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A Case Study: Comparison of LSTM and GRU Methods for Forecasting Oil, Non-Oil, and Gas Export Values in Indonesia

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ABSTRACT

This study explores the forecasting of Indonesia's oil, non-oil, and gas export values, highlighting its critical role in supporting national economic growth. Given the inherent volatility in export values, accurate forecasting is vital for informed economic decision-making. The research employs Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, both well-regarded for their ability to handle sequential data and complex temporal patterns. Model performance was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The findings indicate that although both models produced nearly identical MAPE values of 99.99% across the oil, non-oil, and gas sectors, the GRU model outperformed the LSTM model with RMSE values of 0.0655 for oil and gas exports and 0.0697 for non-oil and gas exports. Moreover, the GRU model's forecasts align closely with data from the Central Bureau of Statistics (BPS), which reported an 11.33% decline in Indonesia's export values by the end of 2023. These results suggest that the GRU model not only offers greater accuracy but is also applicable to other economic forecasting contexts, such as exchange rate and inflation predictions, thereby enhancing economic policy-making.

Keywords : *export; LSTM; GRU; RMSE; MAPE; forecasting;*

1. INTRODUCTION

Indonesia, with its vast natural resource wealth, is well-positioned to fulfil its internal demands while making substantial contributions to the global market through its export activities. These activities, which entail the transfer or sale of goods beyond national borders, are vital for fostering economic expansion. For developing nations, exports play a critical role in bolstering foreign exchange reserves, enhancing per capita income, alleviating balance of payments issues, and generating employment opportunities [1], [2].

Export activities are generally categorized into two principal commodity groups based on production types: the oil and gas sector, which encompasses both oil and natural gas, and the non-oil and gas sector, which includes agricultural products, manufacturing industries, mining, and various other sectors [3], [4]. Both oil and gas exports, as well as non-oil and gas exports, play a pivotal role in influencing a nation's Gross Domestic Product (GDP). GDP serves as a critical measure for evaluating the economic status of a country over a specific period. Consequently, enhancing export values is widely regarded as a critical indicator of a nation's economic development success.

In Indonesia, the oil and gas sector significantly boosts national revenues owing to the high value of energy commodities. Nonetheless, this sector is susceptible to global oil price volatility and faces future uncertainties linked to finite natural resources. Conversely, non-oil and gas exports present an opportunity for economic diversification, potentially fostering sustainable employment and reducing the nation's reliance on the energy sector. By broadening the economic base through non-oil exports, Indonesia can mitigate the risks associated with oil price fluctuations and lessen its dependence on energy resources [5].

Research by Purba et al. [6] indicates that Indonesia's export values experience considerable variability over time. For example, in December 2021, the export value stood at USD 22.38 billion, marking a 2.04 percent decline from November 2021. However, this value also represented a substantial increase of 35.30 percent compared to December 2020. These fluctuations highlight the intrinsic volatility of export values, driven by a multitude of factors, and their tendency to vary across different periods. This variability underscores the imperative for accurate forecasting and predictive analysis. Reliable forecasting is crucial for enabling governments to craft effective economic policies, foster economic growth, and manage uncertainties in the global market.

Time series forecasting, a valuable statistical technique for strategic planning and decision-making, is frequently employed to predict future trends from historical data. As a subset of predictive analytics, it estimates future values of a variable by examining past observations. This forecasting method can be categorized as either multivariate or univariate, depending on whether it involves multiple variables or a single variable [7].

Time series forecasting employs a range of mathematical models and algorithms, encompassing both traditional statistical approaches—such as Autoregressive (AR) models, Autoregressive Integrated Moving Average (ARIMA) models, and Exponential Smoothing techniques [8]–[10], —as well as advanced methods based on Deep Learning (DL), including Recurrent Neural Networks (RNN) [11].

Traditional statistical techniques frequently fall short in capturing intricate nonlinear dependencies within extended multivariate time series data. Conversely, DL methods, particularly RNN, effectively address this limitation by employing neural networks to model complex temporal dependencies in sequential datasets. As a result, DL approaches offer more precise forecasting outcomes compared to conventional methods due to their proficiency in modelling both linear and nonlinear relationships. Furthermore, DL methodologies demonstrate superior performance over traditional statistical approaches in detecting patterns and trends within time series data [12], [13].

Recurrent Neural Networks (RNN) are a class of DL methods specifically designed for long-term learning tasks. However, RNN frequently encounter issues such as vanishing gradients or exploding gradients, where the gradient values can either diminish to near zero or escalate excessively during training [14]. To address these limitations, RNN employ a gating

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mechanism to retain information over extended periods. The primary variants developed to mitigate these challenges are Long-Short Term Memory (LSTM) networks and Gated Recurrent Units (GRU).

Long-Short Term Memory (LSTM) is an advanced time series forecasting algorithm renowned for its effectiveness and reliability. LSTM employs three distinct types of gates—input, forget, and output gates—that facilitate the long-term retention of information and address the vanishing gradient issue prevalent in traditional RNN. By coordinating these gates, LSTM efficiently manages the flow of information, ensuring the preservation of pertinent data while discarding irrelevant details.

