Forecasting of Multivariate Time Series Data of Export and Import Volumes of Coffee Using the Vector Autoregressive (VAR) - Long Short-Term Memory (LSTM) Hybrid Model

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Abstract. The primary objective of this study is to develop a hybrid forecasting model that integrates the Vector Autoregressive (VAR) model with Long Short-Term Memory (LSTM) networks to predict multivariate time series data on coffee export and import volumes. The VAR-LSTM hybrid model represents an advanced methodological approach that combines the strengths of both techniques: the VAR model's ability to capture linear interdependencies and the LSTM network's proficiency in modelling complex non-linear patterns. By integrating these models, this study leverages their complementary advantages to enhance forecasting accuracy for multivariate time series data. This hybrid approach is particularly beneficial as it addresses both linear and non-linear dependencies within the dataset. The results indicate that the VAR-LSTM model effectively replicates the observed data patterns, demonstrating strong predictive performance. The graphical analysis provides compelling evidence of the model's consistency and accuracy, with a Mean Absolute Percentage Error (MAPE) of 0.41% (corresponding to an accuracy of 99.59%) for the predicted data. In comparison, the classical VAR model achieved a MAPE of 0.54% (accuracy of 99.46%). These findings highlight the reliability and accuracy of the VAR-LSTM hybrid model in improving forecasting precision for multivariate time series data.

Keyword. Forecasting, Multivariate Time Series, Vector Autoregressive (VAR), Long Short-Term Memory (LSTM), VAR-LSTM Hybrid Model

1. Introduction

Time series forecasting plays a pivotal role in numerous scientific, economic, and engineering domains. Accurate predictions can drive substantial advancements in fields such as environmental monitoring, energy management, healthcare, and finance. In particular, forecasting is strategically crucial in shaping monetary policies related to coffee exports and imports, given the complexities and uncertainties of the global economy. However, selecting an appropriate and precise time series model for forecasting coffee trade dynamics is a challenging task.

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Classical statistical models, such as ARIMA (Autoregressive Integrated Moving Average) and VAR (Vector Autoregression) models, have long been the backbone of time series analysis. The advantage of these methods lies in their ability to handle sequential data and describe a linear relationship between previous and future data points. The VAR model is an extension of the AR model introduced by Box and Jenkins (1976), incorporating multiple interconnected variables. As noted by [1], the VAR framework assumes that all variables included in the model are endogenous, meaning they are jointly determined within the system. The VAR models are well-suited for analyzing multivariate time series data with linear relationships but face challenges when forecasting nonlinear patterns. Export-import dynamics increasingly exhibit big data characteristics, combining both linear and nonlinear patterns, making traditional VAR models less effective.

On the other hand, deep learning techniques, particularly recurrent neural networks (RNNs) and variants such as LSTM (Long Short-Term Memory) models, have shown remarkable capacity in understanding long-term patterns and dependencies in sequential data. The algorithm is particularly effective in capturing nonlinear dependencies in data. LSTM has the ability to capture long-term patterns in time series data due to its structure that allows it to remember important information over a long period of time, while forgetting less relevant information [9]. This makes LSTMs very effective in modeling long temporal dependencies and handling the vanishing gradient problem often encountered in standard RNNs.

However, the integration of deep learning into time series forecasting is not without its challenges. Deep learning models often require large amounts of data for training, can be black boxes that are difficult to interpret, and require significant computational resources. Therefore, a hybrid approach that blends classical statistics and deep learning offers a promising solution, combining the reliability and interpretability of statistical models with the non-linear modeling power of deep learning. This approach not only improves prediction accuracy but also provides more flexible and adaptive models for analyzing complex multivariate time series data. [14] combined two different approaches: the ARIMA model, which is a classical statistical method, and artificial neural networks, which represent machine learning techniques, to improve time series forecasting accuracy. The main motivation behind Zhang's research was to create a methodology that can effectively capture and model the inherent complexity in time series data, thereby providing more accurate and reliable predictions, which is essential for various practical applications and data-driven decision-making.

