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COMPARISON OF LSTM AND GRU METHODS FOR FORECASTING OIL-NON-OIL AND GAS EXPORT VALUES IN INDONESIA

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ABSTRACT

The increase significantly influences the growth of Indonesia's economy in export value. While the export value may exhibit some stability, it also experiences fluctuations. However, research primarily focuses on enhancing and boosting export value. This study aims to predict the value of Indonesia's exports of oil-non-oil, and gas by utilizing the Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) techniques. The evaluation of the model is performed using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The findings indicated that the RMSE and MAPE of the LSTM models for the oil and gas components were 0.0668 and 0.9998%, respectively, while for the non-oil and gas components, they were 0.0717 and 0.9999%, respectively. The GRU model yields values of 0.0655% and 0.9998% for oil and gas and 0.0697% and 0.9999% for non-oil and gas. The LSTM model predicts a rise in values for both components, but the GRU model predicts a decline. This variation enables the utilization of models to meet the requirements of export planning. By considering both models, decision-makers can implement flexible strategies that adjust to changes in both the oil and gas export markets and the non-oil and gas export markets.

Keywords: *Export, LSTM, GRU, RMSE, MAPS, Forecasting*

I. INTRODUCTION

The field of Science and Technology (IPTEK) is currently experiencing tremendous advancement, and this progress is closely intertwined with the crucial contribution of mathematics. Mathematics is a fundamental basis that offers numerous advantages in daily life, including its application in making predictions. Prediction anticipates future events by utilizing existing information to minimize inaccuracies or mistakes in such estimates [1].

Export activities are vital for sustaining economic equilibrium in the Indonesian economy. Exports play a crucial role in the country's economy, offering substantial advantages to acquiring foreign currency and boosting national income. However, the export

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industry in Indonesia continues to encounter numerous obstacles, including instability that may lead to a decline in the value of foreign exchange. The export sectors significantly impact Indonesia's economic growth, encompassing the oil and gas and non-oil and gas categories.

The Central Statistics Agency (BPS) has graphically represented data demonstrating the periodic fluctuations in the value of oil and gas and non-oil and gas exports in Indonesia, albeit insignificant. Utilizing prediction tools is essential for evaluating the prospective increase in the value of oil-non-oil and gas exports. Forecasts can help the government develop more effective and appropriate strategies to support economic sectors, particularly those associated with export products.

The time series method is a commonly employed approach for making predictions. Introducing deep learning technology has led to substantial advancements in this strategy. Deep learning enables learning with more intricate layers, improving accuracy and efficiency. Deep learning outperforms traditional methods in forecasting accuracy due to its capacity to represent linear and nonlinear data [2].

A Recurrent Neural Network (RNN) is a deep learning technique employed for long-term learning. Nevertheless, this approach frequently encounters the vanishing or inflating gradient issue when the gradient value diminishes significantly or increases dramatically throughout the learning procedure [3]. Recurrent Neural Network (RNN) utilizes a gate-based structure to retain information for extended durations effectively. Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the two primary variations created to overcome the limitations of RNN.

Long-Short Term Memory (LSTM) is a highly efficient and dependable system for making predictions based on time series data. The LSTM model has three distinct types of gates: input, forget, and output. These gates enable the model to effectively store information over extended periods and address the vanishing gradients commonly encountered in RNN. These three gates collaborate to control data transmission, guaranteeing the retention of relevant information while eliminating superfluous data.

The GRU is a modified version of the RNN that aims to streamline the LSTM structure. GRU is equipped with two distinct sorts of gates: reset gates and update gates. GRU utilizes fewer parameters than LSTM and is characterized by its simplicity, rendering it more appropriate for datasets with limited size and mitigating the likelihood of overfitting. Despite its simplicity, the GRU model can achieve outcomes comparable to the LSTM model while converging faster [4].

Generally, LSTM exhibits greater complexity than GRU due to its utilization of three sigmoid activation functions and two tanh activation functions, whereas GRU employs only two sigmoid activation functions and one tanh activation function. The increased intricacy of LSTM enables it to tackle more intricate issues, whereas GRU offers superior computing efficiency and comparable outcomes.

Multiple studies have been conducted on implementing deep learning algorithms, examining various methods to enhance the accuracy of predictions. Research by Aldi et al. [5] examines time series patterns by considering the number of neurons in the hidden layer, the maximum number of epochs, and the percentage distribution of training and testing data. The results indicate that the constructed model accurately predicts Bitcoin prices.