The GRU is a streamlined variant of the RNN, engineered to simplify the LSTM architecture. GRU feature two types of gates: reset gates and update gates. Due to their reduced number of parameters and less complex architecture compared to LSTM, GRU are particularly advantageous for scenarios with limited data and offer a lower risk of overfitting. Despite their simplicity, GRU can deliver performance on par with LSTM, with the added benefit of faster convergence [15].

Overall, LSTM networks exhibit greater complexity compared to GRU due to their utilization of three sigmoid activation functions and two tanh activation functions, whereas GRUs employ only two sigmoid and one tanh activation function. This increased complexity enables LSTM to tackle more intricate problems. Conversely, GRU offers enhanced computational efficiency and yields competitive performance results.

This research seeks to evaluate and compare the efficacy of LSTM and GRU methodologies in forecasting the export values of oil, non-oil, and gas in Indonesia. The study primarily aims to assess the accuracy of these techniques in predicting varying export trends and to identify which approach delivers more precise and dependable forecasts. The outcomes of this analysis are anticipated to assist the government in crafting more effective economic policies, enhancing national economic growth, and navigating global market uncertainties, thereby benefiting industry stakeholders and policymakers.

RNN architectures, notably LSTM and GRU networks, have been extensively employed in forecasting time series data across a variety of sectors such as economics, healthcare, education, and industry. In their study, Ubrani and Motwani [16] evaluated and compared the performance of LSTM and GRU models utilizing data from the Indian Energy Exchange (IEX). The research involved training these models and applying them to predict data for the subsequent day and week. Mean Absolute Percentage Error (MAPE) was calculated for each model's forecasts. The results demonstrated that both LSTM and GRU models performed well, with LSTM exhibiting a slight edge in overall effectiveness.

Budiharto [17] utilized LSTM networks to predict stock prices on the Indonesia Stock Exchange, leveraging data from Bank Central Asia (BCA) and Bank Mandiri obtained through Yahoo Finance. The research revealed that the LSTM models attained a prediction accuracy of 94.57% over a one-year forecast period.

Cahuantzi et al. [18] conducted a comparative analysis of the memorization capabilities of LSTM networks and GRU with respect to string sequences of varying complexity. Symbolic sequences with different complexity levels were generated to simulate training and evaluate the impact of parameter configurations on the learning and inference performance of RNN. The findings indicated that LSTM generally outperformed GRU in memorizing complex sequences, whereas GRU demonstrated superior performance with more straightforward sequences.

Alassafi et al. [19] employed publicly available datasets from the European Centre for Disease Prevention and Control to construct a predictive model for COVID-19 transmission in Malaysia, Morocco, and Saudi Arabia. By applying advanced DL techniques, specifically RNN and LSTM networks, the study assessed the precision of COVID-19 case forecasts. The LSTM model demonstrated a remarkable accuracy rate of 98.58%, surpassing the RNN model, which achieved an accuracy of 93.45%.

Ozdemir et al. [20] conducted a study on nickel price estimation utilizing LSTM and GRU models. The performance of these techniques was assessed using the MAPE. The findings indicated that while both LSTM and GRU demonstrated effectiveness, GRU outperformed LSTM in terms of time efficiency, achieving a MAPE of 6.986% compared to LSTM's 7.060%.

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Abumohsen et al. [21] conducted a comparative analysis of RNN, LSTM, and GRU for forecasting electricity loads utilizing data from Palestinian electricity providers. Their findings indicate that the GRU model outperforms the others, delivering superior accuracy and the lowest error rates, with an R-squared value of 90.228%, a Mean Squared Error (MSE) of 0.00215, and a Mean Absolute Error (MAE) of 0.03266.

Previous studies have established that both LSTM and GRU models offer distinct advantages in the realm of time series data forecasting. Nevertheless, no research has explicitly compared these two models within the specific context of forecasting oil, non-oil, and gas export values in Indonesia. This study addresses this gap by evaluating and contrasting the performance of LSTM and GRU models in predicting export values across these sectors.

2. METHODS

This study encompasses several vital phases: data acquisition, pre-processing, and partitioning into training and testing datasets. The LSTM and GRU models were developed with tuned hyperparameters and subsequently evaluated and compared based on their predictive performance using RMSE and MAPE metrics. The outcomes are utilized to project export values for the period from 2022 to 2023, aiding the government in devising more effective economic policies.

2.1. Input Data

The dataset employed in this study is derived from secondary sources provided by the Central Statistics Agency (BPS). It comprises time series data on the values of oil and gas exports as well as non-oil and gas exports, spanning from January 1993 to December 2021. This dataset encompasses a total of 348 observations for each category of export. It is utilized to analyze trends and patterns in forecasting export values. A sample of this data is presented in Table 1.

Table 1. *Sample export data*

Period	Export Value	
	Oil & Gas	Non-oil and gas
1993-01	864,3	2.137,6
1993-02	767,5	2.125,0
1993-03	892,2	2.116,3

Table 1 continued…

Period	Export Value	
	Oil & Gas	Non-oil and gas
1993-04	744,0	2.213,5
1993-05	888,3	2.229,7
...	...	...
2021-08	1.066,8	20.360,3
2021-09	932,8	19.672,8
2021-10	1.025,3	21.004,4
2021-11	1.332,4	21.512,0
2021-12	1.093,4	21.266,1

2.2. Data Pre-processing

Before embarking on the forecasting process, it is essential to conduct an extensive data pre-processing phase, which includes several pivotal steps. This pre-processing phase generally encompasses data visualization, removal of duplicate entries, verification of missing values, and normalization of the dataset [22].

