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Research Paper

Integrating VAR and CNN Models for Accurate Forecasting of Money Supply in Indonesia

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Keywords

ARIMA, GRU, Hybrid Model, Forecasting

Abstract

Economic forecasting serves as a fundamental element in supporting decision-making processes across multiple sectors. One of the main areas of interest in this field is the estimation of the money supply within an economy. The Vector Autoregressive (VAR) model is a commonly applied method for forecasting; however, it often encounters limitations when processing data with nonlinear patterns. Convolutional Neural Networks (CNNs) offer an alternative approach, particularly effective in identifying nonlinear structures that are not adequately captured by VAR models. A hybrid VAR-CNN model is therefore proposed, combining the respective strengths of both techniques to improve the accuracy of predictions. This research applies to the hybrid VAR-CNN model to forecast economic variables for the period from July 2022 to June 2023. The model consists of two main components: the first utilizes forecasted values generated by the VAR model, while the second processes the residuals from the VAR output using a CNN. With 80% of the data allocated for training and 20% for testing, the hybrid VAR-CNN model demonstrates improved performance over alternative forecasting methods. Evaluation based on Mean Absolute Percentage Error (MAPE), supremum (D) values, and p-values confirms the effectiveness of this hybrid approach.

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1. INTRODUCTION

In an era marked by globalization and rapid transformation, economic forecasting has become an integral aspect of decision-making across diverse sectors. A key focus within this domain is the analysis and prediction of the money supply within an economy [1]. Time series refers to a sequence of data points collected or recorded at successive points in time [2]. Forecasting remains one of the primary objectives in multivariate time series analysis [3]. The Vector Autoregressive (VAR) model, an extension of the Autoregressive (AR) model, employs multiple variables to forecast time-dependent data [4]. While VAR models are effective in capturing linear interdependencies among variables, they often struggle with nonlinear patterns, necessitating the integration of complementary approaches.

The Convolutional Neural Network (CNN), a development of the Artificial Neural Network (ANN), has shown considerable potential in forecasting time series data due to its capacity to capture complex nonlinear structures [5]. Although CNNs are adept at processing spatial and sequential data and identifying nonlinear components in time series, they face limitations in modeling inter-variable relationships. The development of a hybrid multivariate forecasting model that combines VAR and CNN is expected to address the individual shortcomings of each method, thereby improving forecasting accuracy.

Previous studies utilizing the VAR model include the work of Yuliadi [6], employed a Vector Autoregressive (VAR) model to analyze the relationship between money supply (M1), interest rates, and GDP in Indonesia from Q1 2001 to Q1 2013. Abdullah [7] investigated the relationship between monthly oil and gold prices and conducted forecasting, concluding that both variables influence each other across different lags, with VAR(7) and VAR(10) models yielding the best forecasts.

Number of Authors propose classical and deep learning hybrid models. Research applying the neural network method was conducted by Parot et al. [8], who proposed a hybrid ANN-VAR model to forecast the EUR/USD exchange rate, achieving a 19.3% reduction in RMSE and thus enhancing forecasting accuracy. A hybrid methodological approach by integrating the Auto Regressive Integrated Moving Average (ARIMA) model with the Gated Recurrent Unit (GRU) architecture with overall accuracy of 99.9824% is implemented in [9], and a hybrid VAR-FFNN model to forecast air pollution levels in Taiwan, reporting improved forecasting performance is investigated by [10]. Similarly, Savada et al. [11] proposed a hybrid VAR model with one of the variants of the Recurrent Neural Network model, namely Long Short-Term Memory (LSTM) model to forecast the IHSG and the Rupiah–USD exchange rate. The model combines VAR's ability to capture linear patterns with LSTM's strength in modeling nonlinear sequences. Results showed improved accuracy, with MAE reduced by 42.72 points for IHSG and 55.82 points for the exchange rate compared to the VAR model alone.