Addressing the limitations of both VAR and LSTM approaches, this study proposes a hybrid model that integrates the predictive strengths of VAR and LSTM. The VAR-LSTM hybrid model leverages VAR's ability to capture linear dependencies while utilizing LSTM's capacity for recognizing nonlinear patterns, resulting in a more comprehensive framework for multivariate time series forecasting. Combining these models enhances forecasting accuracy by effectively capturing the complex dependencies present in the data. Therefore, the primary objective of this study is to develop and implement a hybrid model that integrates VAR model as a classical statistical model and LSTM as a deep learning model for forecasting multivariate time series data of coffee export and import volumes.

2. The Proposed VAR-LSTM Hybrid Model

2.1 The Statistical VAR Model

Coffee export and import volumes are inherently multivariate time series data. The most commonly used approach to capture the dynamic relationships among multiple interdependent variables within a single system is the VAR model. VAR models based on the normal distribution are widely preferred for characterizing the behavior of macroeconomic multivariate time series data [2], [3].

In a VAR model of order *p*, denoted as VAR(*p*), each component of the vector of interest is modeled as a linear function of its own past values, up to the p^{th} lag, as well as the past values of other variables in the system, also up to the p^{th} lag [4]–[6]. VAR models are extensively employed for forecasting datasets containing two or more interrelated variables [4]. The basic form of the VAR(*p*) model is given by Equation (1):

$$Y_t = A_0 + \sum_{j=1}^{p} A_j Y_{t-j} + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim Multivariate\ Normal\ (0, \Sigma)$; and

Y_t is a vector of time-t independent variables of size (n x 1),
A_0 is a vector of constants of size (n x 1),
A_j is a coefficient matrix of size (n x np) with j > 0,
p is the optimal lag length,
Y_{t-j} is the vector of independent variables at time (t-j) of size (np x 1),
ε_t is the error vector of size (n x 1).

[7] implemented the VAR model while incorporating independent variables. Similarly, [8] utilized the VAR model to examine the relationship between Shariah

stock prices and key economic indicators, including the inflation rate, bank interest rate, and rupiah exchange rate. However, like the ARIMA model, the VAR model exhibits reduced accuracy in long-term forecasting of multivariate time series data, particularly when dealing with nonlinear patterns, such as those observed in multivariate stock price movements. The primary limitation of the VAR model lies in its assumption of linearity, which leads to residuals that still contain nonlinear components. While the VAR model demonstrates high accuracy in short-term forecasting, its performance deteriorates when applied to long-term predictions.

2.2 The LSTM Deep Learning Model

The Long Short-Term Memory (LSTM) model, a type of deep learning architecture, is widely employed for forecasting tasks. As an advanced variant of the Recurrent Neural Network (RNN), LSTM was first introduced by [9] to address the limitations of conventional RNNs. Traditional RNNs struggle with long-term sequential data processing, as they are unable to effectively retain and utilize past information due to the progressive overwriting of older memory with new inputs. In contrast, LSTM overcomes this issue by incorporating memory cells and gate units, which regulate information retention and updating processes at each time step. This enables LSTM to capture long-range dependencies without information loss [9].

LSTM improves upon the standard RNN architecture by replacing its recurrent layers with memory cells governed by a gating mechanism, which consist of a forget gate, an input gate, and an output gate. According to [10], this structure allows LSTM to precisely control the flow of information into and out of the memory cell (also known as the cell state) through its gate layers. The LSTM architecture comprises four key components: three gate layers and one tanh activation layer, all of which play a crucial role in managing information flow. As noted by [11], these mechanisms enable LSTM networks to efficiently learn and retain long-term dependencies, as illustrated in Fig 1.

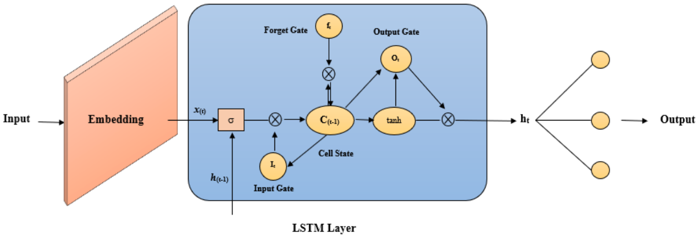


Fig 1. Architecture of the LSTM model.

Based on [10], the LSTM model demonstrates exceptional effectiveness in precisely regulating the flow of information into and out of its memory cell through a well-structured gating mechanism. This mechanism comprises four key components: three gates and a tanh activation layer. Specifically, the LSTM model integrates a forget gate, an input gate, and an output gate, each of which serves a crucial function in governing the network's information flow.