This data processing phase is crucial for guaranteeing that the data utilized in the forecasting procedure is clean, accurate, and consistent, thereby ensuring the reliability and trustworthiness of the resulting analysis.

2.2.1. Data Visualization

Visualizing time series data serves the purpose of comprehending its underlying patterns and attributes. These visualizations enable researchers to identify trends, seasonal variations, or anomalies within the dataset. The outcomes of this time series data visualization are illustrated in Figure 1.

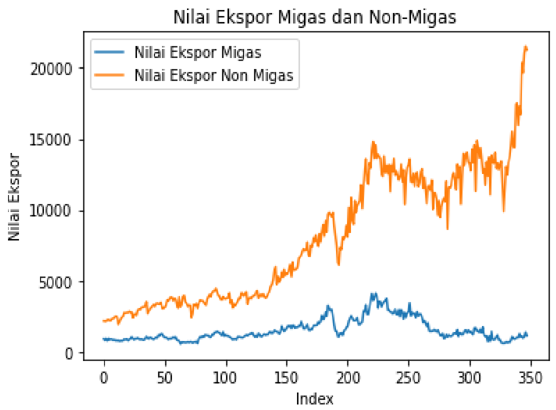

Figure 1. *Time series plotitem similarity*

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2.2.2. Data Transformation

Data transformation is a crucial phase in the data mining process, with data normalization being a prominent technique employed [22]. Data normalization involves adjusting the data scale to achieve a consistent range of values, with min-max normalization being a widely utilized method [23].

During this normalization stage, the original data is modified to ensure that its values range from 0 to 1. This adjustment facilitates more straightforward comparisons between variables and mitigates biases arising from differences in data scales. The mathematical formula for data normalization is provided in Equation (1):

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{1}$$

Furthermore, data normalization using Equation (1) involves the following steps:

a. Determine the minimum and maximum values across the entire dataset.

- Minimum value (x_{min}): 514.0
- Maximum Value (x_{max}): 4072.8

b. Compute the normalized value for each data point or monthly entry. For example, for January 1993 (x = 864.3)

$$x' = \frac{(864{,}3 - 514{,}0)}{(4072{,}8 - 514{,}0)} \approx 0{,}098 \tag{2}$$

Table 2 illustrates a sample of data that has been subjected to this normalization process.

Table 2. *Data transformation results*

Index	Export Value	
	Oil & Gas	Non-oil and gas
0	0,097915	0,011954
1	0,070858	0,011311
2	0,105713	0,010868
3	0,064289	0,015825
4	0,104623	0,016651
...	...	...
343	0,154517	0,941266
346	0,228757	1,000000
347	0,161952	0,987460

2.3. Data Splitting

The primary determinant of success in DL is the effectiveness of the training and testing phases. A robust training process is crucial for enhancing model performance. Researchers commonly partition the dataset into two subsets—training data and testing data—adhering to established guidelines. The proportion of data allocated for training and testing significantly influences the model's success [24].

It is widely recommended to use at least 50% of the dataset for training to ensure the reliability of the test results. Therefore, this study adopts a 70:30 ratio for training and testing data, as detailed in Table 3.

Table 3. *Split data ratio*

No	Data	Sum
1	Training	243
2	Testing	105

2.4. Initial Parameter Configuration

In the process of developing forecasting models, it is crucial to conduct hyperparameter tuning, which involves adjusting factors such as the number of neuron units and incorporating dropout mechanisms to mitigate overfitting and enhance model performance [25]. Additionally, the application of early stopping is essential for automatically halting training once the model achieves optimal performance, thereby conserving both time and computational resources.

Additional parameters, including epoch and batch size, play a crucial role in the training process. An epoch refers to one complete pass through the entire dataset, while batch size denotes the number of samples processed in a single iteration. Optimal batch size selection enhances the efficiency of the training procedure and facilitates more frequent updates of model parameters, contingent on the dataset size and computational resources available [26].

The parameters derived from the hyperparameter tuning process are detailed in Tables 4 and 5.

Table 4. *Ideal configuration of LSTM parameters*

Parameter	Export	
	Oil & Gas	Non-oil and gas
LSTM Unit	16	32
Dropout	0.4	0.4
Epoch	50	29
Batch Size	16	16

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Table 5. *Ideal configuration of GRU parameters*

Parameter	Export	
	Oil & Gas	Non-oil and gas
GRU Unit	16	16
Dropout	0.3	0.3
Epoch	50	50
Batch Size	16	16

2.5. The Model Development Process

2.5.1. LSTM Model

Long Short-Term Memory is a variant of DL algorithms designed on the framework RNN. The LSTM architecture is composed of distinct layers, including the input layer, hidden layer, and output layer [14], each fulfilling a unique function in data processing and information transmission. Figure 2 provides a visual representation of the LSTM architecture, elucidating the interconnections among these layers within the network.

