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Research Paper

A Hybrid ARIMA–GRU Model for Forecasting Palm Oil Prices at PT Sawit Sumbermas Sarana in Central Kalimantan

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Keywords
ARIMA, GRU, Hybrid Model, Forecasting

Abstract
The palm oil industry plays a strategic role in Indonesia's economic landscape. As one of the world's largest producers, Indonesia holds substantial potential in marketing both crude palm oil (CPO) and palm kernel oil on domestic and international fronts. Palm oil prices consistently correlate with CPO prices, given that the pricing of palm oil is benchmarked against CPO, resulting in market fluctuations. Forecasting future palm oil prices becomes an essential measure in response to this volatility. The ARIMA (AutoRegressive Integrated Moving Average) model has been widely recognized as a reliable method for time series forecasting. Despite its strengths, ARIMA faces challenges in identifying the non-linear components that are often present in real-world data. The Gated Recurrent Unit (GRU) model, which incorporates an update gate and a reset gate, offers an alternative that effectively captures complex non-linear patterns. A hybrid model integrating ARIMA and GRU has therefore been developed with the aim of improving predictive accuracy. This hybrid approach includes two stages: the ARIMA model for initial predictions and a GRU model that processes the residuals from the ARIMA output. In this study, the ARIMA-GRU hybrid model demonstrated strong performance, yielding a Mean Squared Error (MSE) of 868.4690, a Root Mean Squared Error (RMSE) of 29.4698, a Mean Absolute Percentage Error (MAPE) of 0.0117, and an overall accuracy of 99.9824%.

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1. INTRODUCTION

The palm oil industry plays a strategic role in Indonesia's economy by serving as one of the largest sources of foreign exchange, a key driver of national economic growth, a stimulant for related economic sectors, and a major provider of employment. The two primary regions for oil palm plantations in Indonesia are the islands of Sumatra and Kalimantan [1]. Indonesia possesses considerable potential for marketing both crude palm oil (CPO) and palm kernel oil, both domestically and internationally [2, 3, 4]. The price of fresh fruit bunches (FFB) is consistently tied to the CPO price, as the latter serves as the pricing benchmark. As a result, price fluctuations are inevitable, making price forecasting essential for future planning.

Forecasting serves as a valuable tool for government policymaking, enabling the design of effective strategies to support economic development. One of the most commonly used models for time series forecasting is the AutoRegressive Integrated Moving Average (ARIMA). While ARIMA is well-regarded for its predictive capabilities, it faces limitations in modeling non-linear patterns inherent in complex datasets. The model also tends to rely exclusively on dependent variables while often excluding independent variables, which constrains its accuracy in certain short-term forecasting scenarios [5].

Beyond ARIMA, alternative approaches such as Recurrent Neural Networks (RNNs) have been explored. RNNs, a class of artificial neural networks, process sequential inputs repeatedly

[6]. However, their inability to retain long-term memory leads to difficulty in recalling earlier information within the sequence, resulting in the vanishing or exploding gradient problem [7].

The Gated Recurrent Unit (GRU) emerged as an advancement over conventional RNNs, specifically designed to avoid these gradient issues while effectively handling both prediction and classification tasks [8]. GRUs incorporate two gating mechanisms—update gate and reset gate—which enable the model to capture complex non-linear dependencies in data [9].

Previous research on ARIMA has demonstrated its utility in various domains. For instance, Wiguna et al. [10] applied the ARIMA model to forecast the spread of COVID-19 in Jakarta, with results indicating an upward trend in daily cases over the following 14-day period. Similarly, Salwa et al. [5] used the ARIMA (0,2,1) model to forecast Bitcoin prices, revealing a gradual decline over the next 30 periods, with predictions closely aligning with actual data. Research involving GRU models has also yielded promising results. Zhao et al. [11] applied GRU combined with data fusion techniques to predict travel time, achieving higher accuracy compared to other fusion-based methods. Arfianti et al. [12] used the GRU algorithm to predict sunspot numbers, reporting better accuracy than LSTM with a MAPE value of 9%.