2.3 The Proposed VAR-LSTM Hybrid Model

In time series forecasting, classical statistical models, such as the VAR model, are often preferred due to their interpretability and effectiveness in modeling linear relationships among variables. These models are widely used to uncover the underlying structure of time series data [12]. However, according to [13], their forecasting accuracy tends to decline in long-term predictions of multivariate time series data, particularly when dealing with nonlinear patterns. A fundamental limitation of the VAR model is its assumption of linearity, which often results in residuals that still contain nonlinear components. In contrast, deep learning models, such as LSTM networks, excel at capturing nonlinear relationships and complex patterns within data. By leveraging hidden layers and nonlinear activation functions, deep learning models can learn and represent intricate interactions between variables in time series data. However, as [14] highlights, extracting nonlinear patterns requires substantial amounts of data, and these models often pose challenges in terms of interpretability and causal inference.

A key challenge in time series analysis is determining whether the underlying pattern is linear or nonlinear. In practice, time series data often exhibit a combination of both, forming mixed linear and nonlinear structures. When this occurs, relying solely on a single forecasting approach is less effective, as it fails to adequately capture the complexity of mixed patterns. Consequently, the development of hybrid models that integrate classical statistical methods with deep learning techniques has become essential. [14] suggests that combining traditional statistical models with deep learning approaches can enhance forecasting accuracy, providing a viable solution for handling time series data characterized by both linear and nonlinear patterns.

Hybrid models that integrate classical statistical techniques with deep learning represent a cutting-edge approach in time series forecasting. According to [14], classical statistical methods excel in identifying linear patterns and relationships between variables, whereas deep learning is particularly adept at capturing nonlinearities and more intricate patterns. By leveraging the strengths of both approaches, hybrid models aim to mitigate the limitations of each individual method, ultimately enhancing predictive accuracy [15]. The fundamental principle behind hybrid forecasting models lies in the strategic integration of two or more methodologies, utilizing their distinct characteristics to identify and model diverse patterns within the data.

Numerous researchers have developed models capable of handling time series data with both linear and nonlinear patterns. For instance, [14] integrated the ARIMA model with an artificial neural network (ANN) to enhance the forecasting accuracy of time series data. [16] demonstrated that the ARIMA-ANN hybrid model produced highly accurate stock price forecasts. [17] applied the VAR-GRU and VAR-LSTM models to stock price data, achieving mean absolute percentage errors (MAPE) of 0.603% and 5.647%, respectively. [15] proposed an ARIMA-LSTM hybrid model for forecasting Indonesia’s export data, reporting a MAPE of 7.38%. Furthermore, [18] employed a VAR-LSTM hybrid model to forecast jet fuel transaction prices at Cengkareng Tangerang Airport, Indonesia.

3. Methods

The time series data on coffee export and import volumes, along with exchange rates used in this study, constitute secondary data sourced from Bank Indonesia (https://www.bi.go.id/id/statistik/ekonomi-keuangan/seki/Default.aspx#headingFour). This dataset spans from January 2010 to December 2023. The research methodology consists of the following steps:

1. Multivariate Statistical Modeling:

a. Developing a VAR model.
b. Assessing stationarity of data through Augmented Dickey-Fuller (ADF) test.
c. Analyzing the causal relationships between variables in both datasets using Granger causality testing.
d. Estimating the parameters of the VAR model.
e. Identifying the optimal model by evaluating lag-length criteria and selecting the model with the lowest Akaike Information Criterion (AIC) value.

2. VAR-LSTM Hybrid Modeling:

a. The dataset is divided into prediction and residual components using the VAR model, which subsequently serve as inputs for the VAR-LSTM hybrid model. The initial partitioning allocates 90% of the data for training and 10% for testing. The training data are utilized to refine the model and enhance performance, while the test data validate the model's optimal parameters for forecasting.
b. The extracted data are normalized using the min-max normalization method, scaling values to a range between 0 and 1.
c. Grid Search is employed to optimize hyperparameters and enhance model performance.
d. The effectiveness of the VAR-LSTM hybrid model is assessed using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics.