The present study aims to construct VAR and CNN models for forecasting the money supply, to develop a hybrid VAR-CNN approach that improves prediction accuracy, and ultimately to produce the most accurate forecasts of money supply using the hybrid VAR-CNN method.

2. METHODS

This study consists of several stages, including data preprocessing, identification of the VAR model, building of the hybrid VAR-CNN model, and evaluation of model performance.

2.1 Dataset

The data used in this study are monthly secondary data obtained from the official website of Statistics Indonesia (*Badan Pusat Statistik*, 2023), which available at: `https://www.bps.go.id/indicator/13/123/1/uang-beredar.html` [12]. The dataset includes two variables: narrow money supply (M1) and broad money supply (M2), both expressed in billions of Indonesian Rupiah. The historical data cover the period from January 2010 to June 2022. Table 1 displays the money supply data.

2.2 Stationary

Stationarity refers to a condition in which a time series does not exhibit a systematic upward or downward trend. In this state, fluctuations in the data occur around a constant mean and the variance remains stable over time [13]. Testing for stationarity can be performed using unit root tests [14]. One commonly employed method for this purpose is the Augmented Dickey-Fuller (ADF) test.

Table 1. Money Supply Data (in Billion Rupiah)

Period	M1	M2
Jan-10	490083.79	2066480.99
Feb-10	494460.84	2112082.70
Mar-10	494717.69	2116023.54
...	...	...
Apr-22	2327208.49	7911484.69
Mei-22	2302911.77	7854186.71
Jun-22	2339449.79	7890747.01

2.3 Cointegration

The concept of cointegration was first introduced by Engle and Granger, who defined it as a long-term equilibrium relationship among time series variables [15]. Cointegration testing is employed to examine whether such a long-run equilibrium exists between multiple variables [16]. In the multivariate context, cointegration can be tested using the Johansen Trace Statistic Test [17]. Equation 1 shows the Johansen Trace Statistic Test.

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{k} \ln\left(1 - \hat{\lambda}_i\right) \tag{1}$$

2.4 Vector Autoregressive (VAR) Model

The Vector Autoregressive (VAR) method is a system of dynamic equations in which the estimation of a variable over specific periods depends on its own past values as well as the past values of other variables included in the system [18]. A VAR model is typically denoted as VAR(p), where p represents the number of lags. Equation 2 displays the general form of the VAR model is:

$$Z_t = \beta_0 + \beta_1 Z_{t-1} + \cdots + \beta_p Z_{t-p} + \varepsilon_t \tag{2}$$

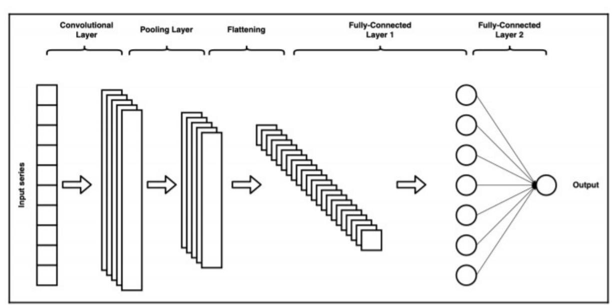


Figure 1. CNN Architecture

2.5 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a deep learning method derived from the Artificial Neural Network (ANN), designed to process two-dimensional data through deep architectures. It is widely applied in the analysis of digital image data

[19]. The CNN operates through a series of sequential stages, beginning with the input layer and progressing through several key components, including convolutional layers, pooling layers, and fully connected layers [20]. Figure 1 displays the CN architecture.

