, the phase of the paper experiment is: (A), provide the model's parameter space (6 models above each); (B) Set the model's parameters after that, then use the training data to train the model (in-sample); (C) Use the evaluation metrics to see if the model produces the most accurate results on the training set. If it doesn't, go back to phase (B) and change the parameter's space (tuning); (D) Analyze the model that performs best on the test set (out-sample), then record the findings. Finally, reflecting on the prediction performance of each model, LGBM was a good fit for the data studied. The prediction performance of LGBM's model was the finest, in the out-sample (test) outscoring all other models, with the score of AE, MAE, MSE, RMSE, and MAPE respectively 0.76, 1.00, 1.00, 1.00, and 1.00. Although, in in-sample (training) set performance, was lost only to one model, that is the XGB model, with the score of AE, MAE, MSE, RMSE, and MAPE respectively 0.00, 1.16, 1.19, 1.09, and 1.08. Even so, the authors indicated that, in terms of generality, the LGBM model performed better, therefore it is still the best model compared to the other.

While others are comparing, using an error Back-Propagation technique, research (Wang and Fang, 2022) combined a normal three-layer feedforward neural network (FNN) with a stochastic time effective function, called the Weight-Feedforward Neural Network (WT-FNN) model. The experiment used data from the Brent Crude Oil Price every day from January 2000 to September 2021. The performance of FNN and No Change models were used as evaluation standards, with the MAPE, MAE, RMSPE, and RMSE error measures as criteria. The study reports that the WT-FNN model was superior compared to both the FNN model and the No Change model.

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With MAPEs of the one-step, two-step, four-step, and eight-step forecasts at 0.0191, 0.0279, 0.0404, and 0. 0592, respectively, WTF-FNN had the best predicting effect. Compared to FNN and No Change model's MAPE, it was minimum.

An innovative method also presented by (Jovanovic et al., 2022), proposing an algorithm with the application of Salp Swarm technique applying a disputation operator in order to tune the LSTM's hyper-parameters, namely LSTM-SSA-DO, to cope with crude oil price problems in terms of forecasting. The study examines the data collected from West Texas Intermediate (WTI) starting January 1986 until July 2022. Additionally, Variational Mode Decomposition (VMD), which divides a complex signal into several sub-signals, was also implemented and utilized as the input for the LSTM models to take into consideration the complicated and volatile data of crude oil price time-series, the author named it VMD-LSTM-SSA-DO. Through the use of two different simulation types, the suggested methods, LSTM-SSA-DO and VMD-LSTM-SSA-DO, were analyzed and evaluated. The first one used a simple LSTM network as input and no VMD (LSTM-SSA-DO), while the second simulation utilized the VMD to the dataset as inputs for the LSTM model (VMD-LSTM-SSA-DO). The suggested approach (LSTM-SSA-DO & VMD-LSTM-SSA-DO) was compared in each simulation to LSTM structures produced by other well-known machine learning models that were successful at handling time-series forecasting, such as the original salp swarm algorithm (LSTM-SSA), ABC method known as Artificial Bee Colony (LSTM-ABC), FA or Firefly Algorithm (LSTM-FA), Sine Cosine Algorithm or SCA for short (LSTM-SCA), and the Teaching-Learning Based (TLB) algorithm (LSTM-TLB). The proposed LSTM-SSA-DO and VMD-LSTM-SSA-DO models were also evaluated with a few common ML models in order to conduct a more thorough comparative study, i.e., Extreme Learning Machine or ELM, Kernel ELM, and Artificial Neural Network (ANN), also by applying and by not applying VMD (same condition as above). Furthermore, both simulations are done by predicting three distinct steps forward: one, three, and five, and by capturing the score MAE, R^2, RMSE, and MSE of regression criterion, the performance's model are validated. Additionally, a strict statistical tests are demonstrated to justify the performance enhancements over other approaches (Friedman aligned test (Friedman, 1940, 1937)). Overall, the VMD-LSTM-SSA-DO outperformed all other models, displaying the best performance. A MSE score of 0.000120, 0.000118, 0.000123 and R^2 score of 0.992600, 0.992671, and 0.992250, for one, three, and five-steps forward respectively, were recorded by the VMD-LSTM-SSA-DO model. Thus, with these outstanding results compared to others, the VMD-LSTM-SSA-DO model was indicated to be the best model for price prediction on the dataset used.