4. Result and Discussion

4.1 Vector Autoregressive (VAR)

Stationarity Test. In this study, we utilize datasets comprising two endogenous variables: Coffee Export Volume and Coffee Import Volume. Applying the VAR method requires first assessing the stationarity of the data, which is accomplished through the ADF test. The ADF test results for both variables are presented in Table 1.

Table 1. Results of the ADF test on the original dataset.

Variables	ADF Probability	Description
Coffee Export Volume	0.005683	Stationary
Coffee Import Volume	4.753932e-07	Stationary

As shown in Table 1, both variables exhibit stationarity in the initial data input. This conclusion is drawn from the ADF test results, where the probability values for each variable are below the significance level ($\alpha = 5\%$). Consequently, the Coffee Export Volume and Coffee Import Volume data can be regarded as stationary.

Granger Causality Test. The subsequent step entails conducting the Granger causality test, a statistical method designed to assess whether one variable exerts a causal influence on another within a VAR model. This approach evaluates the presence of a bidirectional relationship between variables, determining whether past values of each variable significantly impact the other or only influence themselves. A variable is deemed to exhibit a causal effect if the p-value is less than the significance threshold of $< \alpha = 5\%$.

Table 2. Granger causality test results.

Variables	**Coffee Export Volume_X**	**Coffee Import Volume_X**	**Description**
Coffee Export Volume_Y	1.0	0.0171	Granger Causality
Coffee Import Volume_Y	0.0	1.0	Granger Causality

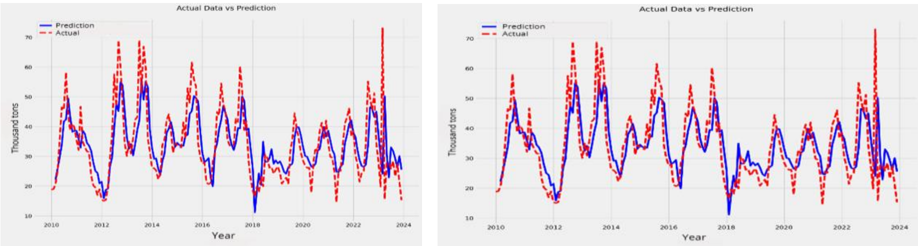
Based on the results presented in Table 2, it can be concluded that the Coffee Export Volume variable significantly influences the Coffee Import Volume variable, and vice versa. This mutual impact is supported by *p-value* $< \alpha = 5\%$ for each variable, providing sufficient evidence to reject H_0. Therefore, the data satisfy the conditions of the Granger causality test, confirming the existence of a causal relationship between the two variables.

Optimum Lag Length. After confirming that the data exhibits stationarity, the next step is to determine the optimal lag length. This process involves an iterative approach to identify the most suitable lag length based on an information criterion, specifically the AIC. The optimal lag length, within the context of this study, is the one that yields the lowest AIC value. The results are presented in Table 3. Based on the results presented in Table 3, the optimal lag is determined to be at lag order 2. Consequently, the appropriate VAR(p) model for this analysis is VAR (2).

Table 3. Criteria for determining the optimal lag value.

Lag	AIC
0	6.793
1	5.527
2	5.463*

VAR Prediction. The next step involves presenting the prediction results using a comparative graph that illustrates the relationship between the actual and predicted data. This visualization provides a clear representation of the observed versus forecasted trends, particularly concerning fluctuations in Coffee Export Volume and Coffee Import Volume. The comparison is depicted in Fig 2.

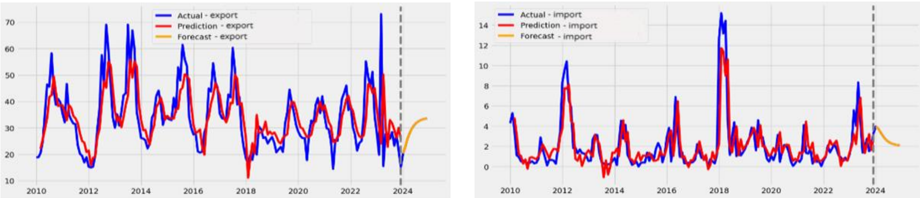


(a) (b)

Fig 2. Graph of Actual vs predicted for (a) coffee export volume and (b) coffee import volume.

