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HYBRID VECTOR AUTOREGRESSIVE AND LONG SHORT TERM MEMORY MODEL FOR PREDICTING ECONOMIC GROWTH INDICATORS IN INDONESIA: A COMPARISON OF ADAM, NADAM, AND RMSPROP OPTIMIZATION METHODS

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ABSTRACT

This study aims to compare the performance of three optimization methods—Adam, Nadam, and RMSProp—in forecasting monthly economic indicators of Indonesia, namely the Consumer Price Index (CPI), Inflation, and Gross Domestic Product (GDP), using a hybrid Vector Autoregressive–Long Short-Term Memory (VAR–LSTM) model. The analysis begins with Vector Autoregression (VAR), where VAR(4) is selected as the best model based on the lowest Akaike Information Criterion (AIC) value of 1.075. Significant parameters from the VAR model are then used as input variables for the LSTM to enhance forecasting accuracy. The experimental results show that all three optimization methods generate similar prediction patterns, with forecasted values closely tracking the actual data. Nevertheless, the best optimizer differs across variables: Nadam performs best for CPI with a Root Mean Square Error (RMSE) of 0.4996, Adam yields the best performance for Inflation with an RMSE of 0.676, and RMSProp performs best for GDP with an RMSE of 1.288. Despite these variations, the overall forecasting performance of the three methods is comparable. These findings indicate that the VAR–LSTM approach can effectively capture the dynamic patterns of multiple economic variables and that the choice of optimization method should be aligned with the specific characteristics of the data, considering both accuracy and computational efficiency.

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1. INTRODUCTION

Economic growth is a key indicator that reflects the health of a country, and Indonesia as a developing country faces major challenges in predicting and planning its growth [1]. In general, economic growth describes the increase in the production capacity of goods and services in the economy, which is usually measured through Gross Domestic Product (GDP) [2] [3]. GDP is the total value of all goods and services produced within a country in a given period [4] [5]. GDP per capita is often used to compare living standards between countries. In the context of Indonesia, stable economic growth is key to improving people's welfare, creating jobs, and attracting foreign investment [6]. At the global level, economic growth experiences dynamics that are influenced by various external factors such as international monetary policy, global trade, and economic crises [7]. The COVID-19 pandemic had a major impact on the world economy, causing a global contraction in 2020 [8]. However, according to data from the World Bank, the global economy was projected to rebound at different rates across countries in 2021 and beyond [9]. In Indonesia, despite a sharp decline of 2.07% in 2020 due to the pandemic, economic growth was expected to stabilize in line with recovery policies implemented by the government [10]. With the easing of restriction measures and the rollout of mass vaccination programs, the economy began to recover, recording growth of 3.69% in 2021. The recovery continued in 2022 with growth reaching 5.31%, while in 2023 the Indonesian economy expanded by 5.05%, with total GDP reaching IDR 20,892.4 trillion and GDP per capita of IDR 75.0 million (US$ 4,919.7) [11]. Despite the slight slowdown compared to the previous year, Indonesia's economy demonstrated resilience amid global challenges such as economic uncertainty and commodity price fluctuations. The differences in economic growth between the pandemic and post-pandemic periods were mainly driven by increased domestic consumption, recovery in the industrial and trade sectors, and fiscal as well as monetary policies that supported economic recovery. Other contributing factors include controlled inflation, stability of the rupiah exchange rate, and rising investment flows. Data from the Central Statistics Agency (BPS) indicate that Indonesia's economic growth in 2024 remains on a positive trajectory with monthly growth of 1.50%, despite external challenges such as the global economic slowdown and geopolitical tensions affecting international trade. Key factors influencing Indonesia's economic performance include inflation, the Consumer Price Index (CPI), and Gross Domestic Product (GDP) [12].

Inflation is a general increase in the prices of goods and services within an economy, which can reduce purchasing power and affect overall stability [13]. Rising costs of necessities trigger inflation, leading to a decline in the real value of money. In other words, inflation reflects the decrease in the purchasing power of currency relative to the general price level of goods and services. Inflation is commonly measured using the Consumer Price Index (CPI), which calculates the average change in the prices of a basket of goods and services consumed by households within a specific period. Changes in the CPI over time indicate the extent of price increases (inflation) or, conversely, general price decreases (deflation) [14]. Indonesia recorded very low inflation in May 2020, at only 0.07%, reflecting a decline in household purchasing power. As of July 2020, the inflation rate even reached -0.01%. This weakening purchasing power contributed to a lower inflation rate [15]. In addition, the CPI plays a crucial role in determining purchasing power: a rapid increase in CPI can erode household consumption capacity, while a moderate CPI growth supports sustainable consumption [16]. Gross Domestic Product (GDP) also serves as a key indicator to measure the size and overall health of Indonesia's economy [17]. Given the complexity of economic growth and its dependence on various interconnected factors, accurate forecasting methods are essential for policymakers, businesses, and investors to make informed decisions. Traditional econometric models such as Autoregressive Integrated Moving Average (ARIMA) have been widely used for time series forecasting, but often struggle to capture non-linear relationships in macroeconomic data [18]. The Vector Autoregressive (VAR) model is an alternative approach that considers the interrelationships among multiple economic indicators, making it useful in macroeconomic analysis and forecasting. In a VAR model, each variable is treated as a linear function of its own lags and the lags of other variables in the system. Determining the optimal number of lags is crucial, as it affects the model's ability to capture the temporal dynamics of the data [19]. Lag selection is usually based on information criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). However, despite its strengths, the VAR model is limited to capturing linear relationships and may fail to represent non-linear and complex patterns that are often present in economic data. This limitation motivates the integration of VAR with more advanced models such as Long Short-Term Memory (LSTM), which can handle non-linearity and long-term dependencies more effectively [20]. Meanwhile, Long Short-Term Memory (LSTM) is a type of artificial neural network designed to overcome the vanishing gradient problem in time series data modeling [21]. LSTM has the ability to capture long-term dependencies in data through complex gate structures, allowing the model to store and access information from previous time steps [22]. However, in the application of LSTM, there are no clear guidelines regarding the selection of input variables and the optimal number of lags for each variable. This creates challenges in determining the appropriate input configuration for the model [23]. To overcome this limitation, a hybrid approach that combines VAR and LSTM models has been proposed. In this approach, the VAR model is first used to determine the optimal lag length for each variable in the system. This lag length information is then used to form the input variables for the LSTM model. In this way, the LSTM model can utilize the temporal structure identified by the VAR, thereby improving forecasting accuracy by capturing both linear and non-linear relationships in the data.