The study by Saputra et al. [6] focuses on making predictions for sequential data and assesses the model's performance by determining the least Root Mean Square Error (RMSE) values obtained from multiple experiments. The findings indicated that the employed model was quite effective. However, the predictive outcomes were suboptimal due to a significant disparity between the predicted and actual values.

Meanwhile, Arunkumar et al. [7] employed Mean Square Error (MSE) and Root Mean Square Error (RMSE) to assess the performance of their model. The model indicators for forecasting are optimal when the MSE and RMSE values are the minimum.

This study will utilize and compare the RNN method, namely LSTM and GRU, to forecast the export statistics of both oil and gas and non-oil and gas sectors in Indonesia based on the findings of previous studies. This strategy was selected based on its efficacy in producing forecasts with a low margin of error. The measurement of error rates is conducted using Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE). This study aims to provide a forecast for the upcoming two years, specifically 2022 to 2023,

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to aid the government in developing more suitable economic policies.

II. METHODOLOGY

The stages of this study consist of multiple sequential steps, which are outlined as follows:

1. Input export data for both the oil–non-oil and gas sectors, covering the time frame from January 1993 to December 2021.
2. The data is preprocessed by applying normalization using the min-max normalization method, which adjusts the scale of the data to a specific range.
3. Divide the data into training and testing sets using a ratio of 70% for training data and 30% for testing data.
4. Identify the necessary initial parameters, including the number of neurons, dropout rate, batch size, and epoch count.
5. Build LSTM and GRU models through hyperparameter adjustment to enhance model performance.
6. Utilize a constructed model to conduct data predictions.
7. Denormalize the prediction results to their original scale to facilitate comparison with the actual data.
8. Visualize and compare the predicted outcomes with the actual data by creating plots.
9. Evaluate the performance of models built using RMSE and MAPE values.
10. Forecast the future value of oil and gas exports and non-oil and gas exports for the upcoming two years, specifically from 2022 to 2023.

This study aims to construct a precise forecasting model by utilizing past data on oil and gas exports and non-oil and gas exports. Additionally, the study intends to support the government in developing more suitable economic policies by providing accurate predictions for future periods.

2.1. Data Preprocessing

Before conducting the forecasting process, it is vital to do the data preprocessing stage, which encompasses various crucial processes. The preprocessing processes often involve data visualization, eliminating duplicate data, verifying missing values, and data normalization [8].

The preprocessing stage is crucial to ensuring the data utilized in the forecasting process is devoid of errors, precise, and uniform, hence establishing trust in the produced analysis results.

2.1.1. Data Normalization

Data transformation is a crucial phase in data mining, and one of the approaches employed is data normalization [8]. Data normalization is a procedure that involves adjusting data to have a consistent range of values. One often employed technique for this purpose is the min-max normalization method [9].

The data will be altered during normalization to have values ranging from 0 to 1. This adjustment facilitates comparisons between variables and eliminates bias caused by variations in data scale. Equation (1) represents a mathematical expression that standardizes or normalizes data.

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

2.2. Data Splitting

The primary determinant of success in machine learning is the training and testing procedure. A well-designed training method is crucial for enhancing the performance of the generated model. Typically, researchers partition datasets into two subsets, training data and test data, according to a specific criterion. The quantity of data utilized for training and testing significantly impacts a model's efficacy [10].

The literature exhibits varying training ratios to testing data, contingent upon the data's features. Typically, using less than 50% of the training data is not advisable since it can harm the accuracy of model testing. Hence, this study will utilize a data-splitting ratio where the proportion of training data exceeds 50%, explicitly allocating 70% for training data and 30% for testing data.

2.3. Hyperparameter Tuning

When constructing a forecasting model, it is essential to engage in hyperparameter tuning, which involves deciding on the number of neuron units in the model and utilizing dropouts. Optimizing these parameters is

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crucial to avoid overfitting and enhance model performance [11].

In addition, early stopping techniques were also implemented at this time. Early stopping is a method to automatically halt the training process when the model attains the optimal value, preventing overfitting and conserving time and computational resources.