Last but not least, study (Jahanshahi et al., 2022) suggested a technique that applies cross-validation for estimating future crude oil prices that takes into account the worldwide impacts of the COVID-19 epidemic and the conflict between Russia and Ukraine. The method used Machine Learning (ML) algorithms, that is support-vector-machine (SVM), linear-regression (LR), and Random Forest (RF), and Deep Learning (DL) algorithms (LSTM network and Bidirectional-LSTM (Bi-LSTM) network). Both algorithms are then compared by using and by not using cross-validation. The research examined a data collection retrieved from Yahoo Finance that included records made between the years 2000 and 2022. With May 2022 as the deadline, the train and test data are specifically mapped by taking 5 periods in a span of 32 months to show the effects of the COVID-19 pandemic and the Russia-Ukraine conflicts. The study shows that deep learning methods are less effective than machine learning methods for the data and problem studied. Moreover, it shows that RF without cross-validation seems to be the optimal solution in terms of performance compared to others (including Deep Learning method) based on MAE and MSE, with the average value over 0.6019 and 1.0194, respectively. Also in the study, it reports that cross-validation doesn't make a big difference in obtaining more precise price prediction data for the problem that was studied at.

Nevertheless, statistical methods as used in (Lee et al., 2022; Mgale et al., 2021) generally rely on presumptions like data being "stationary" and having a linear relationship between past observations, which means that using these techniques will not ensure the creation of a trustworthy

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and solid model for future predictions (Livieris et al., 2020), that might be said, the nonlinear and chaotic nature of the price series is problematic for the standard econometric models. (Gao et al., 2022; Istiake Sunny et al., 2020). On the other hand, the price dataset's sudden swings have a detrimental effect on forecast accuracy from the study that used some of the Machine Learning's method (Jahanshahi et al., 2022; Jovanovic et al., 2022; Wang and Fang, 2022), it demonstrates that even such methods are susceptible to concerns like over-fitting and local optimum problems, which make it difficult to capture the change law. In addition, none of the studies up to this point have used LSTM and it alternatives, Bi-LSTM. From here, we are encouraged to demonstrate a comparison between LSTM and Bi-LSTM in terms of palm oil price predictions. Therefore, this study examined the the performances of deep learning's LSTM and Bi-LSTM models in their ability to predict the daily palm oil price. The main reason why LSTM and Bi-LSTM are adopted because of their ability to learn long-term dependencies, deal with the gradient vanishing problem, improve prediction accuracy, gain insight from historical data, tolerate noise, and discover connections between time series (Adekoya et al., 2021; Jahanshahi et al., 2022; Jovanovic et al., 2022; Livieris et al., 2020).

The model forecasts the palm oil price regarding the price at a specific point, based on an analysis of historical data (with deadline December 2022). Coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) are all utilized to evaluate the performance of each model in this research. The collected findings from these models may give insight on the most accurate methods for predicting the cost of crude oil in the future.

The remainder of this study's parts are structured as follows: The methodologies used in this research are described in Section 2; the experiment results and discussion are presented in Section 3; and the conclusion are shown in Section 4.

2. METHOD

This study contributes by accurately predicting palm oil prices using an LSTMs model and utilizing cutting-advanced deep learning techniques. LSTM models are good at finding both short-term and long-term dependencies. When the extended version of LSTM, called Bi-LSTM, is added, it makes sure that the network has information about its past and future temporal states for the best learning performance. This study objected to comparing these two methods.