Previous studies have shown that the VAR-LSTM hybrid model is capable of improving forecasting performance compared to using VAR or LSTM alone, particularly in financial and macroeconomic applications [24]. However, most of these studies only focused on comparing model accuracy, without explicitly addressing how to optimize the selection of input variables and lags for economic forecasting. This indicates a research gap, as there is still limited work that systematically integrates parameter significance testing in VAR with LSTM modeling to enhance the robustness of forecasting results.

2. RESEARCH METHODS

This research approach uses a combination of Vector Autoregressive - Integrated Long Short Term Memory (VAR-I-LSTM) to predict economic growth in Indonesia. The methodology applied includes several main stages, namely economic data collection, data preprocessing to ensure data quality and readiness, as well as a research process that includes model building, training, evaluation, and analysis of results. The following is a detailed explanation of each stage in this research.

2.1. Data Collection

At this stage, the researchers used monthly data on Indonesia's Gross Domestic Product (GDP) growth rate, inflation, and Consumer Price Index (CPI) covering the period from January 2011 to September 2024, obtained from the official website of the Central Statistics Agency (BPS). This data is collected in the form of time series with a monthly frequency to capture patterns of economic change in the long term. After the collection process, this data will be used as input in the VAR-Based LSTM model, which combines the Vector Autoregression (VAR) approach to capture the relationship between economic variables and Long Short-Term Memory (LSTM) to improve the accuracy of historical data-based predictions.

Table 1. Example of Dataset Used

Date	CPI	Inflation	GDP
Jan-2011	126.29	1.57	6.48
Feb-2011	126.46	1.55	6.48
Mar-2011	126.05	1.71	6.48
⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮
Sep-2024	105.93	6.16	4.95

2.2 Preprocessing Data

Processing data in the context of machine learning involves a series of steps aimed at preparing raw data for use in analysis and model training [25]. Data preprocessing in this study includes a series of steps to ensure that the economic data used is of optimal quality before being incorporated into the model.

2.3 Multivariate Time Series

2.3.1 Vector Autoregressive

The VAR model was first introduced by Sims (1980). This model is designed to estimate the relationship between economic variables without having to pay attention to exogenous issues. In this approach, all variables are considered as endogenous variables, and estimation can be done either simultaneously or stepwise. The Vector Autoregressive (VAR) model is a time series model that evolved from the Autoregressive (AR) model. The VAR model describes the relationship between observations of the variable in the previous time and its relationship with observations of other variables at the same time. In general, the VAR(p) model can be defined as follows [26]

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t, \tag{1}$$

where:

y_t : $\begin{bmatrix} CPI_t \\ INF_t \\ GDP_t \end{bmatrix}$ is the vector of endogenous variabel consisting of the Consumer,

c : is the constant vector,

ϕ_p : is the coefficient matrix for the i-th lag,

ε_t : is the error vector,

where Y_t, Y_{t-1} is a vector of size $n \times 1$ which contains n variables included in the VAR model at times t and $t - i$, $i = 1,2,\ldots p$, ϕ_1 is a coefficient matrix of size $n \times n$ for each $i = 1,2,\ldots p$, $\varepsilon_t$is a residual vector of size $n \times 1$, $(\varepsilon_{1t}, \varepsilon_{2t}, .. \varepsilon_{nt})^T, p$ is the VAR lag, t is the observed period.

1. Lag Optimal

Lag determination aims to determine the optimal lag length to be used in subsequent analysis, which in turn will affect the parameter estimation of the VAR model. VAR lags can be determined by selecting the smallest AIC (Akaike Information Criterion) value. [27]. The lag length of the VAR model was determined using the Akaike Information Criterion (AIC), which is calculated as follows:

$$AIC_{(p)} = \ln\left|\bar{\Sigma}_{(p)}\right| + \frac{2}{T} pn^2 . \tag{2}$$

2. Causality Test

Causality test is a test used to determine the cause-and-effect relationship between variables in a Vector Autoregressive (VAR) system. The purpose of the causality test in VAR modeling is to identify the influence between variables in the long and short term. The existence of a relationship between variables does not automatically indicate causality or influence, so to find out whether the influence is one-way or two-way, a causality test is needed. If the event x occurs before y, then there is a possibility that x affects y, but the opposite is not possible, which is the basic concept in the application of the Granger causality test [28].

The following are causality test statistics.

$$F_{calculated} = (n - k) \frac{RSS_R - RSS_{UR}}{m(RSS_{UR})} . \tag{3}$$

where RSS_R is the residual sum of square from the restricted equation, RSS_{UR} is the residual sum of square from the unrestricted equation, n is the number of observations, m is the number of lagged terms tested, and k is the number of estimated parameters in the unrestricted equation.

The null hypothesis (H_0) states that the lagged values of one variable do not Granger cause another variable (i.e., all corresponding lag coefficients are jointly equal to zero). The alternative hypothesis (H_1) states that at least one lag coefficient is non-zero, indicating the presence of Granger causality. The decision rule is as follows: reject H_0if the calculated statistic $F_{calculate}$ exceeds the critical value of the F-distribution at the chosen significance level α\alphaα. Otherwise, fail to reject H_0.

2.3.2 Long Short-Term Memory

Long Short-Term Memory (LSTM) is one of the methods in artificial neural networks first developed by Sepp Hochreiter and Jurgen Schmiduber in 1997. LSTM is a development of the Recurrent Neural Network (RNN) method, because RNN has a number of weaknesses, such as difficulty in accessing long-term information that is hampered by the existing architecture [29].