Hybrid models that integrate ARIMA and GRU have been explored in recent studies. Shafiri et al. [13] examined the performance of hybrid ARIMA-deep learning models for forecasting Bitcoin prices. Their findings indicated that the ARIMA-GRU hybrid outperformed other combinations, including ARIMA-RNN and ARIMA-LSTM, in terms of RMSE and MAPE metrics. This study aims to evaluate the performance of the ARIMA-GRU hybrid model in forecasting palm oil prices and to generate predictions over a six-month horizon.

2. METHODS

This study employs a hybrid methodological approach by integrating the ARIMA model with the GRU architecture. The combination leverages the strengths of ARIMA in modeling linear components while utilizing the capability of GRU to capture complex non-linear patterns within time series data. Figure 1 illustrates the workflow of the hybrid ARIMA–GRU process, implemented using the Python programming language.

Table 1. Palm Oil Price Data

Date	Closing Price (IDR)
05/01/2014	920
12/01/2014	895
19/01/2014	810
26/01/2014	840
-	-
27/11/2022	1.510

2.1 Dataset

The data in this study consist of secondary information obtained from https://id.investing.com/equities/sawit-sumberma-historical-data, which provides historical palm oil prices for PT. Sawit Sumbermas Sarana over a nine-year period, from January 2014 to November 2022, on a weekly basis. The dataset includes the weekly closing prices of palm oil, totaling 459 data points.

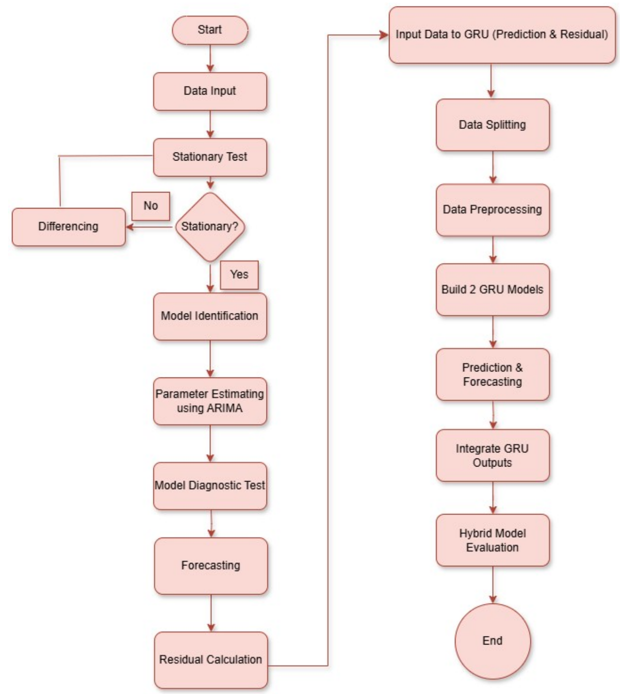


Figure 1. Workflow of the Hybrid ARIMA-GRU

2.2 Forecasting

Forecasting involves the prediction of future trends and represents an important challenge across various fields, including business and industry, economics, environmental science, medicine, politics, and finance. Prediction problems are commonly categorized into short-term, medium-term, and long-term horizons [14].

Forecasting methods are generally divided into two main types: qualitative and quantitative. Qualitative forecasting relies on past qualitative data, drawing on the knowledge and experience of experts. In contrast, quantitative forecasting depends on historical numerical data and utilizes models such as time series and causal models [15].

2.3 Time Series

Time series refers to a sequence of observations on a particular variable recorded sequentially at consistent time intervals [16]. Such data represent measurements of a single subject across multiple periods, which may be daily, weekly, monthly, yearly, or other defined intervals. According to Hanke and Wichern [17], time series data exhibit four primary patterns. The horizontal pattern occurs when data fluctuate around a constant value or mean, indicating stationarity. Seasonal patterns involve regular fluctuations that recur approximately within a year, such as quarterly, monthly, weekly, or daily cycles. Cyclical patterns describe movements characterized by rises and falls in cycles around an underlying trend or normal condition. Finally, trend patterns capture the long-term directional movement of data, reflecting either an upward or downward trajectory. Figure 2 illustrates these various time series data patterns [14].