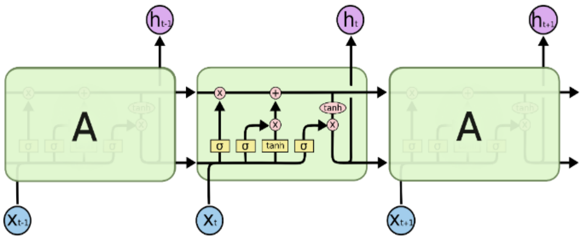

Figure 2. *LSTM architecture*

Memory cells in the LSTM architecture are pivotal components within a layer, which is governed by three fundamental gates: the forget gate, the input gate, and the output gate [27].

a. **Forgot gate**: This gate regulates whether the information entering the cell state should be retained or discarded. It operates by leveraging both the previous output and the current input, as defined by Equation (3):

$$f_t = \sigma(W_f * [h_{t-1,}x_t] + b_f) \quad (3)$$

b. **Input gate**: The input gate incorporates two activation functions, specifically sigmoid and tanh. These functions are crucial for updating the cell state, as described by Equation (4):

$$i_t = \sigma(W_i * [h_{t-1,}x_t] + b_i) \quad (4)$$

c. **Output gate**: This gate identifies which segment of the cell state will be utilized as the output, based on both the input and the memory cell, as described by Equation (5):

$$o_t = \sigma(W_o * [h_{t-1,}x_t] + b_0) \quad (5)$$

The primary benefit of the LSTM cell discussed is its capacity to establish correlations between information from previous time steps and incoming data from subsequent time steps, thereby enabling it to retain and utilize information over extended periods. This characteristic is particularly crucial for time series analysis, where historical data is frequently essential for making precise future predictions.

2.5.2. Model GRU

The GRU, introduced by Chung et al. [28] in 2014, represents an advancement over the RNN architecture. While the GRU is less complex compared to the LSTM network, it remains highly effective for addressing sequential data challenges. Due to its streamlined and efficient design, the GRU has gained widespread adoption across numerous applications involving sequential data.

A vital characteristic of the GRU is its integrated control mechanism for managing the flow of information into and out of the unit. This mechanism is comprised of gates, specifically a reset gate and an update gate [29]. The structural configuration of the GRU is illustrated in Figure 3:

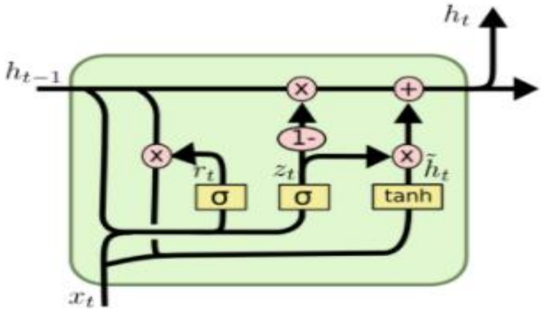

Figure 3. *GRU architecture*

a. **Update gate**: This mechanism is employed to assess the proportion of historical information retained, as defined by Equation (6):

$$z_t = \sigma(W_z * [h_{t-1,}x_t] + b_z) \quad (6)$$

b. **Reset gate**: This mechanism is employed to integrate new input data with historical information, as described by Equation (7):

$$r_t = \sigma(W_r * [h_{t-1,}\ x_t] + b_r) \quad (7)$$

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2.6. Data Denormalization

Denormalization refers to the procedure of reverting prediction data to its original value after normalization has been applied [30]. Normalization is employed to align the data scale with the requirements of the prediction algorithm; however, the resultant predictions remain in their normalized form and must be converted back to their original scale for accurate interpretation. This conversion is performed using Equation (8):

$$X_t = x'(X_{max} - X_{\min}) + X_{\min} \tag{8}$$

The original value, which has been denormalized, is compared with the predicted value, expressed in its normalized form, alongside the maximum and minimum values of the original dataset prior to normalization. This procedure guarantees that prediction values, initially within the normalization range, are accurately converted back to their original scale, thereby facilitating their use in subsequent analyses.

2.7. Model Evaluation

Makridakis et al. [31] highlight that the effectiveness of a forecasting model is measured by its capacity to replicate observed data closely. In essence, accuracy denotes how closely the model's predictions align with the actual values.

Budiman [32] emphasizes that the model's accuracy can be evaluated using a range of error metrics, including the MAE, MSE, and MAPE.

a. **Mean Squared Error (MSE)**: This metric quantifies the average of the squared differences between the actual and predicted values, as determined by Equation (9).

$$MSE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n} \tag{9}$$

b. **Root Mean Squared Error (RMSE)**: This metric quantifies the extent of error or deviation between the values predicted by the model and the actual observed values. The RMSE is derived using the formula specified in Equation (10):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}} \tag{10}$$

c. **Mean Absolute Percentage Error (MAPE)**: This metric evaluates the prediction error as a proportion of the actual value, thus facilitating the interpretation of error in relation to the actual value. The MAPE value is computed using the formula presented in Equation (11).

$$MAPE = 100\% \times \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \tag{11}$$

In evaluating the model's performance, reduced values of MSE, RMSE, and MAPE indicate superior model efficacy. Specifically, within the context of this study, lower scores on these three metrics signify a higher degree of accuracy and reliability in forecasting export values.