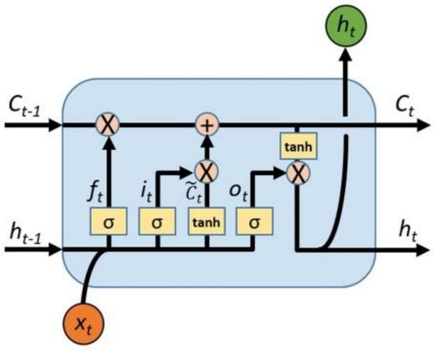


Figure 1. LSTM Architecture
Source: *Hochreiter & Schmidhuber, 1997*

Forecasting is done using an LSTM. The LSTM architecture consists of a memory cell and three gates: input gate (i_t)forget gate (f_t), and output gate (O_t). The input gate serves to regulate how much information should be stored in the memory cell. It prevents the storage of irrelevant data. The forget gate is responsible for setting a fixed value in the memory cell. The output gate controls how much of the value in the memory cell will be used for output. There are several computational stages in the LSTM method, which can be explained further. The calculation of the forget gate value is done by combining the input variables and the hidden state value at a certain period $t-1$ (h_{t-1}) resulting in the following equation.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right). \tag{4}$$

Next, the input gate value and cell state candidate are calculated by combining the input variable value and the previously hidden state value at $t-1$ to update the cell state. The input gate value calculation involves a sigmoid activation function, while the cell state candidate is calculated using a hyperbolic tangent activation function.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \tag{5}$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c). \tag{6}$$

After obtaining the values for the forget gate, input gate, and candidate cell state, the next step is to form a new cell state.(C_t) In a neuron, the combination of values resulting from Eq. (1) is multiplied by the previous cell state (C_{t-1}). Then, the result is added to the multiplication result between the value obtained from Eq. (4) and the result from Eq. (5). The following are the equations.

$$C_t = i_t \times \tilde{C}_t + f_t \times C_{t-1}. \tag{7}$$

The value at the output gate can be calculated by combining the previous input and the hidden state, and involves a sigmoid activation function as seen in the following equation.

$$O_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tag{8}$$

$$h_t = O_t \times \tanh(C_t), \tag{9}$$

$f_t, i_t, \tilde{c}_t, O_t$ In order, there are forget gates, input gates, temporary cell states, and output gates, with tanh as the activation function W_f, W_i, W_c, W_o is the weight value, $b_f, b_i, b_c, b_o$is the bias value. h_{t-1} the input value in the previous period and the input value in t. c_{t-1} is the old state, c_t is the current cell state, h_t is the hidden state.

2.3.3 Model Evaluation with Optimization Algorithm

After the prediction model is successfully built, the training process is carried out using several optimization algorithms, namely Root Mean Square Propagation (RMSProp), Adaptive Moment Estimation (Adam), and Nesterov Adam (Nadam). RMSProp, introduced by Hinton (2012), is designed to adjust the learning rate dynamically by dividing the gradient by an exponentially decaying average of squared gradients, which improves training stability. Adam, proposed by Kingma and Ba (2015), extends RMSProp by incorporating momentum to accelerate convergence while adaptively adjusting the learning rate. Finally, Nadam, developed by Dozat (2016), combines Adam with Nesterov accelerated gradients, further improving convergence in certain scenarios [30].

Nadam is a variant of Adam that introduces Nesterov momentum to improve the efficiency of weight updates. Nesterov momentum works by estimating the future position of the weights before performing the update, thereby reducing oscillations and improving convergence speed. Dozat (2016) showed that Nadam can provide more stable results in some neural network architectures than Adam, especially in conditions with fluctuating gradients [31].

RMSProp was introduced by Geoffrey Hinton in the online course Neural Networks for Machine Learning. It uses the exponential moving average method to control the learning rate based on the mean square of the previous gradient. RMSProp is effective in handling dynamically changing gradients and is often used in recursive models such as Long Short-Term Memory (LSTM) for sequential data processing. Research shows that RMSProp is better than classical algorithms such as Stochastic Gradient Descent (SGD) in handling data with high noise and explosive gradients [32].

Hyndman and Koehler (2006) mentioned that RMSE can be used to compare different forecasting methods on data that have the same scale [33]. Therefore, model evaluation in this study is carried out using the RMSE, which is calculated as follows.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T}(y_t - \hat{y}_t)^2}{T}} \tag{10}$$

In this study, the data are divided into training and testing periods, where the training set is used to build the model, and the testing set is used to evaluate its forecasting performance.

3. RESULTS AND DISCUSSION

3.1 Trend and Pattern Analysis of the Data

Gross Regional Domestic Product (GRDP) is an economic indicator that measures the total value of goods and services produced by each province within a given year. GRDP reflects the level of productivity and economic welfare in a region. Differences in GRDP values between provinces can illustrate variations in natural resources, main industries, investment levels, and infrastructure. In the graph above, the GRDP growth rate in 2024 shows significant variations among Indonesian provinces. West Papua recorded the highest growth rate at 18.89%, followed by North Maluku (12.18%) and Central Sulawesi (8.66%). On the other hand, Bangka Belitung Islands experienced a negative growth rate of -0.52%, representing the lowest among all provinces. Provinces with high GRDP growth generally have abundant natural resources or well-developed industries, such as West Papua and North Maluku. Provinces with lower growth rates tend to be smaller regions or have emerging economic bases, like Bangka Belitung Islands. This pattern highlights the existing economic disparity across Indonesian regions. Statistically, the GRDP growth rates are skewed to the right, with a few provinces showing much higher growth than most others. The median provides a more representative measure than the mean, given the presence of extreme values. Further analysis using variance and standard deviation can quantify the spread of GRDP growth rates across provinces, providing insight into regional economic disparities.