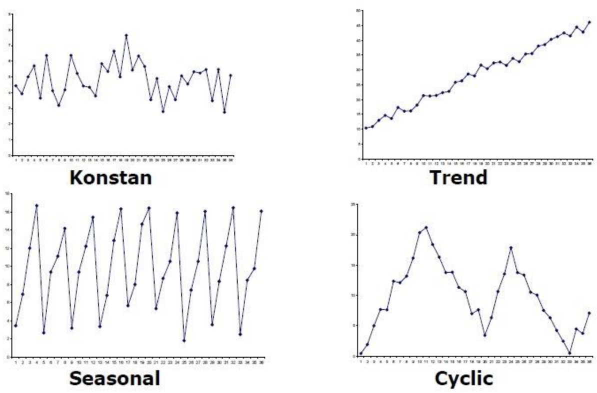


Figure 2. Time Series Data Patterns

2.4 ARIMA Method

Box and Jenkins introduced a practical approach for developing ARIMA models grounded in time series analysis and forecasting. Their framework covers non-seasonal stationary models (Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA)), and extends to non-stationary data with the ARIMA(p,d,q) model through differencing [18]. The AR model explains the current value based on past observations plus random errors, while the MA model expresses it as a function of past errors. The ARMA model combines these elements to capture various stationary data patterns. ARIMA incorporates differentiation to stabilize non-stationary data, enabling effective modeling of trends alongside autoregressive and moving average components. Mathematically, the ARIMA model is expressed by the equation shown in Equation (1).

$$\phi_p(B)\nabla^d Z_t = \zeta + \theta_q(B)\varepsilon_t \tag{1}$$

2.5 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) represents an advanced variant of the traditional RNN specifically designed to mitigate the long-term dependency problem inherent in standard RNNs. This architecture facilitates the retention of long-term information through its recurrent processing structure [19]. The GRU cell comprises two primary gates: the update gate and the reset gate, as illustrated in Figure 3.

The update gate z_t determines how much of the previous hidden state h_{t-1} should be preserved in the current state. It is calculated as Equation (2):

$$z_t = \sigma(w_z * [h_{t-1}, x_t] + b_z) \tag{2}$$

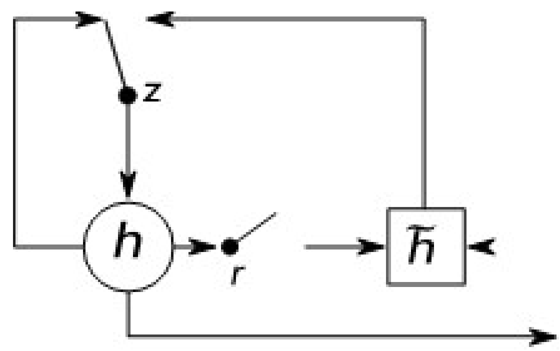


Figure 3. GRU Architecture

The reset gate r_t controls how much past information to forget before combining it with the new input:

$$r_t = \sigma(w_r * [h_{t-1}, x_r] + b_r) \tag{3}$$

The candidate hidden state $\tilde{h}_t$ incorporates the reset-modified past state and current input, passed through a hyperbolic tangent activation:

$$\tilde{h}_t = \tanh(W * x_t + (r_t * h_{t-1}) * W + b_h) \tag{4}$$

The final hidden state h_t is obtained by blending the previous hidden state h_{t-1} and the candidate $\tilde{h}_t$, weighted by the update gate:

$$h_t = (1 - z_t) * \tilde{h}_t + z_t * h_{t-1} \tag{5}$$

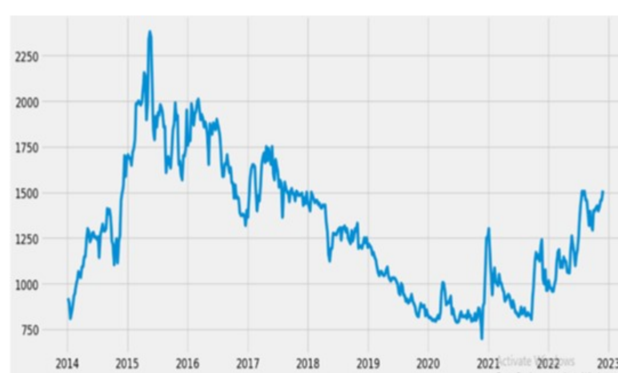


Figure 4. Visualization of Palm Oil Price Data

2.6 Standard Scaler

The standard scaler is a preprocessing technique used to normalize input data by subtracting the mean and scaling to unit variance. This transformation helps ensure that each feature contributes proportionally during model training, thereby avoiding situations where features with larger numerical ranges disproportionately influence the learning process [20]. The standardization is calculated using Equation (6):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

where x' denotes the standardized value, x is the original sample, μ is the mean, and σ represents the standard deviation. This step contributes to improving training consistency and model convergence.