2.1. Long Short-Term Memory (LSTM) Model

LSTM, or Long Short-Term Memory, is a popular type of Recurrent Neural Network (RNN) that can incorporate long-term memory connections via feedback links, developed by Hochreiter and Schmidhuber and first used in 1997 (Hochreiter and Schmidhuber, 1997). Recurrent Neural Networks (RNNs) have a problem called "gradient vanishing," which makes it hard for the model to learn long-term time dependencies. LSTM was made to solve this problem.

Input, output, and forget are the three primary gates that make up each memory cell in a LSTM network. It regulates the information flow, enabling the LSTM to learn long-term dependencies by selecting what to discard and what to keep. More specifically, the new data that is saved into c_t (memory state) at t (time) is controlled by i_t (input gate) and c_t^* (second gate). o_t (Output gate) determines which information might be used for the memory cell's output, while f_t (forget gate) determines the previous information if it must be forgotten or preserved on the memory cell at (t – 1). Below is described mathematically for the training process of LSTM (Li et al., 2017; Livieris et al., 2020):

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$$i_t = \sigma\,(U_i x_t + W_i h_{t-1} + b_i), \tag{1}$$

$$f_t = \sigma\,(U_g x_t + W_g h_{t-1} + b_g), \tag{2}$$

$$c_t^* = tanh(U_c x_t + W_c h_{t-1} + b_c), \tag{3}$$

$$c_t = g_t \odot c_{t-1} + c_t \odot c_t^*, \tag{4}$$

$$o_t = \sigma\,(U_o x_t + W_o h_{t-1} + b_o) \tag{5}$$

Figure 3. Memory State (c_t), Input gate (i_t), Second gate (c_t^*), Output gate (o_t), and Forget gate (f_t) equations

2.2. Bidirectional Long Short-Term Memory (Bi-LSTM) Model

To overcome the drawbacks of standard RNN, which cannot use knowledge about future time steps during the learning process (Kwak et al., 2020; Messner et al., 2018), a Bidirectional RNN, another kind of RNN created by Schuster and Paliwal (BRNN) (Schuster and Paliwal, 1997), allowing the utilization of incoming data sequences from both the present and the future. As illustrated in Fig. 3, data is processed bidirectionally by BiRNN using two distinct hidden layers which are then integrated into one output layer.

Combining BiRNN with LSTM results in Bidirectional LSTM (Bi-LSTM). Different from LSTM, rather than using one LSTM layer, Bi-LSTM incorporates two LSTMs (Althelaya et al., 2018) and runs the system's sequence of input bidirectionally, one from left (past) to right (future) and vice versa for the another (similar as described in Fig. 3). This process is done in parallel and it's for the training process. Thus, the information from the future is protected (Khullar and Singh, 2022).

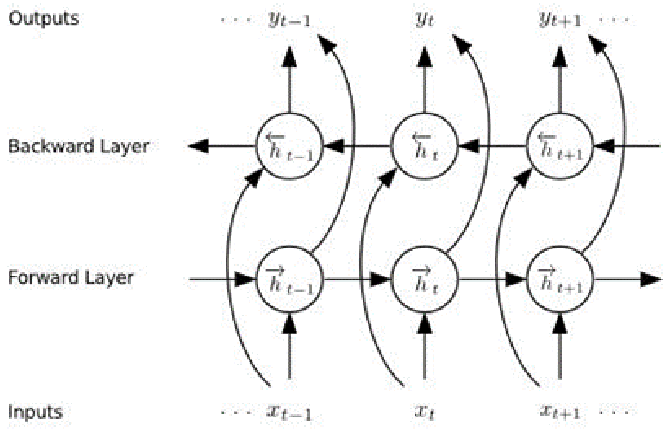

Figure 4. Bidirectional-LSTM Layers

Eq. (7-9) mathematically explain Fig 4. The forward hidden sequence denoted by →h_f is calculated by looping the forward layer starting from f = 1 to F. The backward hidden sequence ←h_f is calculated by looping the backward layer from f = F to 1. Wx_h^l are the input weight matrices, W_h^l are the hidden weight matrices, and →b_h^l, ←b_h^l are the bias terms for the forward and backward hidden layer, respectively. Finally, y_f (output layer) on Equation (9) is calculated using the hidden activations →h_f^(L-1) and ←h_f^(L-1) of the last hidden layer L − 1. W_y are the output weight matrices and b_y is the output bias term.