Additional factors to consider are the era and batch size. An epoch refers to a whole iteration during which the entire dataset is utilized to train a neural network model. The duration of an epoch can be significantly extended, mainly when dealing with a sizable dataset.

Consequently, the dataset is partitioned into batches called batch size to expedite the training process. The batch size refers to the quantity of samples processed simultaneously during a single training iteration. This method is highly efficient for processing vast quantities of data, enabling frequent updates of model parameters within a single epoch. The determination of batch size relies on both the available number of samples and the computational power [12].

2.4. Model Building Process

2.4.1. LSTM Model

Long Short-Term Memory (LSTM) is a machine learning technique built using Recurrent Neural Network (RNN) architecture. The LSTM architecture comprises three layers: the input layer, the hidden layer, and the output layer [3]. Every layer has a distinct function in data processing and information transmission. The LSTM architecture is visually represented in Figure 1, illustrating the interconnections between each layer in an LSTM network.

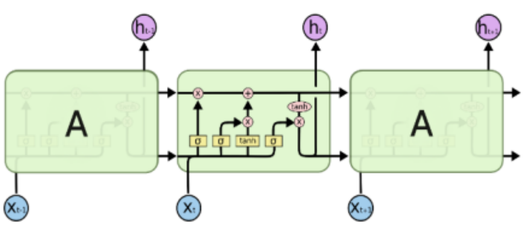

Figure 1. *LSTM architecture*

The memory cells in LSTM architecture are a crucial layer component with three primary gates: the forgot gate, the input gate, and the output gate [13].

1. **Forgot** gate determines whether incoming information should be retained or discarded in the cell state. This method utilizes the preceding output data h_{t-1} and current input data x_t by Equation (2) as stated:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \quad (2)$$

2. **Input gate**: is a gate that has two activation functions: sigmoid and tanh. The activation function is responsible for modifying the cell state according to Equation (3):

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \quad (3)$$

3. **Output gate**: This gate determines the specific portion of the cell state that will be produced as output. This decision is made based on the input and memory cell, using Equation (4):

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_0) \quad (4)$$

The deciphered LSTM cell's primary advantage is its ability to correlate information from a previous time with information that enters later, thereby enabling it to capture and store information over an extended period. This capability is particularly critical in processing time series data, as it is frequently necessary to incorporate past data to make precise predictions.

2.4.2. Model GRU

Chung et al. [14] introduced the Gated Recurrent Unit (GRU) to refine the RNN model. The GRU model is a simplified version of LSTM but remains influential in resolving sequential data issues. GRU has become a favoured choice in sequential data applications due to its more efficient and straightforward design. The presence of a control mechanism for the entry and exit of information from the GRU is one of its most significant characteristics. This mechanism, which comprises a reset gate and an update gate, is called a gate [14]. The GRU architecture is visually depicted in Figure 2 as follows:

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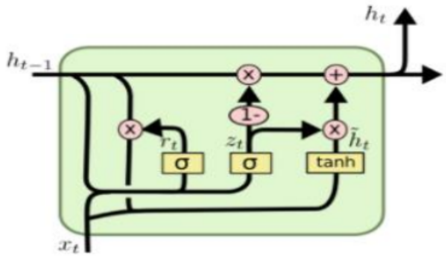

Figure 2. *GRU architecture*

1. **Update gate**: utilized to ascertain the amount of historical data that is still stored, as indicated by Equation (5):

$$z_t = \sigma\left(W_z * \left[h_{t-1,}x_t\right] + b_z\right) \tag{5}$$

2. **Reset gate**: utilized to integrate new input data with historical data by employing the subsequent Equation (6):

$$r_t = \sigma(W_r * \left[h_{t-1,}\ x_t\right] + b_r) \tag{6}$$

2.5. Denormalization

Denormalization is reverting the output of prediction data to its actual value [16]. That is necessary because the prediction data generated by the model is still in a normalized form, which is to say, in the form of a specific interval. Normalization is the initial phase employed to scale data in order to facilitate the processing of predictions by algorithms. Nevertheless, to be interpreted accurately through Equation (7), the data must be converted back to its original scale after making the prediction.

$$X_t = x'(X_{max} - X_{min}) + X_{min} \tag{7}$$

In this Equation, X_t represents the original value that has been denormalized, x' is a predicted value that is still in normalized form, X_{max} represents the maximum value of the original data before normalization, and X_{min} represents the minimum value of the original data before normalization. This process guarantees that predicted values previously within the normalization interval are rescaled to their original value scale, enabling the data to be utilized for additional analysis.