Table 2. Arima Model

ARIMA Model	AIC	Log Likelihood
ARIMA (1,1,1)	5151,95	-2572,97
ARIMA (1,1,2)	5152,68	-2572,34
ARIMA (1,1,3)	5154,67	-2572,33
ARIMA (1,1,4)	5156,65	-2572,32
ARIMA (2,1,1)	5153,79	-2572,89
ARIMA (2,1,2)	5154,67	-2572,33
ARIMA (2,1,3)	5155,33	-2571,66
ARIMA (2,1,4)	5149,39 *	-2567,69 *
ARIMA (3,1,1)	5154,58	-2572,29
ARIMA (3,1,2)	5156,66	-2572,33
ARIMA (3,1,3)	5156,59	-2571,29
ARIMA (3,1,4)	5160,86	-2572,43
ARIMA (4,1,1)	5149,18	-2568,59
ARIMA (4,1,2)	5156,65	-2571,32
ARIMA (4,1,3)	5162,35	-2573,17
ARIMA (4,1,4)	5161,92	-2571,96

2.7 Activation Function

Activation functions play a central role in neural networks by producing outputs based on given inputs, thereby influencing the flow of information throughout the network [21]. These functions determine whether a neuron should be activated and whether the signal should be passed on to subsequent layers [22]. Two commonly used activation functions in deep learning models are the sigmoid and the hyperbolic tangent (tanh) functions.

The sigmoid activation function is a nonlinear function that maps input values into a range between 0 and 1, making it suitable for representing probabilities or scaled intensities. It is expressed as:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

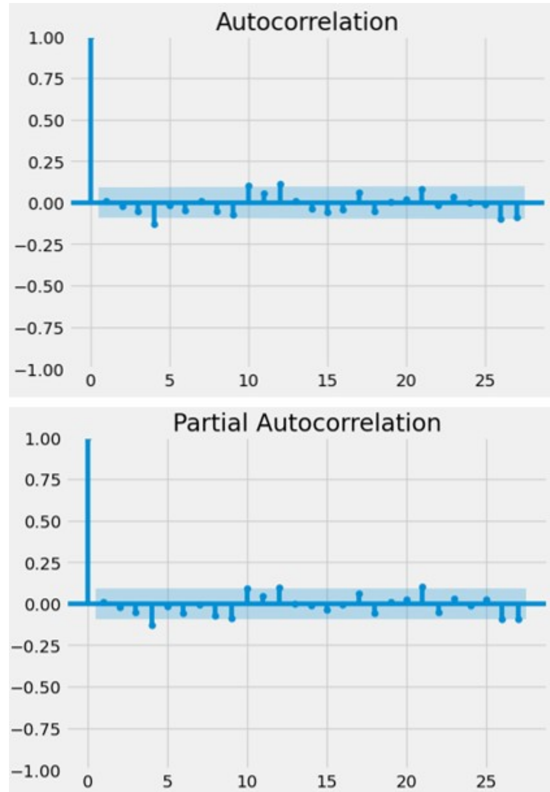


Figure 5. ACF and PACF Plot Results

Table 3. Arima Accuracy

Metrics	Value
MSE	4423.3473
RMSE	66.5082
MAPE	0.0347
Accuracy	99.9653%

The hyperbolic tangent (tanh) function serves as an alternative to the sigmoid function. It maps real-valued inputs into the range of -1 to 1, offering better centering of the data, which can facilitate faster convergence during training. The tanh function is defined as:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{8}$$

These activation functions allow neural networks to capture complex, non-linear relationships within the data and are fundamental in enabling deep learning models to perform classification, prediction, and representation learning tasks effectively.

2.8 Hybrid Model

The hybrid modeling approach for time series forecasting integrates both linear and nonlinear components to improve prediction accuracy. One such combination is the integration of the ARIMA model with a GRU network. This structure enables the model to capture linear trends via ARIMA and nonlinear patterns through GRU. The general hybrid formulation can be expressed as Equation (9):

$$y_t = L_t + N_t \tag{9}$$

where y_t denotes the actual value at time, L_t represents the linear component, and N_t denotes the nonlinear component [23].