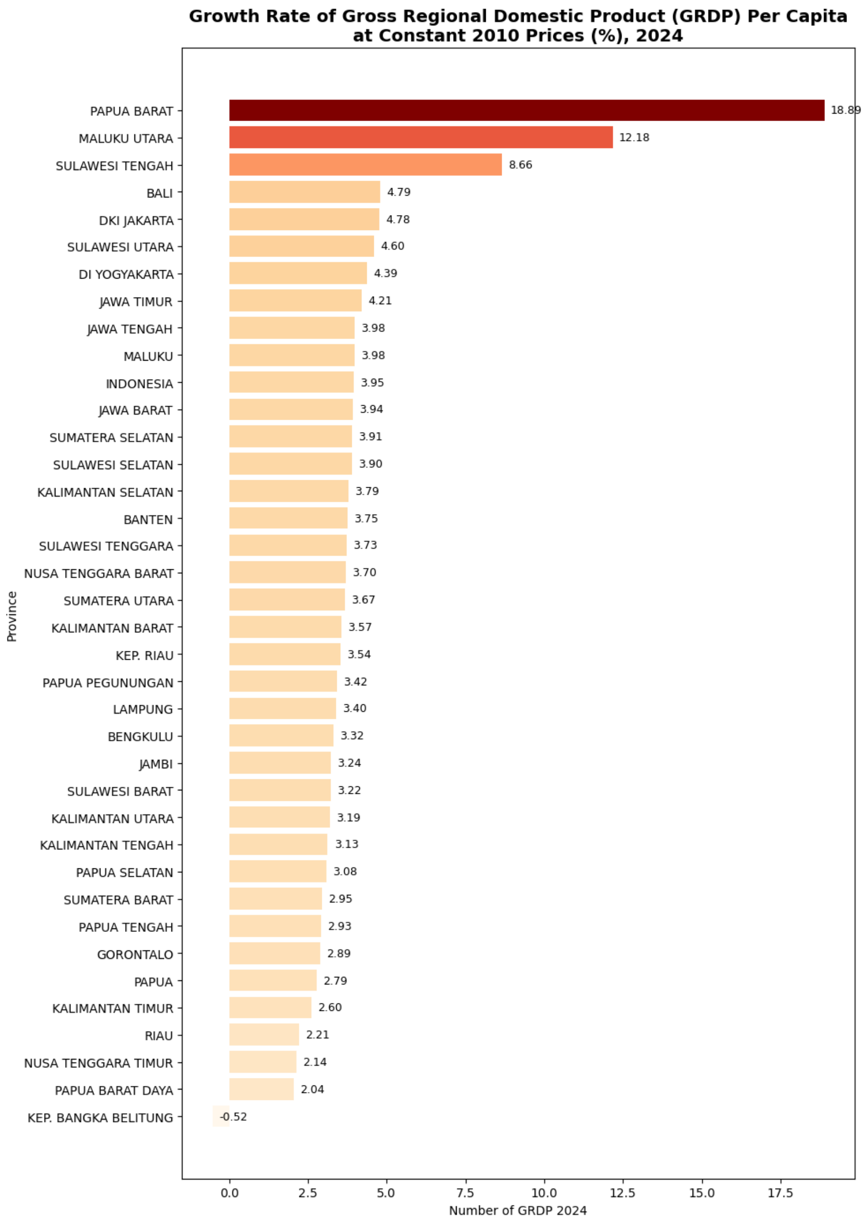


Figure 2. Gross Regional Domestic Product 2024

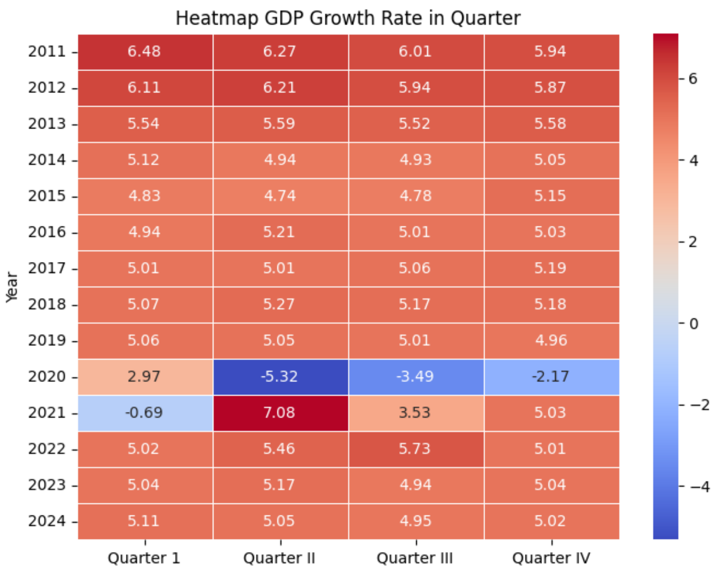


Figure 3. Gross Domestic Product in Indonesia

The Fig. 3 shows the Gross Domestic Product (GDP) growth rate per quarter from 2011 to 2024. Red color indicates positive growth, while blue color indicates negative growth. In general, almost all years have stable growth rates with values ranging from 4% to 6% in each quarter. However, there is a significant anomaly in 2020, where economic growth experienced a large contraction, especially in Quarter II (-5.32%), Quarter III (-3.49%), and Quarter IV (-2.17%). This indicates a major disruption to the economy, most likely caused by the COVID-19 pandemic and the impact of economic activity restriction policies. In 2021 showed a significant recovery, especially in Q2 which recorded the highest growth in this dataset (7.08%). This reflects the recovery of the economy after a large contraction in the previous year, which could have been influenced by the easing of economic policies, increased business activity, and economic stimulus programs from the government. After 2021, GDP growth stabilized at around 5%, indicating that the Indonesian economy has returned to a normal growth path after experiencing high volatility in 2020-2021. This data serves an important function in economic analysis, especially in understanding economic growth trends over time. Governments and businesses can use this information to identify patterns of economic growth, anticipate recession risks, and plan fiscal and monetary policy strategies. In addition, this data can help investors make investment-related decisions based on economic trends across various periods. With regular monitoring of quarterly GDP growth, various parties can be more proactive in responding to economic changes that occur.