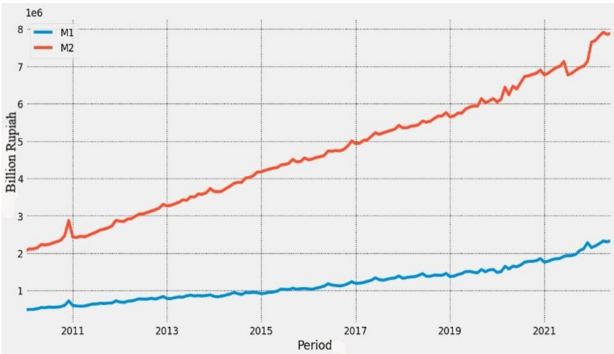


Figure 2. Time Series Visualization of M1 and M2

2.6 Data Scaling

Data scaling, or normalization, is a technique used to transform numerical values within a dataset into a common scale without altering the underlying meaning of the data [21]. One widely used method for scaling is min-max scaling. This normalization technique converts actual data values into a standardized range, typically [0, 1], to produce a balanced comparison between the original and transformed data [22]. The Equation (3) shows the min-max scaling formula [23].

$$x^* = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

2.7 Activation Function

An activation function defines the relationship between a neuron's internal activity—typically represented by a summation function—and its output, which may follow either a linear or nonlinear pattern. This function determines whether a neuron should be activated or remain inactive [24]. Among the commonly used activation functions are the Rectified Linear Unit (ReLU) and the sigmoid function. The Rectified Linear Unit (ReLU) is a nonlinear activation function in which neuron activation occurs only when the output of the linear transformation is greater than zero. This selective activation contributes to computational efficiency and sparse representations. The Equation 4 shows the ReLU function [25].

$$f(x) = \max(0, x) \tag{4}$$

On the other hand, the sigmoid function is used to measure the extent to which information can pass through a neuron. It is commonly applied in the output layer of binary classification models, where the predicted outcome ranges between 0 and 1. The Equation 5 displays the sigmoid function [26].

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

2.8 Dropout

Dropout is a regularization technique in neural networks aimed at preventing overfitting and improving training efficiency [27]. It is typically applied toward the end of certain layers to ensure that no single unit becomes overly reliant on other units within the network.

2.9 Forecasting Accuracy

The hybrid VAR-CNN method consists of two main stages. The first stage employs the Vector Autoregressive (VAR) model to capture the linear components of the data. The second stage uses the Convolutional Neural Network (CNN) to model the nonlinear components. The Equation 6 displays the hybrid model [28]:

$$Y_t = L_t + NL_t + a_t \tag{6}$$

3. RESULTS AND DISCUSSION

This discussion proceeds through several stages, including data input, application of the VAR method, implementation of the hybrid VAR-CNN approach, and evaluation of the optimal model using goodness-of-fit measures.