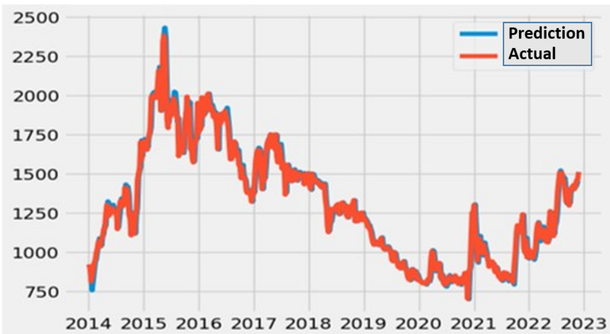


Figure 6. ARIMA Predicted Data

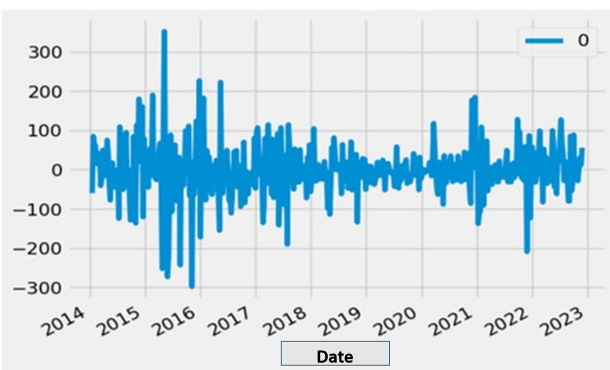


Figure 7. Residual Plot

In the hybrid ARIMA–GRU approach, ARIMA is first employed to capture the linear structure of the time series. The residuals, representing the portion not explained by ARIMA and potentially containing nonlinear patterns. These residuals are then modeled using GRU, which learns a nonlinear function of past residuals with random noise. The final hybrid prediction combines the ARIMA and GRU outputs, integrating both linear and nonlinear components to improve forecasting accuracy.

2.9 Forecasting Accuracy

Briggs et al. [15] describe forecasting accuracy as the extent to which a model can replicate actual data, commonly evaluated using the error between predicted and observed values. Metrics such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are frequently applied. MAPE expresses the average percentage difference

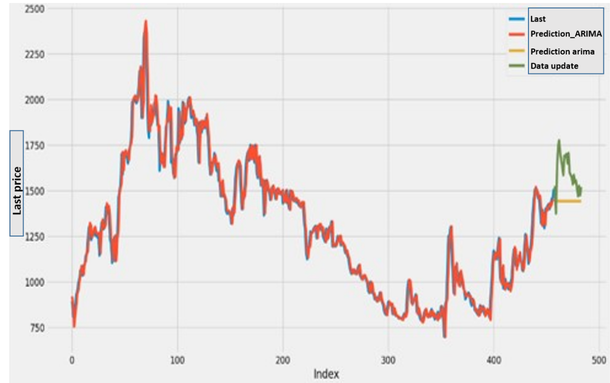


Figure 8. ARIMA Forecasting

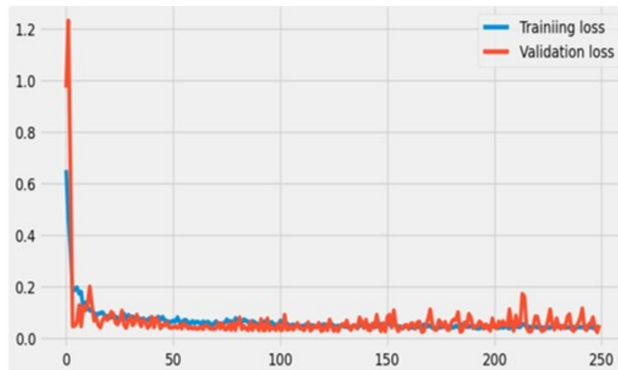


Figure 9. Training and Validation Loss (80% - 20%)