The results of the time series analysis for VAR model parameter estimation provide a significant contribution to assessing the model's reliability and accuracy. During the evaluation process, the Root Mean Squared Error (RMSE) was recorded at 6.28, while the Mean Absolute Percentage Error (MAPE) was 0.54. Overall, the evaluation demonstrated an optimal accuracy rate of 99.46%. These findings indicate that the VAR model developed for this research data problem is a robust and reliable tool for predictive analysis.

VAR Forecasting. Fig 2 illustrates the final step of the VAR method, which entails forecasting using the optimized VAR model at lag order 2, as previously determined. The forecasting results are presented below in graphical form, with Fig 3 depicting the VAR-based forecasts.



(a) (b)

Fig 3. Graphical representation of VAR model forecasts for (a) coffee export volume, and (b) coffee import volume.

Based on Fig 6, it can be seen that the plot of forecasting results using the VAR model tends to form a straight line. Therefore, it can be concluded that the VAR forecasting results are less able to follow the recent trends in the data. Overall, this VAR method is not optimal for forecasting based on the characteristics of the observed data.

4.2 Hybrid Model

Hybrid Model Prediction with VAR-LSTM Prediction Data. Data splitting is conducted using two dataset schemes: prediction result data and residual result data from the VAR model. Both dataset schemes are further divided into two parts following a 90%:10% ratio. Specifically, 90% of the data is allocated for training, while the remaining 10% is reserved for testing. The training data is utilized for model learning and performance enhancement, whereas the testing data is employed for validating the optimal parameters, which will subsequently be used for forecasting.

After generating predictions using the VAR-LSTM hybrid model on the VAR residual data, the next step involves employing the same VAR-LSTM hybrid model for further prediction. The final forecast produced by this model is a combination of two components: the VAR model's predictions based on VAR-processed data and the LSTM model's predictions derived from the VAR residuals. By integrating insights from both sources, this approach aims to enhance the accuracy and granularity of the predicted trends and underlying dynamics in the dataset. The results are illustrated in Fig 4.

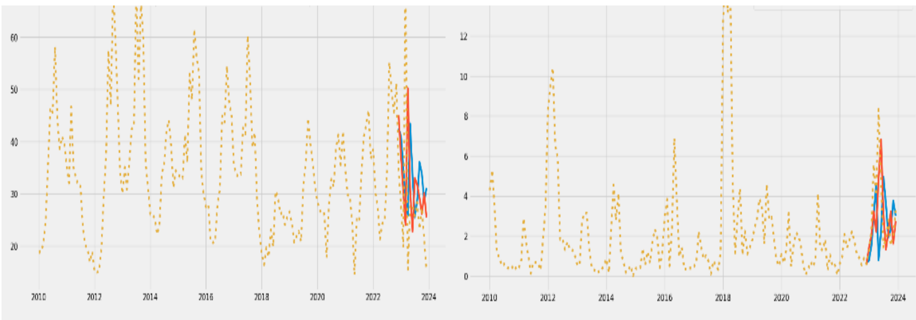
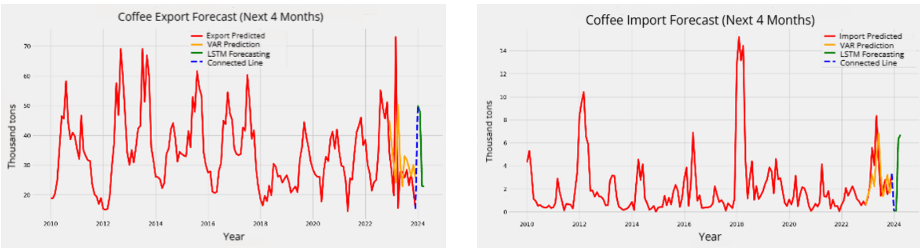


Fig 4. Forecasting results of the VAR-LSTM hybrid model for (a) coffee export volume, and (b) coffee import volume.

According to Fig 4, it can be observed that the graph generated by the model exhibits fluctuations like those in the actual data. Furthermore, the model evaluation results, with an RMSE of 6.78 and a MAPE of 0.41 with an accuracy of 99.59%, indicate that the model has a low error rate. Therefore, the VAR-hybrid model is well-suited for application to the testing data.