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$$\overrightarrow{h}^{l}_{f-1} = g\left(W^{l}_{x\overrightarrow{h}} x^{l}_{f} + W^{l}_{\overrightarrow{h}\overrightarrow{h}} \overrightarrow{h}^{l}_{f-1} + b^{l}_{\overrightarrow{h}}\right), \quad (7)$$

$$\overleftarrow{h}^{l}_{f-1} = g\left(W^{l}_{x\overleftarrow{h}} x^{l}_{f} + W^{l}_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h}^{l}_{f-1} + b^{l}_{\overleftarrow{h}}\right), \quad (8)$$

$$y_f = m\left(W_{\overrightarrow{h}y} \overrightarrow{h}^{L-1}_{f} + W_{\overleftarrow{h}y} \overleftarrow{h}^{L-1}_{f} + b_y\right) \quad (9)$$

Figure 5. Bidirectional-LSTM equations

2.3. Performance Metrics

For evaluating the effectiveness of all models' regressions, several statistical methods are available. We employed the following metrics for this study: coefficient of determination, which is denoted as R^2, Mean Absolute Percentage Error or MAPE, and Root-Mean Square Error or RMSE, all of which are represented in Equation (10-12). These measures provide better goodness of fit and efficiency by directly clarifying measurement units:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Ac_i - Pr_i)^2} \quad (10)$$

$$R^2 = 1 - \frac{\sum_{t=0}^{n-1}(Ac_i - Pr_i)^2}{\sum_{t=0}^{n-1}\left(Ac_i - \left(\sum_{t=0}^{n-1} Ac_i - Pr_i\right)\right)^2} \quad (11)$$

$$MAPE = \frac{1}{n}\sum_{n=1}^{n}\frac{|Ac_i - Pr_i|}{|Ac_i|} \quad (12)$$

Figure 6. RMSE, Coefficient of Determination (R^2), and MAPE equation

From the equations above, Pr_i is the projected value of the dependent variable for time in range i, Ac_i denote the observed value, and n denote the total number of observations. Combining BiRNN with LSTM results in Bidirectional LSTM (Bi-LSTM). Different from LSTM, rather than using one LSTM layer, Bi-LSTM incorporates two LSTMs (Althelaya et al., 2018) and runs the system's sequence of input bidirectionally, one from left (past) to right (future) and vice versa for the another (similar as described in Fig. 3). This process is done in parallel and it's for the training process. Thus, the information from the future is protected (Khullar and Singh, 2022).

For forecasting, it would be better to use the model with lower values for these measurements (Lee et al., 2022). If the RMSE are close to 0, it shows that the model performs well. (Chicco et al., 2021; Lee et al., 2022). If MAPE is below 10%, it means that predictions are very accurate; MAPE between 10% and 20% is regarded as a reasonable range for forecasts; the estimates are quite accurate if MAPE is between 20% and 50%; poor prediction is shown by MAPE more than 50% (Lewis, 1982).

2.4. Data

The palm oil price data used in this work are obtained from Markets Insider's and recorded between 2007 and 2022. This dataset has multiple features, which are the opening, closing, highest, and lowest prices for palm oil, as well as the volume of palm oil sold. All of these things are each in their own column in the dataset.

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Table 1. Dataset Descriptive Information

Index	Open	High	Low	Close
Count	3328.0	3328.0	3328.0	3328.0
Mean	2709.72	2742.30	2696.92	2902.98
STD	1218.78	1232.42	1199.24	984.97
Min	0.0	0.0	0.0	1418.0
25%	2199.75	2215.0	2187.0	2272.0
50%	2565.5	2585.0	2557.5	2612.0
75%	3141.0	3162.0	3130.0	3218.0
Max	8200.0	8757.0	7780.0	8163.0

Table 1 presents the descriptive statistics, which include the count, mean, standard deviation (SD), minimum, value in 25% of data, value in 50% of data, value in 75% of data, and maximum values. These numbers describe how the data is spread out, while Fig. 3 illustrates the trend of palm oil price trend from May 2007 to December 2022. This work estimates the daily prices of palm oil at the end of the day, it means the values from column “Close”. Figure 4. shows the trend of the price observed in this study. 80 percent of the data was used for training, while the remaining 20 percent was used for testing.