2.6. Model Evaluation

Makridakis et al. [17] assert that the accuracy of a forecasting model or the accuracy of a forecasting model is determined by the model's capacity to replicate known data. Accuracy measures the model's capacity to generate predictions that closely resemble the data.

Several specific error metrics are employed to assess the model's accuracy, as per Budiman [18]. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are among the most frequently employed metrics.

1. **MSE**: calculate the average of the squared difference between the actual and predicted values using Equation (8) as follows:

$$MSE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n} \tag{8}$$

2. **RMSE**: ascertains the degree of error or deviation between the model's predicted value and the observed value. For mathematical purposes, the formula in Equation (9) is employed to calculate RMSE as follows:

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

3. **MAPE** conveys the prediction error as a percentage of the actual value, which facilitates the interpretation of the error's relative magnitude to the actual value. The MAPE value is determined using Equation (10) as the underlying equation.

$$MAPE = 100\% \times \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \tag{10}$$

III. RESULTS AND DISCUSSION

3.1. Data Input and Selection

The data utilized in this study are the values of oil and gas and non-oil and gas exports from January 1993 to December 2021, with 348 data points for each category. A sample of the data that will be utilized is presented in Table 1 as follows:

Table 1. *Export data samples*

Period	Export value	
	Oil and 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
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

3.2. Data Preprocessing

3.2.1. Time Series Data Visualization

Preprocessing data necessitates the completion of numerous critical stages. Visualizing time series data plots is one of the initial stages in comprehending the data's patterns and characteristics. These visualizations assist researchers in identifying trends, seasonal patterns, or anomalies in the data. Figure 3 illustrates the outcomes of the time series data visualization.

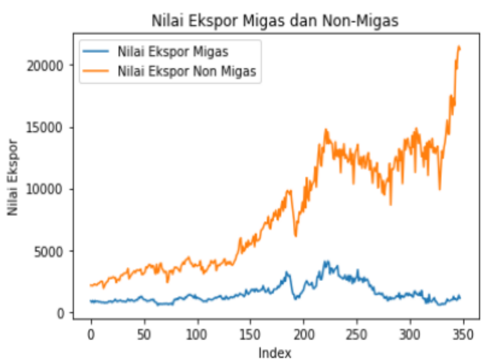

Figure 3. *Time Series Plot*

3.2.2. Data Normalization

Data transformation is the subsequent phase following the completion of data visualization. The min-max normalization method is employed in this study to adjust the data to ensure that all values fall within the range of 0 to 1. Table 2 displays examples of data that have undergone the normalization procedure.

Table 2. *Data normalization results*

Index	Export value	
	Oil and 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

3.3. Data Splitting

The data that is to be divided at this stage is normalized data. The data is partitioned into two sets: test data and training data. The data in this study is divided into 70% training data and 30% testing data, as detailed in Table 3.

Table 3. *Composition of splitting data*

No	Data	Total
1.	Training	243
2.	Testing	105

3.4. Hyperparameter Tuning

Hyperparameter tuning is conducted to ascertain the optimal values of parameters to be employed in model-testing situations. Several parameters are modified, including the number of units, which influences the quantity of LSTM and GRU units, dropouts, epochs, and batch size. The set of parameters obtained from this hyperparameter tuning method is presented in Table 4 and Table 5.

Table 4. *LSTM optimal parameter combination*

Parameter	Export	
	Oil and 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. *The optimal combination of parameters GRU*

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

In addition, the training results produced by combining parameters from the hypertuning procedure are presented in Table 6.

Table 6. *Comparison of loss function and running time*

Model	Export	Loss function	Running time
LSTM	Crumbs	0.00506	300.13 s
	Non-oil	0.00095	300.24 s
CRANE	Crumbs	0.00402	300.18s
	Non-oil	0.00080	300.18s

Table 6 demonstrates that the GRU model exhibits a lower loss function than the LSTM model. A lower loss function value signifies that the GRU model outperforms the LSTM model regarding learning performance. Moreover, the GRU model also demonstrates superior efficiency in training time and computational requirements. Consequently, GRU models provide more accurate predictions and demand less time and computational resources for training. This efficiency renders GRU a superior choice over LSTM in this particular scenario.