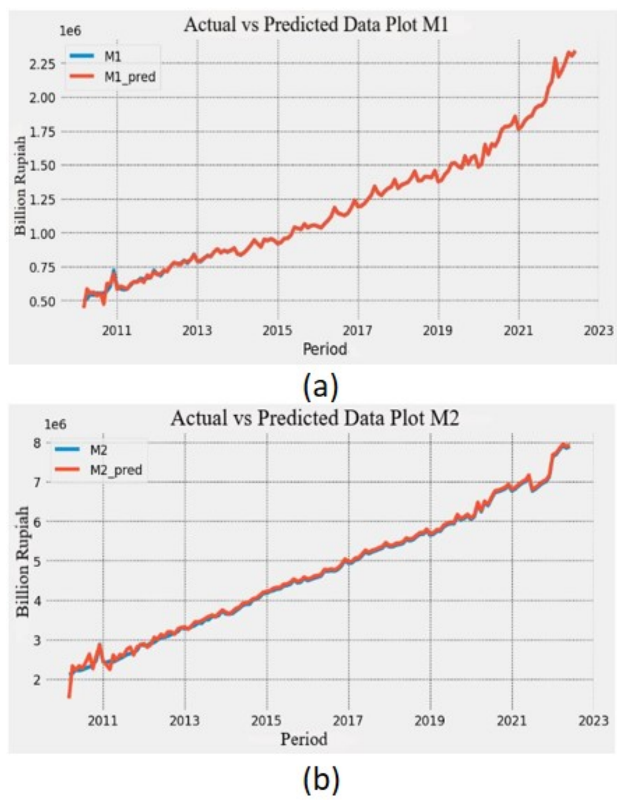


Figure 3. Plot of Actual Data and VAR Predictions

3.1 Data Input and Visualization

The initial stage of this study involves data input, followed by the visualization of the narrow money supply (M1) and broad money supply (M2) through plotted graphs in Figure 2. Figure 2 displays the visualization of M1 and M2 data over time. The plot reveals a consistent upward trend in both variables from January 2010 to June 2022, indicating a steady increase in the money supply throughout the observed period.

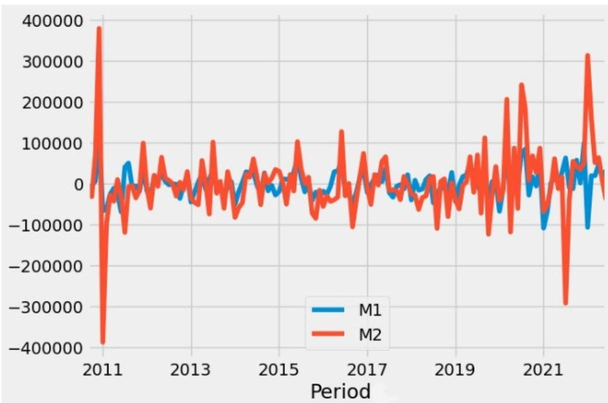
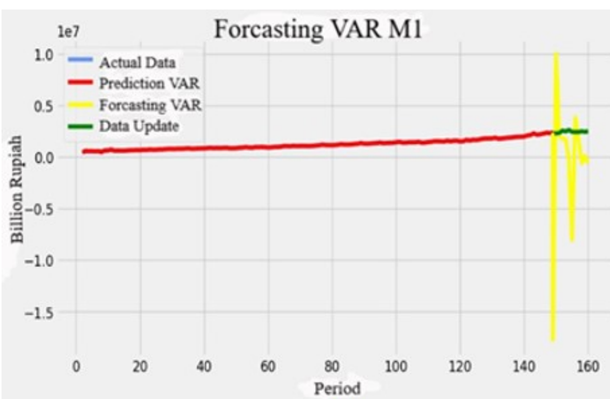
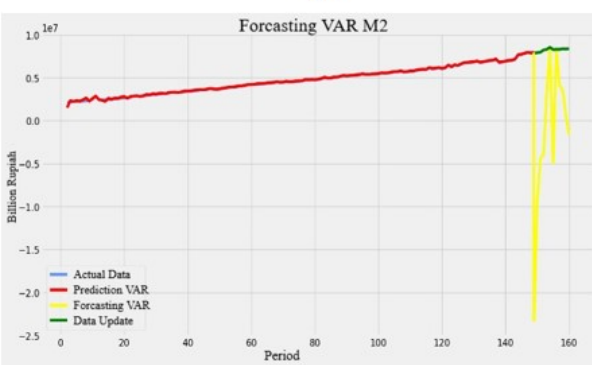


Figure 4. VAR Residual Plot



(a)



(b)

Figure 5. VAR Forecasting Data Plot

3.2 Vector Autoregressive (VAR) Model

The Vector Autoregressive (VAR) method constitutes a widely utilized technique within Multivariate Time Series (MTS) analysis, particularly suited for forecasting the future behavior of interrelated time-dependent variables. This study employs the VAR model through a sequential process that includes stationarity testing, cointegration analysis, model selection based on optimal lag criteria, and performance evaluation through forecasting.