Figure 7. Daily Close Palm Oil Price Trend from May 2007 to December 2022

2.5. Experiment and Model’s Setup

In this section, contains the comparison of how well the LSTM model and the Bi-LSTM model work. As mentioned, the work applied LSTM and Bi-LSTM model to predict palm oil price based on dataset that were recorded between May 2007 to December 2022. Below, Fig. 8 and Fig. 9 describes the architectural model that is built in this work.

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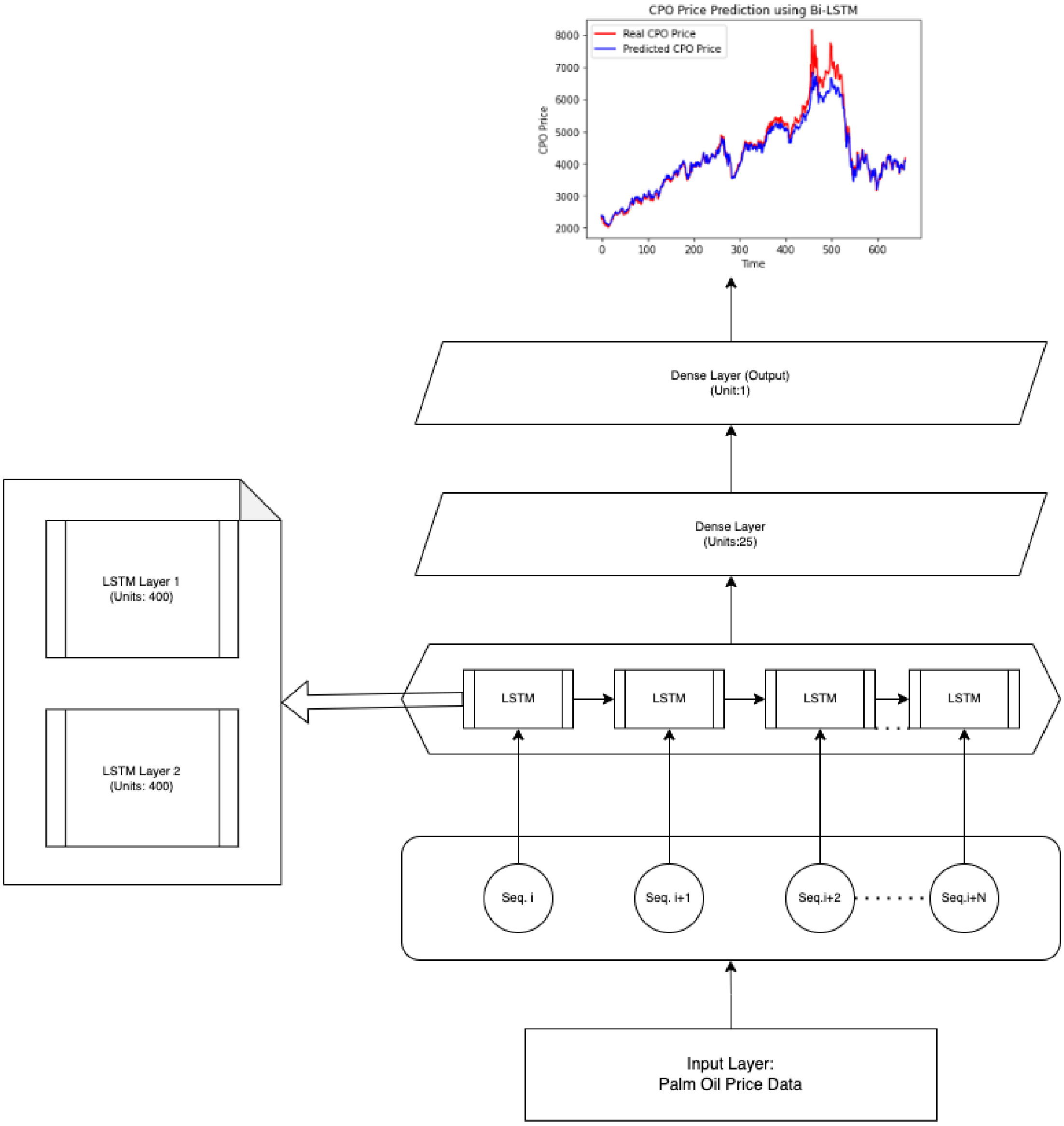