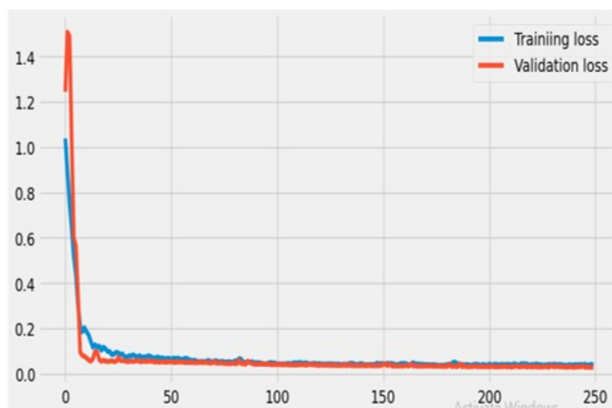


Figure 10. Training and Validation Loss (90% and 10%)

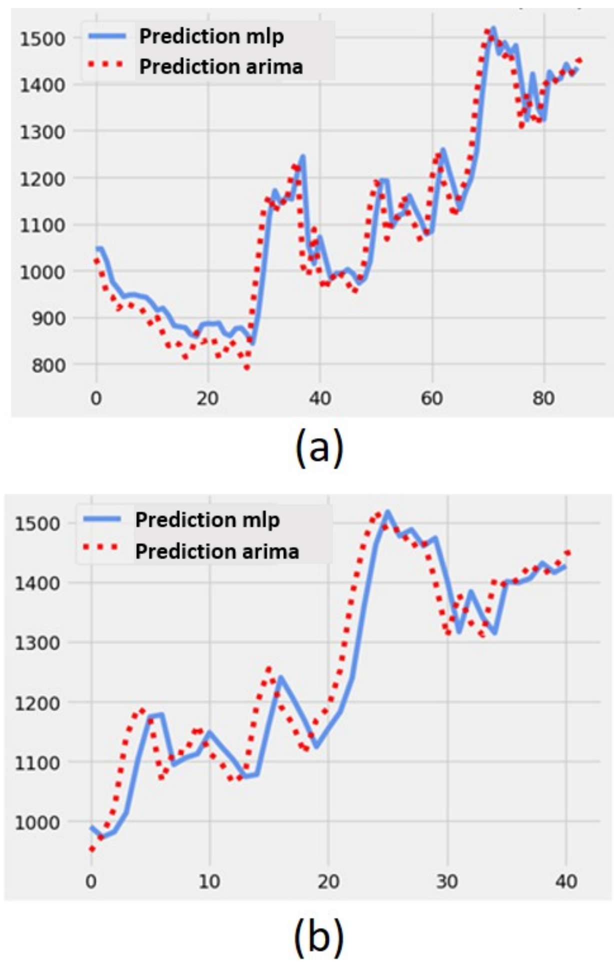
between predicted and actual values [24], while MSE and RMSE measure the magnitude of squared prediction errors, with lower values indicating higher predictive performance.

3. RESULTS AND DISCUSSION

3.1 Data Input and Visualization

The initial step in this study involves importing data into the Python environment. The dataset, consisting of palm oil prices, is first uploaded to Google Drive and then loaded into Python using the Pandas library for further analysis.

Figure 4 presents a visualization of palm oil price data, illustrating the overall movement and fluctuations over time. The visual analysis indicates the presence of a noticeable trend in the data.



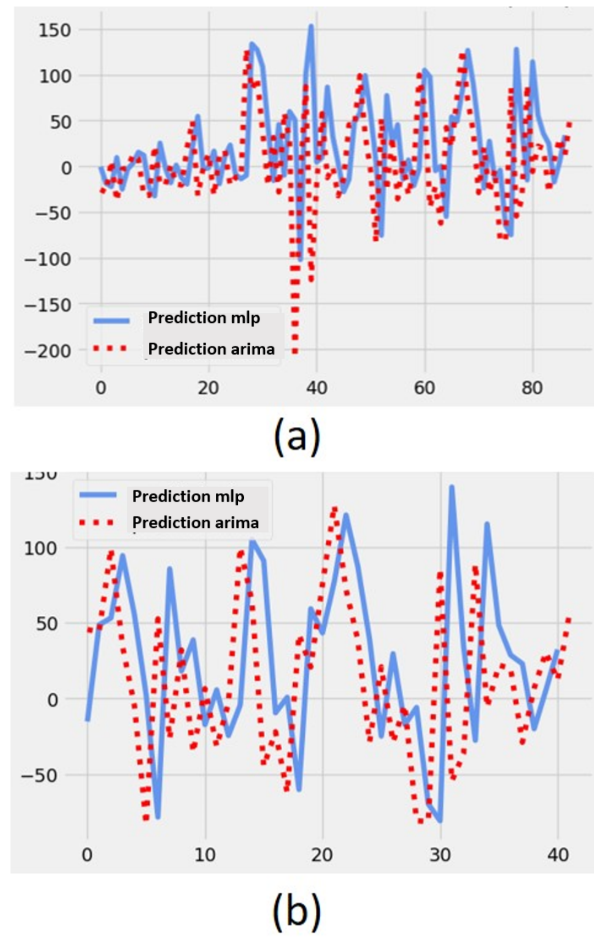
(a) (b)