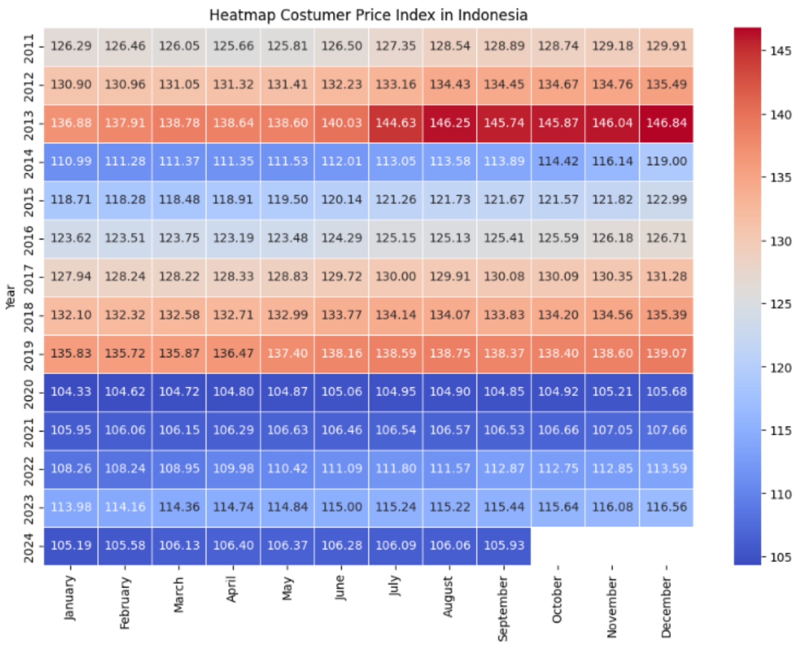


Figure 4. Costumer Price Index in Indonesia

The Consumer Price Index (CPI) is a leading indicator used to measure the inflation rate and changes in the prices of goods and services consumed by the public. The CPI is used by governments, central banks, and businesses to assess economic stability, set monetary policy, and adjust wages and prices of goods. In the context of Indonesia, understanding the trend of the CPI is crucial for controlling inflation to stay within reasonable limits, maintaining people's purchasing power, and designing appropriate economic policies. From the heatmap above, it can be seen that the CPI value has increased from year to year, especially in the period before 2020, which is indicated by the increasingly intense red color. This reflects the significant inflation in that period. A higher increase in CPI is seen in certain months, such as June to December, which can be attributed to seasonal factors such as Ramadan, Eid al-Fitr, Christmas, and the end of the year which usually encourage increased public consumption. However, after 2020, the CPI experiences a slowdown in growth and tends to stabilize, which is shown by the blue color on the heatmap. This is most likely influenced by the impact of the COVID-19 pandemic, which caused a decline in purchasing power and economic activity.

In 2023 and 2024, the CPI value is still in a lower range compared to the years before the pandemic, indicating that inflation is relatively under control. The predominant blue color in this period indicates price stability, which may reflect the success of economic policies in keeping inflation low. However, if inflation is too low in the long run, it could be an indication of weak economic growth and purchasing power. Therefore, this CPI analysis is very useful for the government and the business sector in anticipating price changes and devising appropriate economic strategies to maintain a balance between inflation and economic growth.

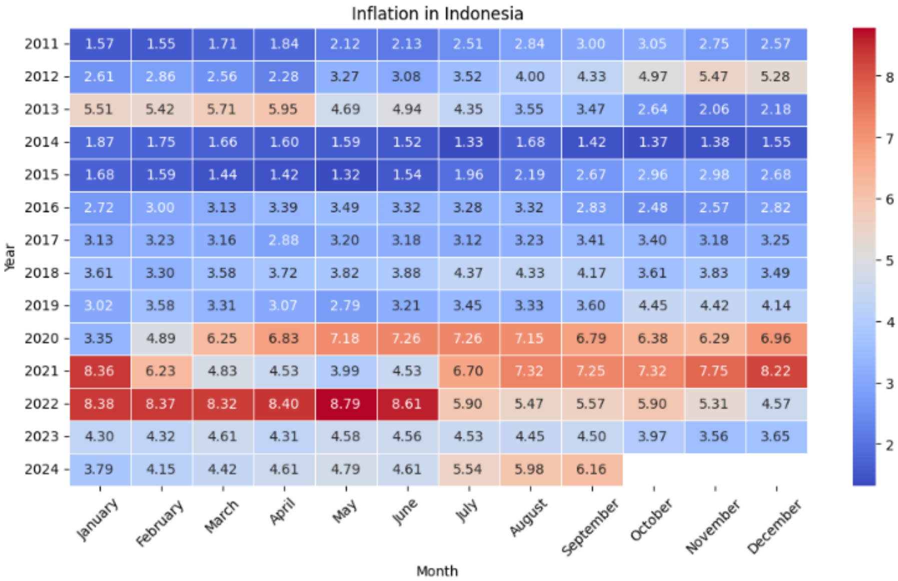


Figure 5. Inflation in Indonesia

From Indonesia's 2011 to 2024 inflation data displayed in the heatmap, it can be seen that the inflation rate is relatively stable in the period 2011 to 2019. During this time, monthly inflation was in a relatively low range, with figures ranging from 1.5% to 5%. There were no significant spikes in inflation, indicating a fairly manageable economic condition. The dominant blue color in the heatmap during this period reflects the relatively low and stable inflation rate, although there are some small variations in certain months. However, there is a drastic change in 2022, where inflation increases sharply, especially from July to December. This spike is shown in a more prominent red color, with inflation rates exceeding 8% in some months. This increase is most likely caused by external factors such as the global crisis, rising energy prices, or domestic economic policies that impact the prices of goods and services. The year 2023 still shows a relatively high inflation rate, albeit slightly lower than the previous year. In 2024, inflation seems to start showing a moderating trend compared to the peak inflation in 2022 and 2023. Although still at a higher level than the period prior to 2022, monthly inflation appears to be more manageable, with figures in the range of 3.79% to 6.16% until August 2024. This indicates the government's possible economic stabilization efforts through monetary and fiscal policies. Overall, Indonesia's inflation trend in the 2011-2024 period reflects a stable economy at the beginning, experiencing a spike in 2022-2023, and starting to adjust towards stability again in 2024.

3.2. VAR Based LSTM

This study applies a VAR-Based LSTM model to predict Indonesia's economic growth indicators by comparing optimization algorithms (Adam, RMSprop, and SGD), with the analysis emphasizing prediction accuracy and efficiency in processing economic time series data.