Figure 8. LSTM Architecture Model

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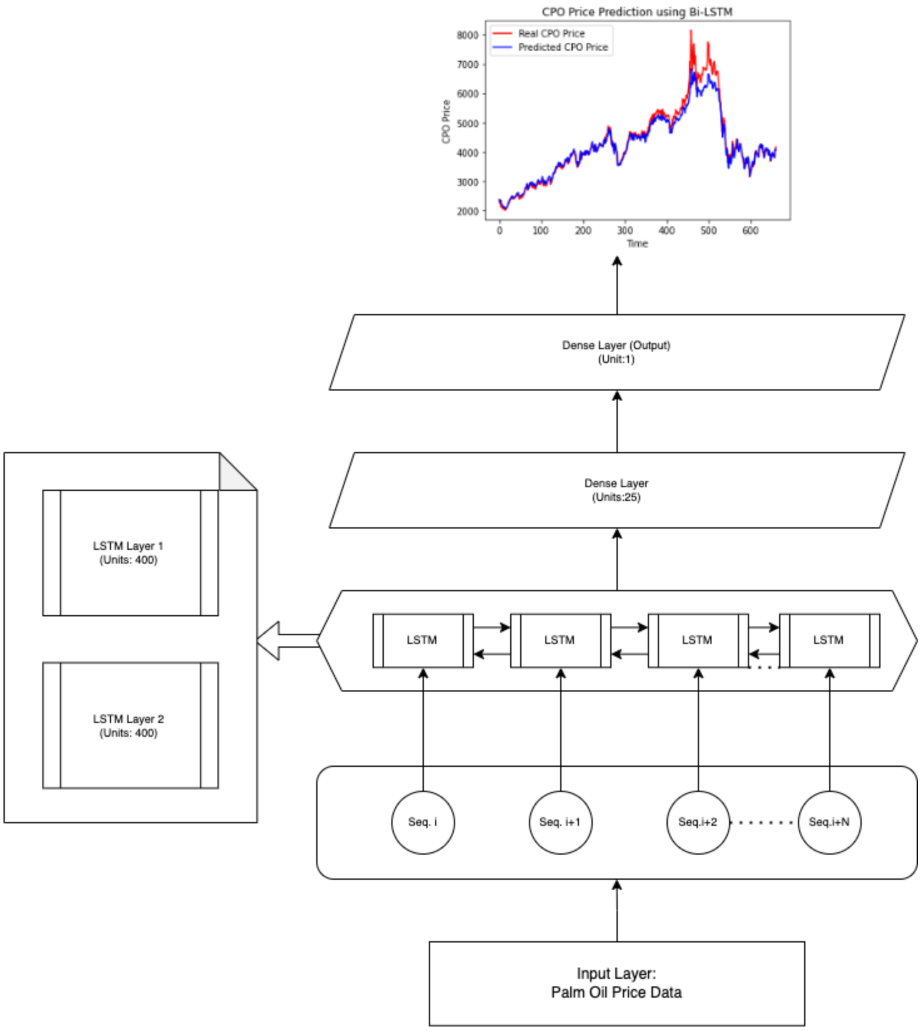

Figure 9. Bi-LSTM Architecture Model

Based on Fig. 8 and Fig. 9, LSTM model that is applied consists of two hidden layers LSTM with 400 hidden units, followed by two dense layers, the first one consisting of 25 units and the second one which is the output layer, consists of one unit. Whereas for the Bi-LSTM model, the work used two hidden layers of LSTM that consist of 400 (800 recorded as bidirectional) hidden units, one dense layer with 25 units, and an output layer that is a dense layer with one unit. After that, can be seen from the figures, both the model generates the predicted price.