Figure 11. ARIMA - GRU Prediction Plot using Predicted Data

3.2 Data Prediction using ARIMA

The ARIMA model parameters—p, d, and q—were determined through analysis of the time series data. The differencing order d was established by testing stationarity using the Augmented Dickey-Fuller (ADF) test. Initially, the p-value was 0.4722, indicating non-stationarity and failure to reject the null hypothesis. After the first differencing, the data became stationary with a p-value of 2.04×10^{-7}, setting d to 1.

Values for p and q were identified from the PACF and ACF plots (Figure 5), which showed significant spikes at lag 4, suggesting $p = 4$ and $q = 4$. Several ARIMA models with different combinations of parameters were evaluated using AIC and log-likelihood criteria (Table 2). The ARIMA(2,1,4) model achieved the lowest AIC (5149.39) and highest log-likelihood (-2567.69), marking it as the optimal choice.



(a) (b)

Figure 12. ARIMA - GRU Prediction Plot using Residual Data

The parameter estimates of ARIMA(2,1,4) showed statistically significant AR and MA coefficients, confirming their impact on palm oil price prediction. Visualization of predicted versus actual values (Figure 6) demonstrated that the model closely captured the data's pattern. Accuracy metrics calculated via Python (Table 3) revealed a low MAPE of 0.0347, MSE of 4423.35, and RMSE of 66.51, indicating high prediction accuracy of approximately 99.97%.

Residual analysis (Figure 7) showed that residuals ranged between -300 and 400 and were used as nonlinear components in hybrid modeling. However, forecasting for 26 weeks ahead (Figure 8) revealed a divergence between ARIMA predictions and updated prices, suggesting that ARIMA(2,1,4) alone may not be adequate for long-term palm oil price forecasting.

3.3 Data Prediction using Hybrid ARIMA-GRU

The hybrid model combines two principal components: the ARIMA forecast enhanced by a GRU network and the ARIMA residuals predicted via GRU. Hyperparameter tuning optimizes parameters such as GRU units and batch size to achieve the best performance.