3.5. Prediction Results

Once the ideal parameter values for each model have been determined, the next step is to denormalize the data. Denormalization is converting data back to its original range of values after it has been normalized. The data, first normalized to a range of 0 to 1, is now restored to its original scale.

The model's anticipated outcomes will be compared to the data following the denormalization procedure. This comparison is conducted via visual representation in the form of a graph.

Figures 4 to 7 represent the predicted values of oil and gas exports and non-oil and gas exports in Indonesia. These figures were obtained following the denormalization and data visualization procedure. This plot demonstrates the model's capacity to accurately forecast export values, allowing for direct comparison with the actual data.

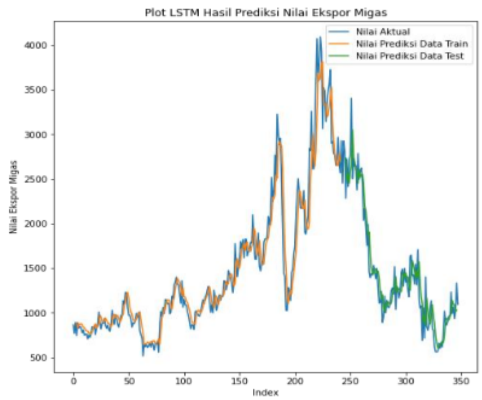

Figure 4. *LSTM plot for oil and gas export*

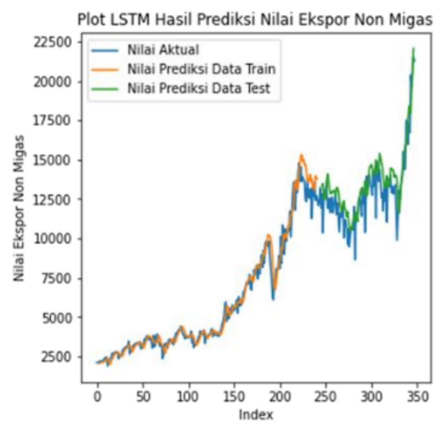

Figure 5. *LSTM plot for non-oil and gas*

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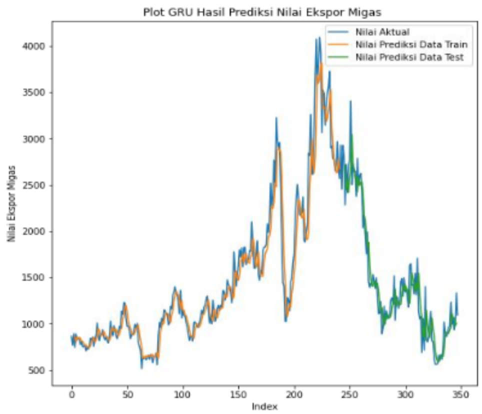

Figure 6. *GRU Plot for Oil and Gas Export*

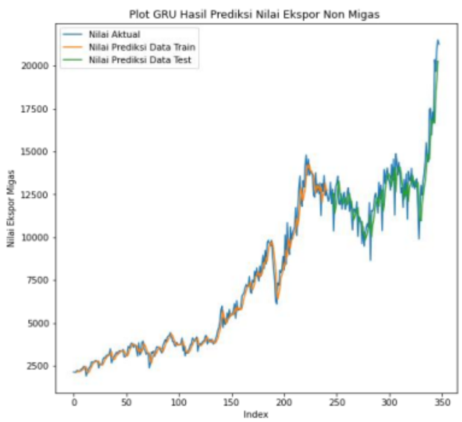

Figure 7. *GRU Plot for non-oil and gas export*

Figures 4 to 7 depict the expected results using LSTM and GRU models in a plot representation. The four photos depict a composite graph illustrating the correlation between the predicted results and the actual data for export values of oil and gas and non-oil and gas commodities.

The blue line in the graphic represents the factual data, precisely the accurate values of oil and gas exports and non-oil and gas exports. The training data is designated orange, whereas the test data is designated green. The x-axis index corresponds to the variable of time.

The plot visualization shows that the model's predictions closely align with the data patterns. Next, to provide a clear understanding of the numerical analysis, the comparison of forecast outcomes and actual data for each export component is presented in Table 7 and Table 8.