Assessment of stationarity was carried out using the Augmented Dickey-Fuller (ADF) test, where the null hypothesis posits non-stationarity and the alternative suggests stationarity. Initial test results yielded p-values of 0.999032 for M1 and 0.995001 for M2, exceeding the 0.05 threshold. These results indicate a failure to reject the null hypothesis, implying that both monetary aggregates are non-stationary in their original form. Differencing was applied as a corrective measure, and subsequent ADF tests showed p-values of 3.51e-10 for M1 and 0.000003 for M2. These significantly lower values support the rejection of the null hypothesis, confirming that the differenced series are stationary.

Table 2. Data Splitting

Schemes	Data Splitting	
	Training	Testing
M1	99	43
M2	113	29

Cointegration testing was conducted using the Johansen Trace Statistic Test, which examines the existence of long-term equilibrium relationships among multiple time series variables. Results demonstrated that the trace statistics for M1 (14.32) and M2 (3.57) were both below their corresponding critical values of 15.4943 and 3.8415. These findings indicate no cointegration, suggesting the absence of a stable long-term relationship between M1 and M2 during the observed period.

Model selection proceeded through evaluation of the Akaike Information Criterion (AIC) across various lag lengths. Among the tested specifications, VAR(6) achieved the lowest AIC value of 43.61, establishing it as the optimal model for capturing the temporal dynamics of the data.

Forecasting was implemented using the VAR(6) model. Figure 3 illustrated the predicted values closely follow the actual observations, supported by a Mean Absolute Percentage Error (MAPE) of 0.0111 and a corresponding accuracy of 99.9888%. Residuals derived from the fitted model were visualized in Figure 4, enabling assessment of model adequacy and randomness of forecast errors. A twelve-month forward projection was also generated using the same model, with the forecast results presented in Figure 5, highlighting the expected trajectory of monetary aggregates over the next year