3. RESULTS AND DISCUSSION

3.1. Prediction Result

The training outcomes for each model are comprehensively illustrated in Figures 4 through 7. These figures depict the predictions for oil and gas, as well as non-oil and gas exports from Indonesia, following the processes of denormalization and data visualization. The plots demonstrate the models' capabilities in forecasting export values with precision, allowing for a direct comparison with actual data. A detailed explanation and analysis of these results will be provided in the subsequent sections.

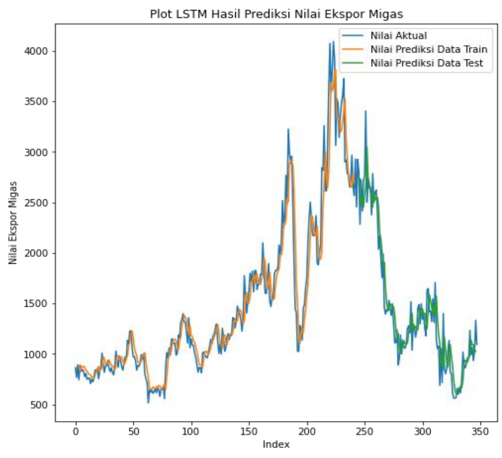

Figure 4. *LSTM plot for oil and gas export*

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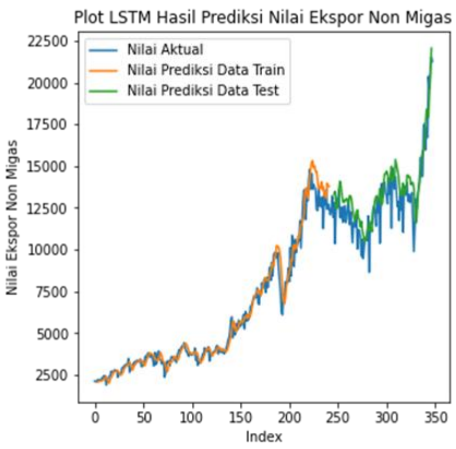

Figure 5. *LSTM plot for non-oil and gas export*

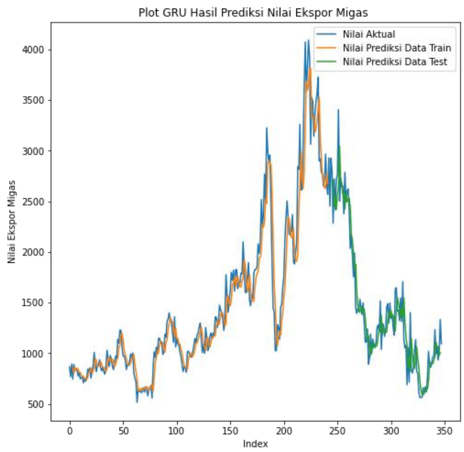

Figure 6. GRU plot for oil and gas export

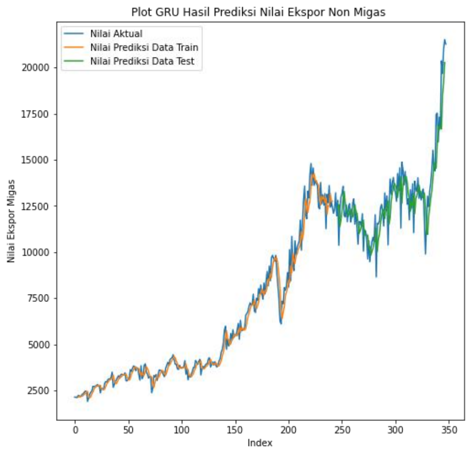

Figure 7. *GRU plot for non-oil and gas export*

Figures 4 through 7 present the visualizations of prediction outcomes generated by the LSTM and GRU models sequentially. These figures include graphs that juxtapose predicted values with actual data for oil and gas as well as non-oil and gas export values. In these graphs, the blue line denotes actual export values, the orange line represents training data, and the green line indicates test data. The x-axis reflects the temporal dimension.

The visual analysis suggests that both LSTM and GRU models effectively mirror the actual data trends. For a more comprehensive quantitative assessment, a detailed comparison of the prediction results against actual data for each export category is provided in Tables 6 and 7.

Table 6. *Comparative analysis of prediction results for oil and gas*

Period	Oil and Gas (Million US$)		
	Actual Value	**Result Predictions LSTM**	**Result Predictions CRANE**
January	2.501,7	3.050,093	3.043,138
February	2.729,1	2.741,615	2.707,857
…	…	…	…
October	2.413,2	2.553,303	2.530,660
November	2.035,4	2.458,978	2.432,741
December	2.168,0	2.199,298	2.168,529

Table 7. *Comparative analysis of prediction results for non-oil and gas*

Period	Non-Oil and Gas (Million US$)		
	Actual Value	**Result Predictions LSTM**	**Result Predictions CRANE**
January	11.970,6	14.094,986	13.280,796
February	11.904,9	13.830,561	12.647,166
…	…	…	…
October	12.879,6	12.757,471	12.179,159
November	11.509,3	13.230,566	12.577,725
December	12.268,4	13.209,386	12.110,825

The comparative analysis of the predictive outcomes presented in Tables 6 and 7 reveals that the discrepancies between the predicted values and the actual data are minimal. The forecasts indicate a declining trend in oil and gas exports, while non-oil and gas exports are projected to rise, aligning closely with the observed data trends.