Optimizer plays a major role in the algorithm's convergence rate; it is of utmost importance to select the optimal optimizer for an LSTM model (Nti et al., 2021). Therefore, in this experiment, the Adaptive Moment Estimation (ADAM) optimizer was implemented as the optimizer for the LSTM's model, considering that ADAM's optimizer is a hybrid of the best features of optimizers ADAgrad and RMSprop, it clearly stands out as the best option, and it makes sure that the training steps don't change much depending on how large or small the gradients of the parameters are made. This study utilized the use of "Early Stopping", where it prevents the model from overfitting by checking the network's performance on a validation set while it's being trained and terminating the training process if the network's performance on the validation set starts to degrade. This helps to ensure that the network is not memorizing the training data.

3. RESULTS AND ANALYSIS

After proper scaling, training, and testing between the train data, and tested data, the score of RMSE, MAPE, and R^2 was observed for the LSTM and Bi-LSTM using 2 layers of LSTM,

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each with 400 units (recorded 800 for BiLSTM) and 2 dense layers with 25 units and one unit that is an output layer. The models were fit with 200 epochs and a batch size of 32, but with help of Early Stopping and Model Checkpoint to prevent the model from overfitting, the models only reach 60 epochs and 70 epochs, respectively is LSTM and BiLSTM.

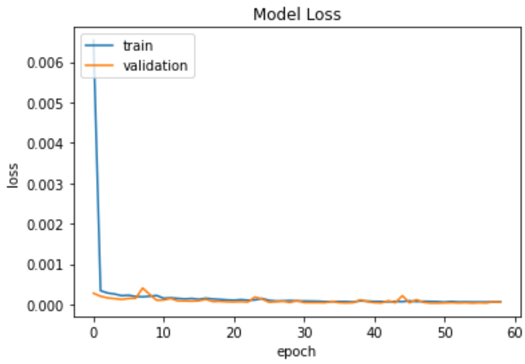

Figure 10. LSTM Model Loss

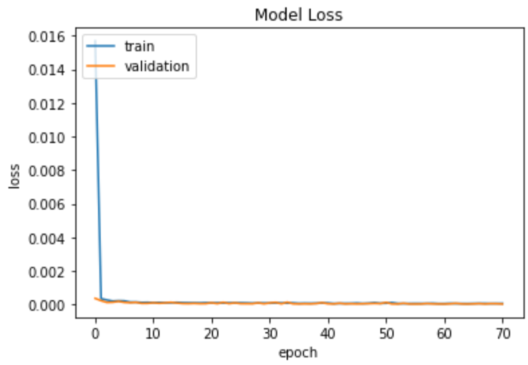

Figure 11. Bi-LSTM Model Loss

Fig. 10 and Fig. 11 reports the model loss error comparison between the train data and tested data. It is worth noticing the fact that both the LSTM and Bi-LSTM model was built and performed well for the dataset studied and had a reasonable error of MSE, as can be seen in the model's train and validation data performance figures.

Table 2. Performance comparison between models

Evaluation Metrics	**LSTM**	**Bi-LSTM**
RMSE	0.000601	0.0000833
MAPE	0.97%	0.76%
R^2	0.747	0.9166

As presented in Table 2, the models performed best overall performance with a very balanced comparison of results between the two models, LSTM exhibited 0.000531 score of RMSE, 0.67% of MAPE, and 0.747 score of R^2. Where Bi-LSTM exhibited 0.00007233 score of RMSE, 0.46% of MAPE, and 0.9166 score of R^2. Highlighting from the explanation of MAPE's performance from Section 3, both models show MAPE's percentage below 10%, which means that predictions are very accurate and reliable. After that, we can have a look at the error the model had. When predicting with LSTM, the prediction result scored an error of 0.000531 RMSE, while Bi-LSTM reports lower error than the LSTM, with 0.000072 score of RMSE.