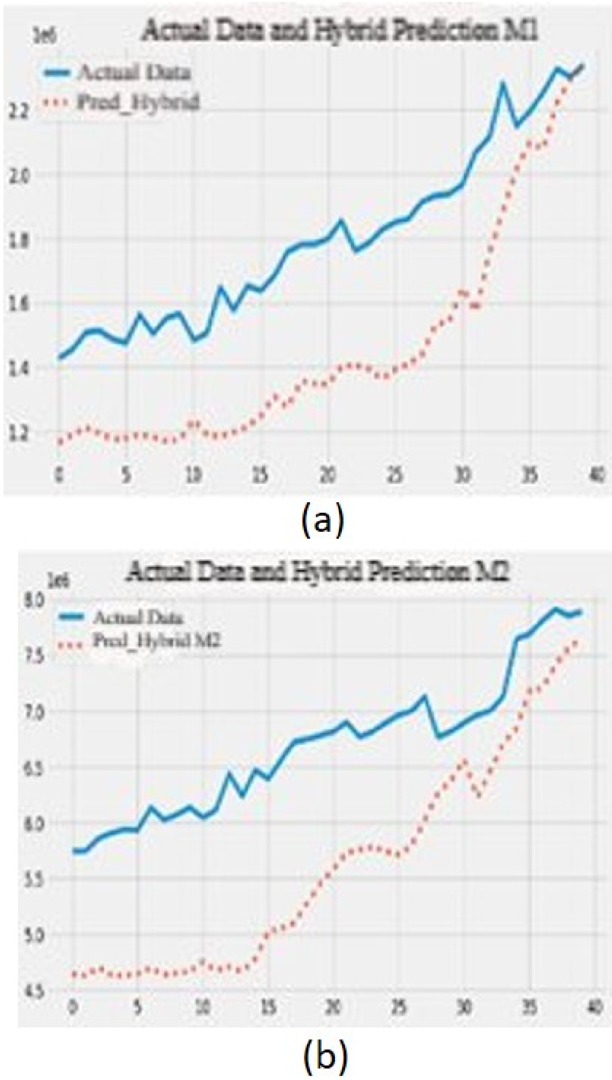


Figure 6. Prediction Plot of Hybrid VAR-CNN Model with 70/30 Scheme

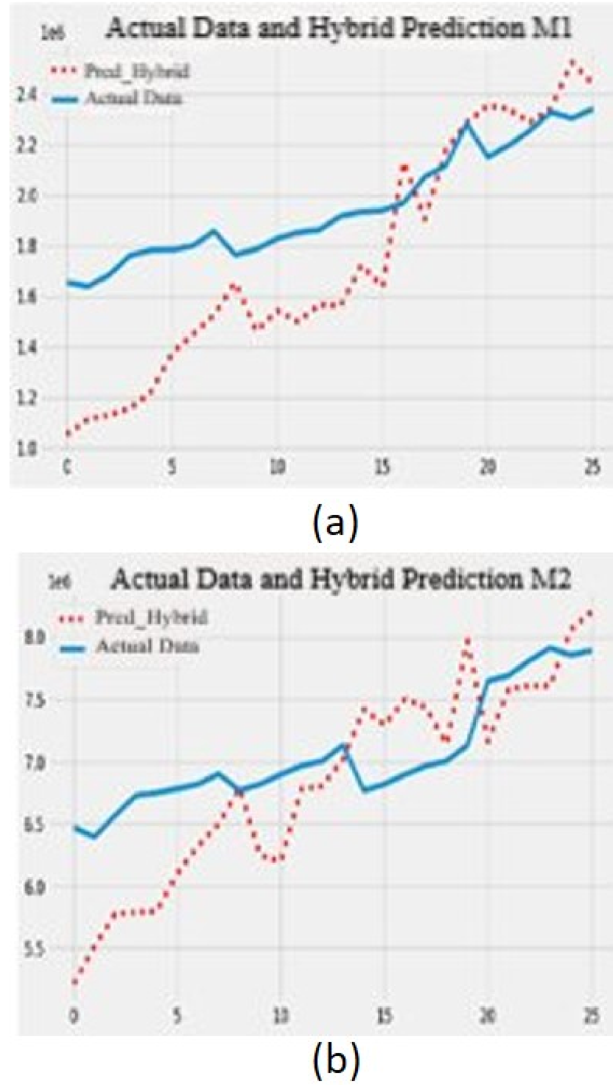


Figure 7. Prediction Plot of Hybrid VAR-CNN Model with 80/20 Scheme

3.3 Data Splitting and Scaling

The predicted data and residuals from the VAR model will be partitioned according to two schemes: 70% for training data and 30% for testing data, as well as 80% for training data and 20% for testing data. Table 2 outlines the distribution of training and testing data for both the predicted values and the residuals derived from the VAR model.

3.4 Hybrid Model VAR-CNN

The hybrid VAR-CNN model is designed by integrating two primary components: a Convolutional Neural Network (CNN) model based on the predicted data from the Vector Autoregression (VAR) model, and a CNN model constructed using the residuals of the VAR model. The CNN model utilizing the VAR predicted data is developed using the outputs generated by the VAR, employing an architecture comprising three convolutional layers and two hidden layers with a dropout rate of 0.1 and ReLU activation functions, followed by an output layer using the sigmoid activation function.

Hyperparameter tuning is conducted to estimate the optimal configuration for batch size, CNN units, filter size, kernel size, and pool size. Under the 70% training and 30% testing data split, the optimal hyperparameters are found to be 32, 8, 8, 5, and 2, respectively. For the 80% training and 20% testing scheme, the best-performing values are 16, 32, 16, 3, and 2. Similarly, the CNN model constructed using the residual data from the VAR model adopts the same architecture, including three convolutional layers and two hidden layers with a dropout rate of 0.1 and ReLU activations, concluding with a sigmoid-activated output layer. Hyperparameter tuning is likewise applied, resulting in optimal values of 8, 32, 32, 3, and 4 for the 70%-30% split, and 8,