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3.2. Prediction Evaluation

The evaluation of prediction outcomes is conducted through the analysis of RMSE and MAPE metrics, which gauge the proximity of predicted values to actual data. Tables 8 and 9 provide the evaluation results for both LSTM and GRU models, focusing on oil and gas exports as well as non-oil and gas exports. Additionally, to evaluate the model's efficiency in terms of time, the assessment includes an analysis of the model's training duration, detailed in Table 10.

Table 8. *Evaluation of the LSTM model's performance*

Metric	Export	
	Oil & Gas	Non-oil and gas
RMSE	0.0668	0.0717
MAPE	0.9998%	0.9999%
Accuracy	99%	99%

Table 9. *Evaluation of the GRU model's performance*

Metric	Export	
	Oil & Gas	Non-oil and gas
RMSE	0.0655	0.0697
MAPE	0.9998%	0.9999%
Accuracy	99%	99%

Table 10. *Comparative analysis of loss functions and computational runtime*

Model	Export	Loss Function	Running Time
LSTM	Oil & Gas	0.00506	300.13 *s*
	Non-oil and	0.00095	300.24 *s*
GRU	Oil & Gas	0.00402	300.18s
	Non-oil and	0.00080	300.18s

Based on the data presented in Tables 8 and 9, the Mean Absolute Percentage Error (MAPE) values for the oil and gas and non-oil and gas components are 0.9998% and 0.9999%, respectively, for both the LSTM and GRU models. A MAPE value below 10% signifies that both models exhibit exceptional predictive accuracy, achieving an accuracy rate of 99%.

Furthermore, the Root Mean Squared Error (RMSE) values for the oil and gas and non-oil and gas components indicate that the GRU model outperforms the LSTM model, with RMSE values of 0.0655 and 0.0697 for GRU compared to 0.0668 and 0.0717 for LSTM. Despite minor differences in computational time between the two models, the GRU demonstrates superior performance in terms of RMSE for both components.

In conclusion, the GRU model is more effective than the LSTM model for forecasting the values of oil and gas and non-oil and gas components, as evidenced by RMSE and MAPE evaluations. Additionally, Table 10 illustrates that the GRU model is more efficient regarding training time and computational resource utilization. Thus, the GRU model not only provides more accurate predictions but also trains more rapidly and requires fewer resources, making it the preferred choice for forecasting oil, non-oil, and gas exports in Indonesia.

3.3. Forcasting

Once the model's performance has been validated as satisfactory, the subsequent phase involves forecasting for the subsequent two-year period, from January 2022 to December 2023. Figure 8 and Figure 9 illustrate the plot visualizations of the combined export values for oil, gas, and non-oil and gas components in Indonesia, incorporating both preliminary data and forecast outcomes for the optimal model, which is the GRU model.

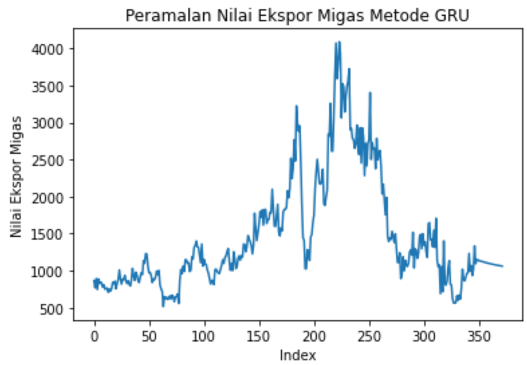

Figure 8. *Outcomes of GRU forecasting for oil and gas*

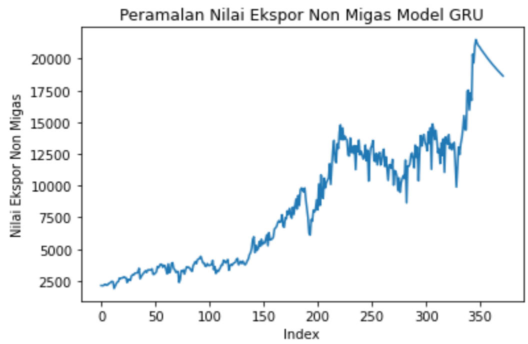

Figure 9. *Outcomes of GRU forecasting for non-oil and gas*

Figures 8 and 9 illustrate the forecasting outcomes produced by the GRU model for both oil and gas, as well as non-oil and gas sectors.

These figures indicate that the forecasted values for both sectors in Indonesia exhibit an upward trend over a specific period, followed by a decline towards the end of 2023. This observation aligns with data from BPS, which reports that Indonesia's export value from January to December 2023 totalled USD 258.82 billion, reflecting an 11.33 percent decrease compared to the same period in 2022 [33].