Table 2. Data Stationarity Check

Variable	ADF Test (before difference)	ADF Test (after difference)	Conclusion
CPI	0.188	0.01	Stationary Data
Inflation	0.198	0.01	Stationary Data
GDP	0.182	0.01	Stationary Data

The Augmented Dickey-Fuller (ADF) Test results in the table show that all variables-CPI (Consumer Price Index), Inflation, and GDP-have a p-value before differentiation greater than 0.05 (CPI: 0.188, Inflation: 0.198, GDP: 0.182). This means that before differentiation, the three variables are non-stationary, or have trends and seasonal patterns that are not constant in the long run. However, after the first differencing, the p-value for all variables became 0.01 (smaller than 0.05), indicating that after differencing, the data became stationary. Data that has been stationary can be used in time series analysis because it has fulfilled the stationarity assumptions required in models such as VAR.

After checking the stationarity of the data, the next step is to determine the AIC value for the Inflation and BI-RATE variable. The identification results of the ACF and PACF plots show significant lags up to about lag 6 so that the best AIC value will be selected based on the significant lag. The following table 2 is the result of the AIC value from lag 1 to 5.

Table 3. AIC Value of VAR(p) with Lag p = 1 to 5

Criteria	**1**	**2**	**3**	**4**	**5**
AIC	1.448	1.388	1.332	**1.075**	1.128

Based on the Akaike Information Criterion (AIC) value, the selection of the optimal number of lags in the VAR model is determined by selecting the lag that has the lowest AIC value. From the results obtained, the AIC value decreases from lag 1 (1.448) to lag 4 (1.075), but increases again at lag 5 (1.128). Since the lowest AIC value is at lag 4, lag 4 is considered the best choice for this model. If there are too few lags, the model may lose important information, while if there are too many, the model may become too complex and prone to overfitting. Therefore, lag 4 is the optimal choice in capturing the pattern of relationships between variables in the model. After obtaining the initial model of the VAR(4) equation, the next step is to conduct a parameter significance test to determine whether the estimated coefficient has a significant effect on the dependent variable. This test is conducted by looking at the p-value of each parameter in the equation. If there are parameters that are not significant, then the model can be adjusted or simplified by eliminating lags that do not contribute significantly.

Table 4. Significance Test

Parameters	**Estimation**	***p-value***	**Conclusion**
Y_1 (CPI)			
$\boldsymbol{Y_{1(t-1)}}$	0.949	<2e-16 ***	Reject H_0
Y_2 (Inflation)			
$\boldsymbol{Y_{1(t-1)}}$	-0.022	0.0233	Reject H_0
$\boldsymbol{Y_{2(t-1)}}$	1.201	<2e-16	Reject H_0
$\boldsymbol{Y_{2(t-2)}}$	-0.388	0.0025	Reject H_0
$\boldsymbol{Y_{3(t-4)}}$	-0.085	0.0417	Reject H_0
Y_3 (GDP)			
$\boldsymbol{Y_{3(t-1)}}$	0.925	<2e-16	Reject H_0
$\boldsymbol{Y_{1(t-3)}}$	0.090	4.51e-05	Reject H_0
$\boldsymbol{Y_{2(t-3)}}$	1.064	5.34e-07	Reject H_0
$\boldsymbol{Y_{1(t-4)}}$	-0.098	3.57e-09	Reject H_0
$\boldsymbol{Y_{2(t-4)}}$	-0.458	0.00136	Reject H_0
$\boldsymbol{Y_{3(t-4)}}$	0.137	0.03847	Reject H_0

Based on the significance level α = 5%, it is concluded that the results of the parameter significance test above are significant, so the final VAR (4) model is as follows.

$$\hat{Y}_1 = 8.179 + 0.949\, Y_{1(t-1)}, \tag{11}$$

$$\hat{Y}_2 = 0.981 - 0.022Y_{1(t-1)} + 1.201Y_{2(t-1)} - 0.388Y_{2(t-2)} - 0.085Y_{3(t-4)}, \tag{12}$$

$$\begin{aligned}\hat{Y}_3 = 1.369 + 0.925Y_{3(t-1)} + 0.090Y_{1(t-3)} + 1.064Y_{2(t-3)} \\ -0.098Y_{1(t-4)} - 0.458Y_{2(t-4)} + 0.137Y_{3(t-4)}\end{aligned} \tag{13}$$

The estimation results of the VAR(4) model indicate that the variables Y_1, Y_2, and Y_3 exhibit dynamic interrelationships, with certain lags found to be statistically significant. The regression coefficients obtained indicate the influence of the variables on the future value of their respective target variables. Furthermore, the results of this VAR model will be used as the basis in selecting input variables for the LSTM (Long Short-Term Memory) model. LSTM, as a type of neural network designed to capture long-term dependencies in time series data, will utilize the identified significant lags to improve forecasting accuracy. With this approach, LSTM models are expected to cope with complex patterns in the data and produce more accurate predictions than traditional statistical methods.

Before performing forecasting with the LSTM model, several steps are undertaken, including determining the training and testing datasets, normalizing the data, configuring the hidden layers, batch size, and epochs for the LSTM model, and evaluating the model using RMSE and MAPE metrics. Similar to most neural network algorithms, LSTM employs sigmoid and tanh activation functions, which are sensitive to data with large scales, making normalization essential. In this experiment, the Min-Max Normalization method is applied to rescale the data to a specific range, typically between 0 and 1. The data is divided into training and testing data with a proportion of 80% train data and the remaining 20% as testing data. Furthermore, model selection is carried out on each variable. In this study, we want to form an LSTM model with variable input with the optimum lag in the vector autoregressive model for forecasting. Table 7 informs the comparison of RMSE values between 3 algorithms with 3 variables used after the training and testing process on the LSTM model.