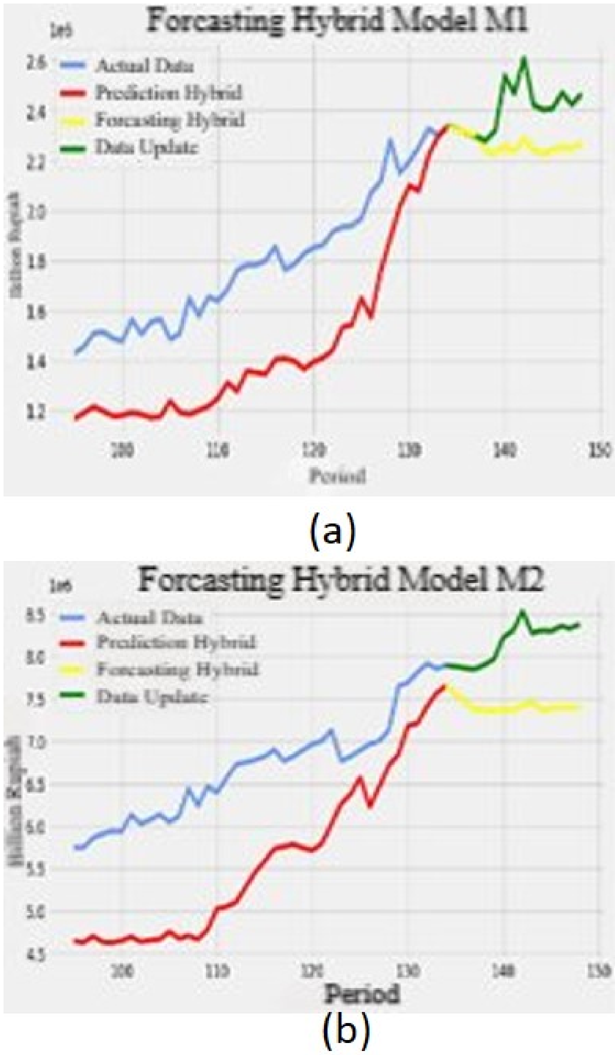


Figure 8. Forecasting Plot of Hybrid VAR-CNN Model with 70/30 Scheme

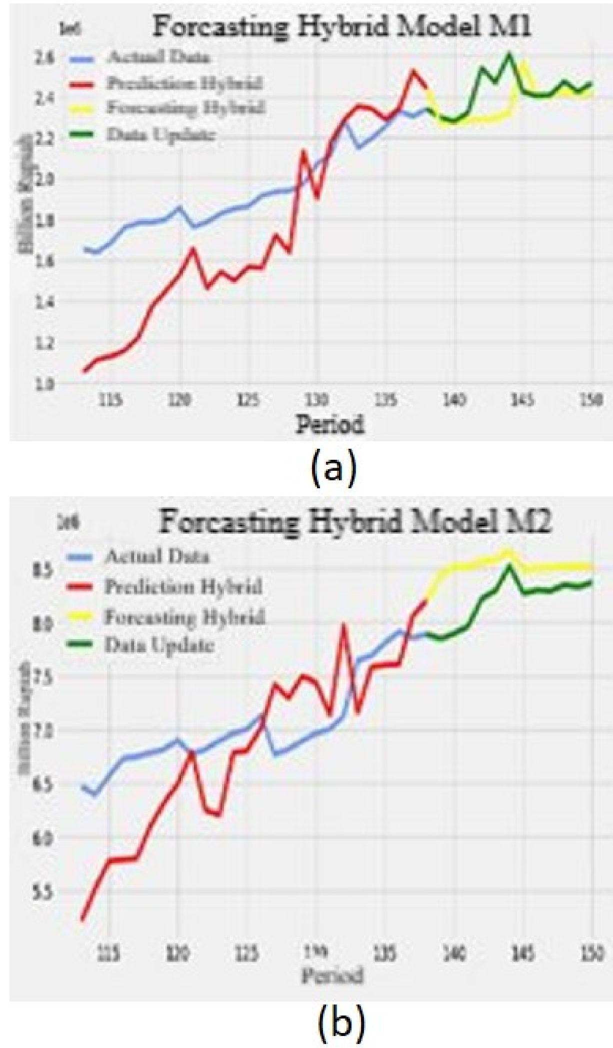


Figure 9. Forecasting Plot of Hybrid VAR-CNN Model with 80/20 Scheme

32, 16, 5, and 4 for the 80%-20% configuration.

3.5 Hybrid Model VAR-CNN Prediction

The hybrid VAR-CNN model is formulated by combining the CNN model based on VAR predicted data and the CNN model based on VAR residual data through an additive integration method. Visualization of the prediction results generated by the hybrid VAR-CNN model is presented to illustrate its performance under two data splitting schemes: 70% training and 30% testing, as well as 80% training and 20% testing. The corresponding plots are shown in Figures 6 and 7. Under the 70:30 scheme, the model achieves a Mean Absolute Percentage Error (MAPE) of 0.1806, corresponding to a prediction accuracy of 99.8194%. Meanwhile, under the 80:20 scheme, the model records a lower MAPE of 0.1130, reflecting an improved accuracy of 99.8870%.

3.6 Hybrid Model VAR-CNN Forecasting

The forecasting process involved the use of 142 data points for model training and 12 data points for prediction. The hybrid VAR-CNN model generates forecasts by combining the outputs from the CNN model based on VAR predicted data and the CNN model based on VAR residual data. Figures 8 and 9 illustrates the forecast plots produced by the hybrid VAR-CNN model under two data splitting configurations: 70% training with 30% testing, and 80% training with 20% testing. Under the 70:30 scheme, the model recorded MAPE values of 0.0657 and 0.0967, corresponding to forecast accuracies of 99.9342% and 99.9033%, respectively. Under the 80:20 scheme, lower MAPE values of 0.0229 and 0.0441 were obtained, indicating higher forecast accuracies of 99.9771% and 99.9559%, respectively.