This result underscores the model's potential applicability in diverse economic forecasting scenarios, including projections for exchange rates, inflation, and sector-specific performance. The model's ability to accurately capture the downward trend in export values at the end of 2023 demonstrates its utility in economic decision-making, offering valuable insights for governments and industry stakeholders in crafting more effective policies and strategies.

CONCLUSION

The conclusion of this study affirms that the GRU method outperforms forecasting the values of oil and gas as well as non-oil and gas exports in Indonesia. The evaluation, based on RMSE, indicates that the GRU method achieved superior performance with an RMSE of 0.0655 for oil and gas components and 0.0697 for non-oil and gas components, surpassing the LSTM method. Furthermore, when assessing prediction accuracy through MAPE, both methods demonstrated commendable accuracy rates below 10%; however, the GRU method exhibited more consistent accuracy across the board.

The forecast outcomes for the 2022 to 2023 period, aligning with the most recent data from BPS, reveal that the GRU method surpasses LSTM in both accuracy and realism in capturing the downward trend. The disparity in prediction performance between GRU and LSTM highlights GRU's superior reliability under dynamic and complex market conditions. As a result, the GRU method is recommended as the primary approach for forecasting values related to oil, gas, and non-oil and gas exports, enhancing adaptability and responsiveness in decision-making processes and thereby significantly contributing to national economic planning.

REFERENCES

[1] P. Djatmiko and N. SBM, "Impact Non-Oil and Gas Exports and Oil and Gas Exports on The Position of Indonesia Foreign Exchange Reserves," *J. Pendidik. Ekon. Dan Bisnis*, vol. 7, no. 1, pp. 87–100, 2019, https://doi.org/10.21009/jpeb.007.1.8

[2] K. Martikasari, "Analisis Faktor Yang Mempengaruhi Ekspor Nonmigas Di Indonesia," *J. Pendidik. Ekon. dan Akunt.*, vol. 15, no. 2, pp. 47–56, Apr. 2022, https://doi.org/10.24071/jpea.v15i2.4623

[3] S. E. Rahayu, "Analysis of Indonesian Non-Oil and Gas Export Development by Manufacturing Sector 2016-2020 Period," *J. Int. Conf. Proc.*, vol. 4, no. 2, 2021, https://doi.org/10.32535/jicp.v4i2.1294

[4] K. A. Rijal, A. Vega Vitianingsih, Y. Kristyawan, A. Lidya Maukar, S. Fitri, and A. Wati, "Forecasting Model of Indonesia's Oil & Gas and Non-Oil & Gas Export Value using Var and LSTM Methods," vol. 10, pp. 59–69, 2024, [Online]. Available: http://http//jurnal.unmer.ac.id/index.php/jtmi

[5] R. W. Ramadhan, F. Iqbal, N. P. Utamy, and A. N. Ananda, "Pengaruh Ekspor Sektor Migas dan Nonmigas Terhadap PDB Indonesia," *J. Ekon. Manaj. dan Sos.*, vol. 6, no. 2, pp. 62–71, 2023, https://doi.org/10.56071/jemes.v6i2.602

[6] M. L. Purba, M. Sihombing, and J. Sihotang, "Analisis Pengaruh Ekspor Migas, Ekspor Non Migas Dan Penanaman Modal Asing Terhadap Pertumbuhan Ekonomi Indonesia Tahun 2000-2019," *J. Econ. Bus.*, vol. 2, no. 2, pp. 40–51, 2021, https://doi.org/10.36655/jeb.v2i2.557

[7] J. Hao and F. Liu, "Improving long-term multivariate time series forecasting with a seasonal-trend decomposition-based 2-dimensional temporal convolution dense network," *Sci. Rep.*, vol. 14, no. 1, 2024, https://doi.org/10.1038/s41598-024-52240-y

[8] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time series analysis: Forecasting and control: Fourth edition*.

2013. https://doi.org/10.1002/9781118619193

[9] M. Alizadeh, S. Rahimi, and J. Ma, "A hybrid ARIMA–WNN approach to model vehicle operating behavior and detect unhealthy states," *Expert Syst. Appl.*, vol. 194, 2022, https://doi.org/10.1016/j.eswa.2022.116515

[10] S. Smyl, "A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting," *Int. J. Forecast.*, vol. 36, no. 1, pp. 75–85, 2020, https://doi.org/10.1016/j.ijforecast.2019.03.017

[11] S. Li, W. Li, C. Cook, C. Zhu, and Y. Gao, "Independently Recurrent Neural Network (IndRNN): Building A Longer and Deeper RNN," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018, pp. 5457–5466. https://doi.org/10.1109/CVPR.2018.00572

[12] G. P. Zhang, *Neural Networks in Business Forecasting*. 2011. https://doi.org/10.4018/978-1-59140-176-6

[13] M. K. Sandhya Arora, "Forecasting the Future: A Comprehensive Review of Time Series Prediction Techniques," 2024. https://doi.org/10.52783/jes.1478

[14] L. Wiranda and M. Sadikin, "Penerapan Long Short Term Memory pada Data Time Series untuk Memprediksi Penjualan Produk PT. Metiska Farma," *J. Nas. Pendidik. Tek. Inform.*, vol. 8, no. 3, 2019.