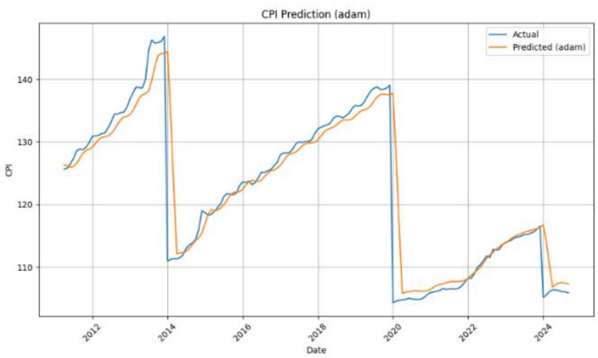
Table 5. RMSE Value Result

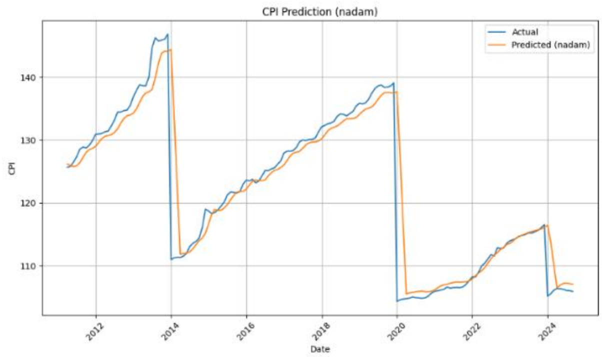
Optimization Type	CPI	Inflation	GDP
Adam	5.007	**0.676**	1.301
Nadam	**4.996**	0.718	1.352
RMSProp	5.126	0.735	**1.288**

Based on the comparison of RMSE values of three optimization algorithms (Adam, Nadam, and RMSProp) on three variables (CPI, Inflation, and GDP), Nadam shows the best performance in minimizing error on CPI with the lowest RMSE value (0.676), while Adam has the highest error (5.007). For the Inflation variable, Adam has the lowest RMSE value (0.676), followed by Nadam (0.718), while RMSProp has the largest error (0.735). Meanwhile, in GDP prediction, RMSProp shows the best performance with the lowest RMSE (1.288), while Nadam has the highest error (1.352). Thus, there is no one algorithm that is superior overall, but each algorithm has advantages in certain variables.

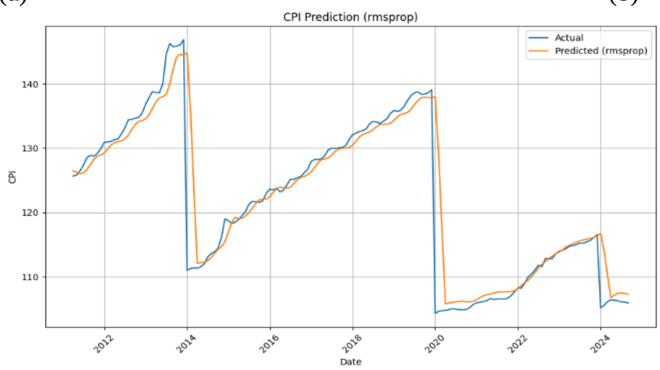
Based on the comparison of the analyzed RMSE values, it can be seen that each optimization algorithm has an advantage on certain variables, indicating that no one method is consistently better in all cases. To further understand how each algorithm works in predicting data, visual analysis through graphs of predicted and actual data is important. These graphs provide an overview of how close the prediction results from Adam, Nadam, and RMSProp are to the actual values, as well as how each optimization captures the trend patterns of the CPI, Inflation, and GDP variables. The following time series plots illustrate the comparison of predicted and actual data for each optimization algorithm.

1. Costumer Price Index





(a) (b)

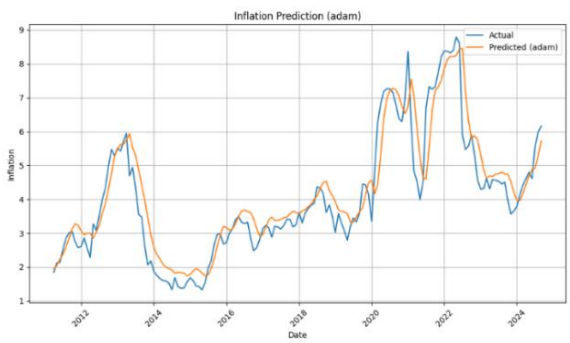


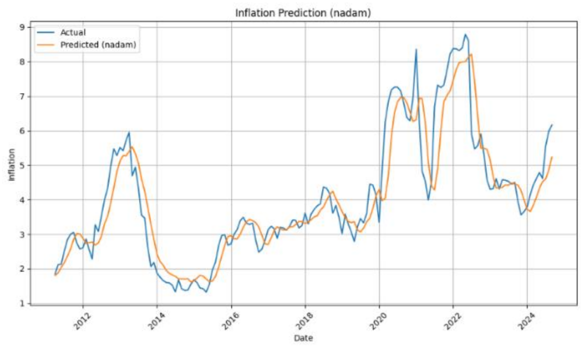
(c)

Figure 6. The Results of the Comparison of Prediction Results and actual data with Adam Optimization (a), Nadam Optimization (b), RMSProp Optimization (c)

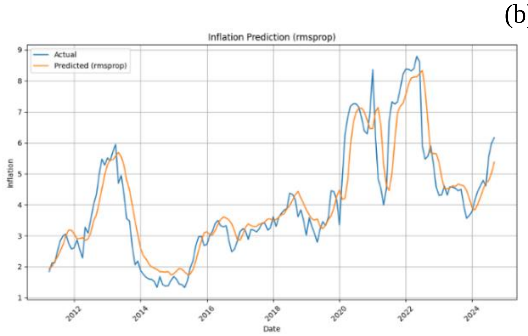
The Fig. 6 compares the prediction results with the actual data using three optimization algorithms: Adam (a), Nadam (b), and RMSProp (c). Adam shows the prediction performance with a gradient-adaptive approach, while Nadam adds momentum to speed up convergence, and RMSProp focuses on the stability of weight updates to handle varying gradients. A visual comparison between the three helps determine which algorithm gives the closest prediction results to the actual data, with Nadam giving the best RMSE for CPI of 0.4996.