Table 3. Goodness of Fit for M1

Forecasting Model	Supremum Value (D)	Test Statistics (p-value)
VAR	3645243.23	0.833
Hybrid 70 : 30	162337.51	0.833
Hybrid 80 : 20	540076.78	0.417

Table 4. Goodness of Fit for M2

Forecasting Model	Supremum Value (D)	Test Statistics (p-value)
VAR	9806904.75	0.833
Hybrid 70 : 30	796147.98	1
Hybrid 80 : 20	348537.27	0.916

3.7 Hybrid Model VAR-CNN Forecasting

Following the forecasting process using the hybrid VAR-CNN method, a goodness-of-fit test was conducted to identify the most appropriate model for predicting the narrow money supply (M1) and broad money supply (M2) in Indonesia. The Kolmogorov-Smirnov test was employed for this purpose, assessing the supremum value (D) and test statistics under the following hypotheses:

1. H_0: The model fits the data
2. H_1: The model does not fit the data.

Table 3 displays the hybrid VAR-CNN model with an 80:20 data split demonstrates the best forecasting performance for M1. This conclusion is based on the model's lowest supremum (D) value and a p-value exceeding 0.05, leading to a failure to reject the null hypothesis (H_0). This implies a statistically significant fit between the updated data and the forecasts generated by the hybrid VAR-CNN 80:20 model for narrow money supply.

Similarly, Table 4 indicates that the hybrid VAR-CNN 80:20 model also outperforms the others in forecasting M2. It yields the smallest supremum value and a p-value greater than 0.05, suggesting the null hypothesis cannot be rejected. Thus, there is strong evidence of a significant goodness of fit between the updated data and the hybrid VAR-CNN 80:20 forecast model for broad money supply.

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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