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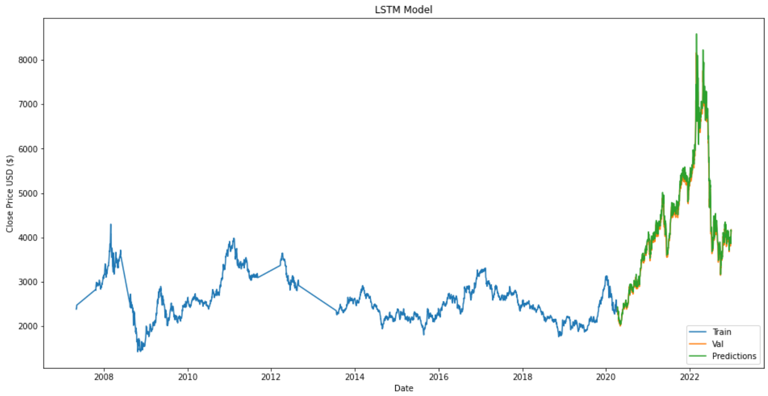

Figure 12. Palm Oil Price Prediction with LSTM

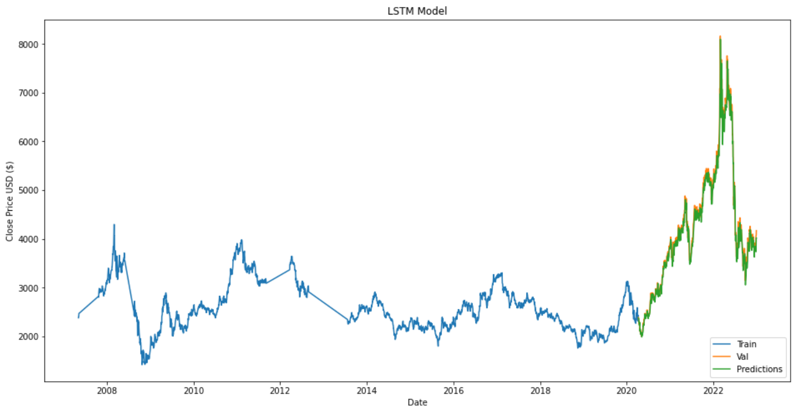

Figure 13. Palm Oil Price Prediction with Bi-LSTM

The prediction curves are plotted in Fig. 12 and Fig. 13 to further define the distinction between the two models. Based on these findings, Bi-LSTM is preferable statistically for predicting the palm oil price trend, shows the lowest error of RMSE, tie score of MAPE and a score of R^2 that is closer to value 1.0. Thus, the models utilized in this research can be used as valid tools for future price forecasting of palm oil, or any other commodities price, based on a results that is acceptable and competing with previous study.

4. CONCLUSION

This study utilized the use of LSTM and Bi-LSTM model and evaluated the models for palm oil price prediction. Evaluation of the LSTM and Bi-LSTM performance using three performance measures, that is RMSE, MAPE, and R^2. Both models can produce the lowest error for palm oil price prediction, in line with other studies. Both LSTM and BI-LSTM models perform a good fit with the data used and thus can be utilized to forecast the price of palm oil. Based on the performance score, Bi-LSTM model generates slightly lower score of error compared to LSTM model with a small margin difference on RMSE. For future work purposes, it is important to note that, without the need for any additional modifications or restrictions, the framework applied in this study can be easily expanded to cover a wider area of time-series forecasting objects, such as stock market predictions, bitcoin price predictions, cryptocurrency price predictions, and any commodity price predictions.

5. ACKNOWLEDGEMENTS

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6. DECLARATION OF COMPETING INTEREST

We declare that we have no conflict of interest.

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