2. Inflation





(a) (b)

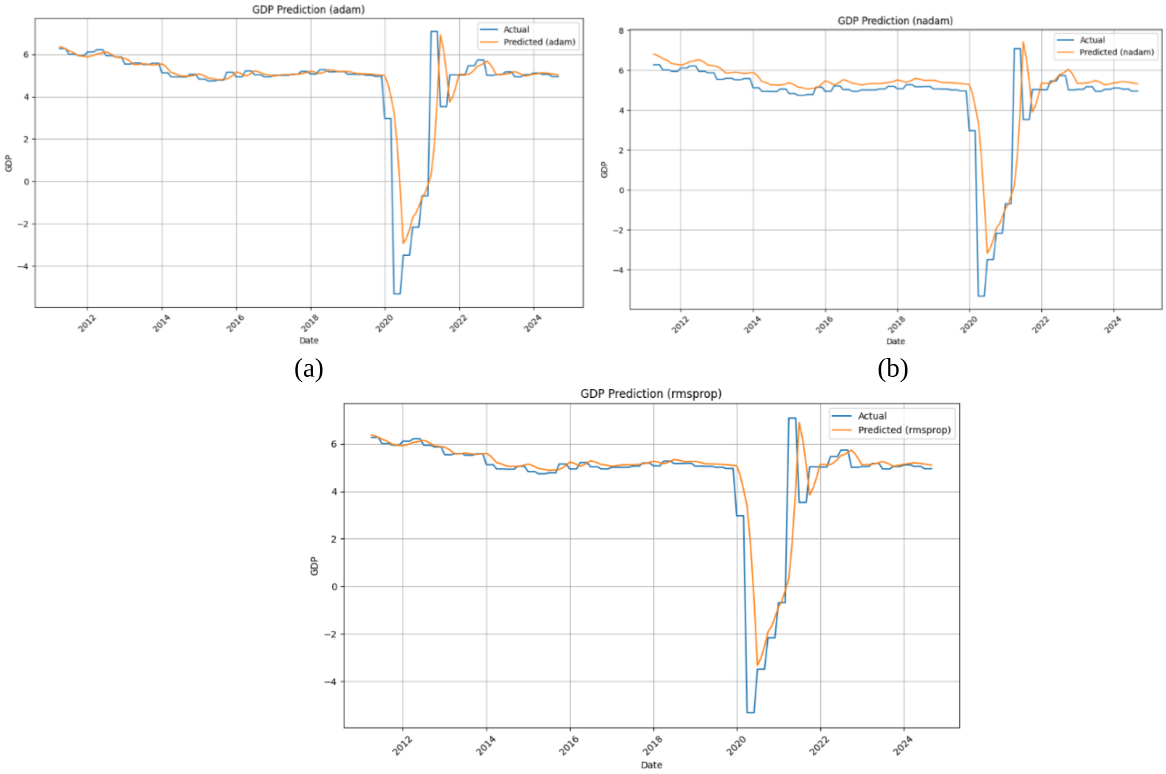


(c)

Figure 7. The Results of the Comparison of Prediction Results and Actual Data with Adam Optimization (a), Nadam Optimization (b), RMSProp Optimization (c)

The Fig. 7 compares inflation prediction results with actual data using three optimization algorithms: Adam (a), Nadam (b), and RMSProp (c). Adam adapts to the gradient for more efficient weight updates, while Nadam adds momentum to speed up convergence, and RMSProp adjusts the learning rate based on the average square of the most recent gradient for better stability. The visual difference between the three shows the extent to which each algorithm is able to capture the inflation pattern and produce predictions closest to the actual data, with Adam giving an RMSE for inflation of 0.676.

3. Gross Domestic Product



(a) (b)

(c)

Figure 8. The Results of the Comparison of Prediction Results and Actual Data with Adam Optimization (a), Nadam Optimization (b), RMSProp Optimization (c)

The Fig. 8 compares the predicted Gross Domestic Product (GDP) with the actual data using three optimization algorithms: Adam (a), Nadam (b), and RMSProp (c). Adam adjusts the gradient for more efficient weight updates, Nadam adds momentum to speed up convergence, while RMSProp adjusts the learning rate based on the mean square of the most recent gradient to improve stability. The visual difference between the three shows each algorithm's ability to capture the GDP pattern and produce predictions closest to the actual data, with RMSProp providing the best RMSE for GDP at 1.288. However, despite these slight differences, the overall forecasting performance remains consistent. Given the relatively small RMSE differences, no single optimization method is significantly superior in this forecasting context. As a result, the choice of optimization method can be determined based on factors such as computational efficiency, training stability, or user preference rather than prediction accuracy alone. These findings reinforce the effectiveness of the VAR-LSTM approach in economic forecasting, highlighting its ability to model complex time-series patterns across different economic indicators.

4. CONCLUSION

The modeling process in this study begins with the application of the VAR model, where VAR(4) was selected as the best specification based on the lowest AIC value of 1.075. A parameter significance test was then conducted to identify variables with significant influence, which were subsequently used as input variables for the LSTM model in forecasting CPI, Inflation, and GDP. By incorporating the temporal relationships identified by the VAR model, the LSTM forecasts are expected to be more accurate and relevant. The analysis results show that the optimization methods Adam, Nadam, and RMSProp produce broadly similar prediction patterns, with forecasted values closely following actual data. However, the best optimizer varies across variables: Nadam performs best for CPI (RMSE = 0.4996), Adam for Inflation (RMSE = 0.676), and RMSProp for GDP (RMSE = 1.288).

Although each variable has a different optimal optimizer, the overall forecasting performance of the three methods is relatively comparable. These findings suggest that the choice of optimization method may be guided not only by prediction accuracy but also by computational efficiency and training stability. Moreover, the results confirm the effectiveness of the VAR–LSTM hybrid approach in capturing both linear and nonlinear patterns of economic data, thereby providing more reliable forecasts. The implications of this study are twofold: for policymakers, more accurate forecasts of key economic indicators can support evidence-based decision-making, while for practitioners and researchers, the VAR–LSTM framework offers a methodological contribution that enhances the robustness of time-series forecasting in macroeconomic contexts.

Author Contributions

Ariska Fitriyana Ningrum: Conceptualization, Data Curation, Formal Analysis and Methodology. Mulil Khaira: Software Development, Validation and Visualization. All authors have read and approved the final manuscript.

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Declarations

The authors declare no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

ChatGPT was used only to improve the readability and grammatical structure of the manuscript. No AI tool was used to generate or alter the research data, methodology, results, or interpretations. All content was verified by the authors for accuracy and consistency with the study.

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