Table 7. *Comparison of oil and gas prediction results*

Period	Oil and gas components (Million US$)		
	Actual value	**Predictions LSTM**	**Predictions GRU**
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 8. *Comparison of non-oil and gas prediction results*

Period	Non-oil and gas components (Million US$)		
	Actual value	**Predictions LSTM**	**Predictions GRU**
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

Upon comparing the prediction results presented in Table 7 and Table 8, it can be concluded that the disparity between the predicted outcomes and the actual data is negligible. The forecasted data indicates a decline in oil and gas exports and an increase in non-oil and gas exports, aligning with the observed data. Therefore, it can be inferred that the LSTM and GRU models constructed for the prediction process are deemed proficient and capable of generating precise predictions.

3.6. Evaluation of Prediction Results

The prediction results are evaluated by utilizing RMSE and MAPE values to quantify the degree of proximity between the predicted outcomes and the actual data. Table 7 and Table 8 present the outcomes of model assessment for two types of models, specifically LSTM and GRU, on export components of both oil and gas and non-oil and gas.

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Table 7. *LSTM model evaluation*

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

Table 8. *Evaluation of the GRU model*

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

The MAPE values for oil and gas and non-oil and gas components in the LSTM model, as determined from Table 7 and Table 8, are 0.9998% and 0.9999%, respectively. Similarly, in the GRU model, the MAPE values for these components are also 0.9998% and 0.9999%. When the MAPE number is below 10%, both models have great predictions, each achieving an accuracy rate of 99%.

Furthermore, the RMSE values for the oil and gas and non-oil and gas components indicate that the GRU model exhibits lower RMSE values than the LSTM model. Specifically, the GRU model has RMSE values of 0.0655 and 0.0697, whereas the LSTM model has RMSE values of 0.0668 and 0.0717. While LSTM and GRU models exhibit modest variations in computation times, GRU models outperform LSTM models in terms of RMSE values for both oil and gas and non-oil and gas components.

Therefore, it can be inferred that the GRU model outperforms the LSTM model in forecasting the values of oil and gas components and non-oil and gas components, as shown by the evaluation using RMSE and MAPE.

3.7. Forecasting Results

Once the model review confirms satisfactory performance, the subsequent task involves conducting a two-year projection for the period spanning from January 2022 to December 2023. The export value of oil and gas and non-oil and gas components in Indonesia is visualized through plots in Figure 8 to Figure 11. These plots depict both the preliminary data and the forecasting outcomes.

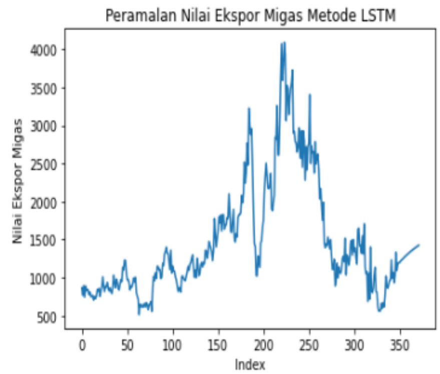

Figure 8. *LSTM forecasting results for oil and gas*

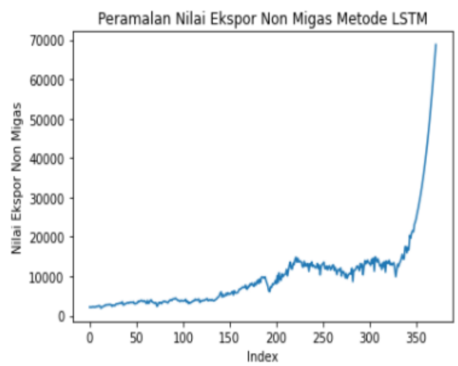

Figure 9. *LSTM forecasting results for non-oil and gas*

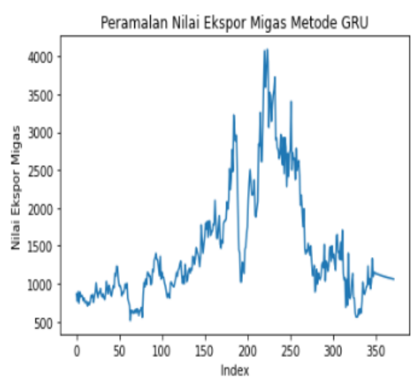

Figure 10. *GRU forecasting results for oil and gas*

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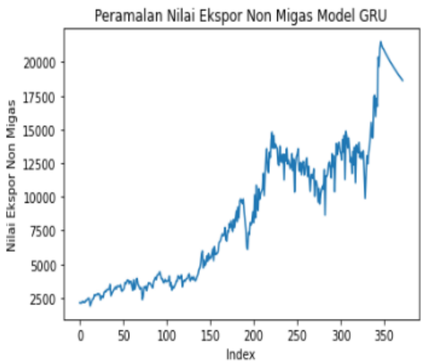