Forecasting Predicted Data of VAR-LSTM Hybrid Model. After implementing the VAR-LSTM hybrid model, the subsequent step involves forecasting its predicted data. The forecasted results derived from the VAR-LSTM hybrid model provide insights into the projected trends of Coffee Export Volume and Coffee Import Volume. The visual representation of these forecasts is illustrated in Fig 5.

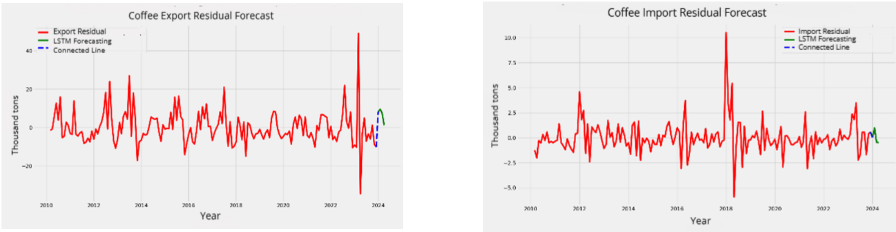


(a) (b)

Fig 5. Forecasting results of the hybrid VAR-LSTM model predicted coffee for (a) export and (b) import volumes.

Based on Fig 5, the graph generated by the model exhibits fluctuations similar to those observed in the actual data. This indicates that the forecasting results of the VAR-LSTM hybrid model effectively capture the underlying pattern of the actual data.

Forecasting Residual Data of VAR-LSTM Hybrid Model. After predicting the residual data of the VAR-LSTM hybrid model, the next step is to forecast these residuals. Fig 6 presents the forecasting results of the residual data from the VAR-LSTM hybrid model.



(a) (b)

Fig 6. Forecasting residuals of the hybrid VAR-LSTM model for (a) coffee export, (b) and import.

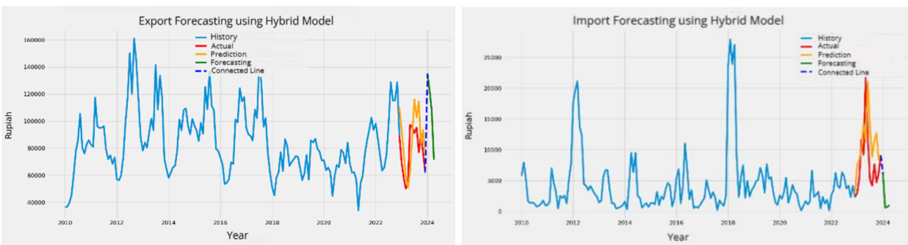
Fig 6 illustrates that the graph produced by the model exhibits fluctuations comparable to those observed in the actual data. This indicates that the forecasting results of the VAR-LSTM residual data hybrid model effectively capture and follow the underlying pattern of the real data.

Forecasting VAR-LSTM Hybrid Model. After predicting the residual data using the VAR-LSTM hybrid model, the next step is to forecast the overall VAR-LSTM hybrid model. Table 4 presents the forecasting results of the hybrid VAR-LSTM model, obtained by summing the predicted values from the VAR component and the residuals generated by the hybrid VAR-LSTM model.

Table 4. Forecasting results of hybrid VAR-LSTM model.

Time	**Forecast Hybrid Volume Coffee Export**	**Forecast Hybrid Volume Coffee Imports**
September 2023	58.300751	0.084459
October 2023	57.385498	1.069489
November 2023	30.364573	5.858284
December 2023	24.068853	6.208777

Referring to Table 4, the variable values for Coffee Export Volume and Coffee Import Volume are illustrated in Fig 7.



(a) (b)

Fig 7. Forecasting results of hybrid VAR-LSTM: (a). coffee export, and (b) import volumes.

Based on Fig 7, the graph produced by the model demonstrates fluctuations that closely mirror those in the actual data. This indicates that the hybrid VAR-LSTM prediction model effectively captures the patterns in real data. As a result, the graph provides strong evidence of the model's reliability and accuracy in generating forecasts that align with actual observed conditions.