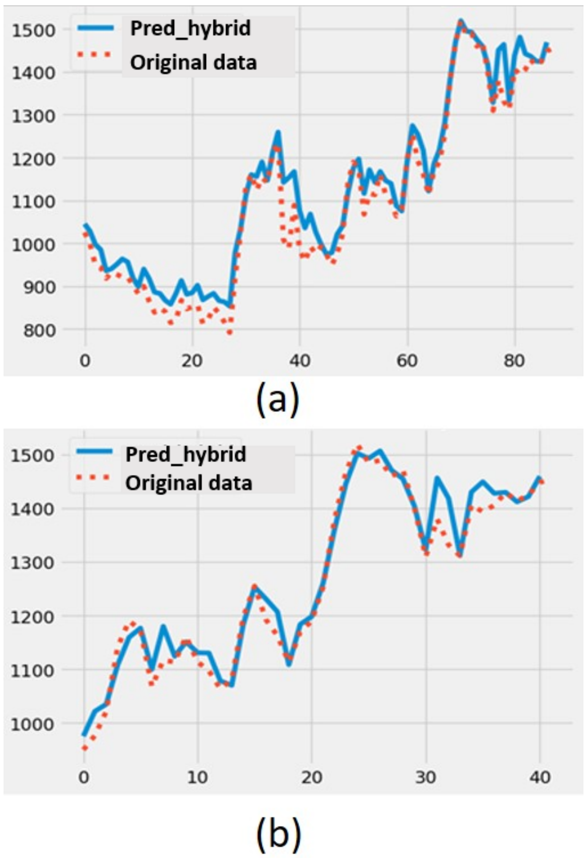


Figure 13. Hybrid Model Visualization and Evaluation Values

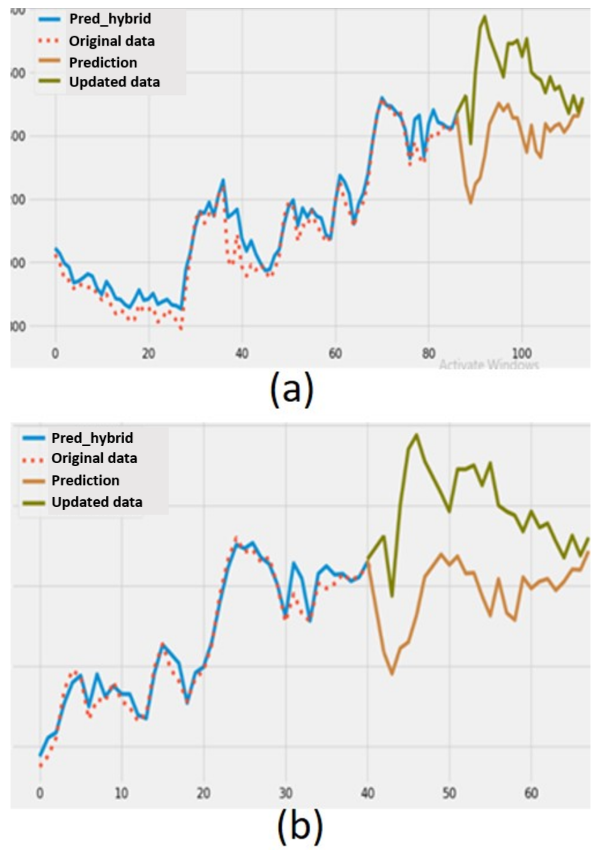


Figure 14. Forecasting Plot using Hybrid ARIMA – GRU

Data is split into training and testing sets under two schemes: 80% training–20% testing and 90% training–10% testing. Prior to modeling, data scaling is applied using the StandardScaler technique to improve efficiency and reduce errors.

The GRU model architecture includes two hidden layers and one output layer, with neuron counts of 64 or 128, batch sizes of 64 or 128, 250 epochs, and a dropout rate of 0.2. Hyperparameter tuning results indicate the optimal units and batch sizes for each data split.

Training and validation loss plots (Figures 9 and 10) demonstrate minimal overfitting, with training and validation losses closely aligned in both data split schemes.

The ARIMA-GRU prediction model achieves high accuracy, with MAPE values corresponding to approximately 99.95% and 99.96% for the 80/20 and 90/10 splits, respectively, as detailed in Figure 11.

Similarly, the residual ARIMA-GRU model shows robust performance with accuracy around 97.31%, illustrated in Figure 12. Again, the 90/10 split yields superior results with 97.53%.

The hybrid model, integrating ARIMA-GRU predictions and residual GRU forecasts, further improves accuracy, reaching up to 99.98% in the 90/10 split Figure 13. Meanwhile, forecasts over 26 weeks are showing in Figure 14.

4. CONCLUSIONS

The hybrid ARIMA–GRU method proves to be highly effective for forecasting palm oil prices. The standalone ARIMA model achieved an accuracy of 99.9653%, whereas the hybrid model improved the accuracy to 99.9824%. Forecasts generated by the ARIMA model did not closely track the most recent data updates; in contrast, the hybrid ARIMA–GRU forecasts aligned well with the updated data. This indicates that the hybrid ARIMA–GRU model is a superior approach for both prediction and forecasting of palm oil prices. Among the evaluated configurations, the hybrid model using 90% training and 10% testing data split demonstrated the best parameter performance. The six-month forecast produced by this model followed the recent data trends more accurately and showed better evaluation metrics compared to the 80%-20% split. The 90%-10% scheme achieved an MSE of 868.4690, RMSE of 29.4698, MAPE of 0.0117, and accuracy of 99.9824%.

5. ACKNOWLEDGEMENT

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