Figure 11. *GRU forecasting results for non-oil and gas*

Figure 8 and Figure 9 display the outcomes of predictive analysis utilizing LSTM models for both the oil and gas sector and the non-oil and gas sector. These two graphs indicate that the projected value of oil and gas exports and non-oil and gas component exports in Indonesia has shown a general growth from January 2022 to December 2023.

Figure 10 and Figure 11 exhibit the predicted outcomes of the GRU model for both the oil and gas sector and the non-oil and gas sector. These two data indicate that the projected value of oil and gas exports and non-oil and gas component exports in Indonesia is expected to decline during the same time.

Based on the visual representation of the forecasting data, it can be inferred that the LSTM and GRU models yield distinct predictions for future periods. The LSTM model demonstrates an upward trend in export values, but the GRU model exhibits a decline. This disparity can offer valuable insights for decision-makers when formulating plans for exporting oil and gas and non-oil and gas commodities.

The forecasting results for January 2022 to December 2023, utilizing the LSTM and GRU models for each export component, are presented in Table 9 and Table 10, respectively.

Table 9. *LSTM model forecasting results*

Period	LSTM	
	Oil and gas (Million US$)	**Non-oil and gas (Million US$)**
Jan 2022	1.179,802	23.137,773
Feb 2022	1.195,587	23.843,038
March 2022	1.198,399	24.707,264
…	…	…
Oct 2022	1.288,275	34.312,112
Nov 2022	1.299,506	36.030,256
Dec 2022	1.310,484	37.872,655
…	…	…
Jan 2023	1.321,211	39.829,454
Feb 2023	1.331,691	41.902,378
March 2023	1.341,927	44.102,033
…	…	…
Oct 2023	1.407,136	62.736,247
Nov 2023	1.415,582	65.741,735
Dec 2023	1.423,823	68.775,988

Table 10. *GRU model forecasting results*

Period	GRU	
	Oil and gas (Million US$)	**Non-oil and gas (Million US$)**
Jan 2022	1.143,512	20.986,772
Feb 2022	1.148,036	20.844,326
March 2022	1.131,287	20.715,630
…	…	…
Oct 2022	1.104,574	19.904,826
Nov 2022	1.100,761	19.797,442
Dec 2022	1.097,063	19.692,059
…	…	…
Jan 2023	1.093,477	19.588,598
Feb 2023	1.089,999	19.486,998
March 2023	1.086,624	19.387,199
…	…	…
Oct 2023	1.065,686	16.108,223
Nov 2023	1.063,046	18.734,612
Dec 2023	1.060,485	18.647,387

IV. CONCLUSION

According to the model evaluation results, the GRU method accurately predicted both components using RMSE. Specifically, the oil and gas component had an RMSE value of 0.0655, while the non-oil and gas component had an RMSE value of 0.0697.

Mean Absolute Percentage Error (MAPE) is employed to evaluate the precision of predictions for both components. The MAPE value of the LSTM method is 0.9998% for oil and gas components and 0.9999% for non-oil and gas components. The MAPE value for oil and gas components is 0.9998%, while it is 0.9999% for non-oil and gas components in the GRU method. The MAPE value of less than 10% suggests that both methods are highly predictive in predicting the value of oil and gas and non-oil and gas exports.

The forecasting results indicate that the LSTM method anticipates increased oil and gas and non-oil and gas components from 2022 to 2023. Conversely, the GRU method demonstrated a reduction in predictions for both components.

These findings indicate that the predictions of the LSTM and GRU models differ and can be adjusted to meet the specific requirements and objectives of export planning. Decision-makers can develop strategies that are more adaptable and responsive to prospective changes in oil and gas and non-oil and gas export markets by incorporating information from both models.

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