5. Conclusion

The primary objective of this study is to develop and implement a hybrid model that integrates a classical statistical model with a deep learning model for forecasting multivariate time series data of coffee export and import volumes. This study introduces a hybrid forecasting model that integrates the VAR model with the LSTM network to predict multivariate time series data, specifically focusing on coffee export and import volumes. The VAR-LSTM hybrid model represents an advanced approach to multivariate time series forecasting by leveraging the strengths of both methodologies. This integration allows the model to capture both the linear and non-linear dynamics present in complex time series datasets. The VAR model captures linear dependencies, while the LSTM network excels at identifying complex non-linear patterns. By synergizing these techniques, the proposed model enhances predictive accuracy, effectively addressing both linear and non-linear relationships within the data. Empirical results of this study indicate that the VAR-LSTM model generates forecasts that closely align with observed data trends, demonstrating its efficacy in multivariate time series prediction.

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References

1. Gujarati, D, N.: Basic Econometrics - Gujarati. Fourth Edition. Basic Econometrics, 2004.
2. Sims, C, A.: Macroeconomics and Reality. Econometrica **48**(1), 1-48 (1980). 10.2307/1912017
3. Juselius, K.: The Cointegrated VAR Model: Methodology and Applications. Oxford University Press, (2006). 10.1093/oso/9780199285662.001.0001.
4. Wei, W, W, S.: Time Series Analysis Univariate and Multivariate Methods. 2nd edn. Greg Tobin, (2006)
5. Kirchgässner, G., Wolters, J.: Introduction to modern time series analysis. Springer, (2007). 10.1007/978-3-540-73291-4.
6. Lütkepohl, H.: New introduction to multiple time series analysis. Springer, (2005). 10.1007/978-3-540-27752-1.
7. Warsono., Russel, E., Wamiliana., Widiarti., Mustofa, U.: Modeling and forecasting by the vector autoregressive moving average model for export of coal and oil data (Case study from Indonesia over the years 2002-2017). Int. J. Energy Econ. Policy **9**(4), 240–247 (2019). 10.32479/ijeep.7605
8. A'yun, A, Q., Fatwa, N.: Vector Autoregression Analysis of The Relationship Between Inflation Rate, Interest Rate, and Exchange Rate To The Jakarta Islamic Index. J. Strateg. Glob. Stud **5**(1), (2022). 10.7454/jsgs.v5i1.1095
9. Hochreiter, S., Schmidhuber, J.: Long Short-Term Memory. Neural Comput **9**(8), 1735–1780 (1997). 10.1162/neco.1997.9.8.1735.
10. Luo, X., Zhang, D., Zhu, X.: Deep learning based forecasting of photovoltaic power generation by incorporating domain knowledge. Energy **225**, 1-14 (2021). 10.1016/j.energy.2021.120240.
11. Minaee, S., Kalchbrenner, N., Cambria, E., Nikzad, N., Chenaghlu, M., Gao, J.: Deep Learning-Based Text Classification. ACM Computing Surveys **54**(3), 1-40 (2021). 10.1145/3439726.
12. Tsay, R, S.: Analysis of financial time series. Wiley, (2010). 10.1002/9780470644560.
13. Caliwag, A, C., Lim, W.: Hybrid VARMA and LSTM Method for Lithium-ion Battery State-of-Charge and Output Voltage Forecasting in Electric Motorcycle Applications. IEEE Access **7**, 59680–59689 (2019). 10.1109/ACCESS.2019.2914188.
14. Zhang, P, G.: Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing **50**, 159–175 (2003). 10.1016/S0925-2312(01)00702-0.
15. Dave, E., Leonardo, A., Jeanice, M., Hanafiah, N.: Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM. Procedia Computer Science **179**, 480–487 (2021). 10.1016/j.procs.2021.01.031
16. Wang, L., Zou, H., Su, J., Li, L., Chaudhry, S.: An ARIMA-ANN Hybrid Model for Time Series Forecasting. Syst. Res. Behav. Sci **30**(3), 244–259 (2013). 10.1002/sres.2179
17. Munkhdalai, L., Li, M., Theera-Umpon, N., Auephanwiriyakul, S., Ryu, K, H.: VAR-GRU: A Hybrid Model for Multivariate Financial Time Series Prediction. Intelligent Information and Database Systems Lecture Notes in Computer Science, pp. 322–332. Springer, (2020). 10.1007/978-3-030-42058-1_27.
18. Aji, A, B., Surjandari, I.: Hybrid vector autoregression-recurrent neural networks to forecast multivariate time series jet fuel transaction price. IOP Conference Series: Materials Science and Engineering **909**, 1-10 (2020). 10.1088/1757-899X/909/1/012079