[15] W. Hastomo, A. S. B. Karno, N. Kalbuana, E. Nisfiani, and L. ETP, "Optimasi Deep Learning untuk Prediksi Saham di Masa Pandemi Covid-19," *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 2, p. 133, 2021, https://doi.org/10.26418/jp.v7i2.47411

[16] A. Ubrani and S. Motwani, "LSTM- and GRU-based time series models for market clearing price forecasting of Indian deregulated electricity markets," in *Advances in Intelligent Systems and Computing*, 2019, pp. 693–700. https://doi.org/10.1007/978-981-13-3393-4_70

[17] W. Budiharto, "Data science approach to stock prices forecasting in Indonesia during Covid-19 using Long Short-Term Memory (LSTM)," *J. Big Data*, vol. 8, no. 1, 2021, https://doi.org/10.1186/s40537-021-00430-0

[18] R. Cahuantzi, X. Chen, and S. Güttel, "A Comparison of LSTM and GRU Networks for Learning Symbolic Sequences," in *Lecture Notes in Networks and Systems*, 2023, pp. 771–785. https://doi.org/10.1007/978-3-031-37963-5_53

[19] M. O. Alassafi, M. Jarrah, and R. Alotaibi, "Time series predicting of COVID-19 based on deep learning," *Neurocomputing*, vol. 468, pp. 335–344, 2022, https://doi.org/10.1016/j.neucom.2021.10.035

[20] A. C. Ozdemir, K. Buluş, and K. Zor, "Medium- to long-term nickel price forecasting using LSTM and GRU networks," *Resour. Policy*, vol. 78, 2022, https://doi.org/10.1016/j.resourpol.2022.102906

[21] M. Abumohsen, A. Y. Owda, and M. Owda, "Electrical Load Forecasting Using LSTM, GRU, and RNN Algorithms," *Energies*, vol. 16, no. 5, 2023, https://doi.org/10.3390/en16052283

[22] E. R. Ziegel, U. M. Fayyad, G. Piatetski-Shapiro, P. Smyth, and R. Uthurusamy, "Advances in Knowledge Discovery and Data Mining," *Technometrics*, vol. 40, no. 1, p. 83, 1998, https://doi.org/10.2307/1271414

[23] S. H. Javaheri, M. M. Sepehri, and B. Teimourpour, "Response Modeling in Direct Marketing. A Data Mining-Based Approach for Target Selection.," in *Data Mining Applications with R*, 2013, pp. 153–180. https://doi.org/10.1016/B978-0-12-411511-8.00006-2

[24] M. K. Uçar, M. Nour, H. Sindi, and K. Polat, "The Effect of Training and Testing Process on Machine Learning in Biomedical Datasets," *Math. Probl. Eng.*, vol. 2020, 2020, https://doi.org/10.1155/2020/2836236

[25] H. Abhirawa, M. S. Jondri, and A. Arifianto, "Pengenalan Wajah

Menggunakan Convolutional Neural Network Face Recognition Using Convolutional Neural Network," 2017.

[26] A. Santoso and G. Ariyanto, "Implementasi Deep Learning berbasis Keras untuk Pengenalan Wajah," *Emit. J. Tek. Elektro*, vol. 18, no. 1, pp. 15–21, 2018, https://doi.org/10.23917/emitor.v18i01.6235

[27] R. Vinayakumar, K. P. Soman, and P. Poornachandran, "Long short-term memory based operation log anomaly detection," in *2017 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2017*, 2017, pp. 236–242. https://doi.org/10.1109/ICACCI.2017.8125846

[28] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling," Dec. 2014, [Online]. Available: http://arxiv.org/abs/1412.3555

[29] N. Giarsyani, "Komparasi Algoritma Machine Learning dan Deep Learning untuk Named Entity Recognition : Studi Kasus Data Kebencanaan," *Indones. J. Appl. Informatics*, vol. 4, no. 2, p. 138, 2020, https://doi.org/10.20961/ijai.v4i2.41317

[30] N. M. Ashar, I. Cholissodin, and C. Dewi, "Penerapan Metode Extreme Learning Machine (ELM) Untuk Memprediksi Jumlah Produksi Pipa Yang Layak (Studi Kasus Pada PT. KHI Pipe Industries)," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 11, pp. 4621–4628, 2018.

[31] M. V Makridakis, S., Wheelwright S.C, "Metode dan Aplikasi Peramalan," *Ed. Kedua Jilid Satu. Jakarta Erlangga*, vol. 6, no. 1, pp. 48–58, 2017, [Online]. Available: http://journal.unnes.ac.id/sju/index.php/ujm

[32] H. Budiman, "Analisis Dan Perbandingan Akurasi Model Prediksi Rentet Waktu Support Vector Machines Dengan Support Vector Machines Particle Swarm Optimization Untuk Arus Lalu Lintas Jangka Pendek," *Syst. Inf. Syst. Informatics J.*, vol. 2, no. 1, pp. 19–24, 2016, https://doi.org/10.29080/systemic.v2i1.103

[33] "Perkembangan Ekspor dan Impor Indonesia Desember 2023," *Badan Pusat Statistik*, pp. 1–16, 2023.