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Multi-industry stock forecasting using GRU-LSTM deep transfer learning method

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Abstract — After the Covid-19 pandemic, the number of investors in Indonesia has proliferated. In managing a good stock portfolio, investors need the right strategy too. One approach that can be applied is to predict stock movements by considering the company's industrial sector. This paper proposed a new framework for applying deep transfer learning for stock forecasting in multi-industry. The model used in the framework is a combined algorithm between gated recurrent unit (GRU) and long-short term memory (LSTM). The author built the pre-trained model using *indeks harga saham gabungan* (IHSG) and transferred it to predict Indonesia's stock indexes based on industry classification (IDX-IC) as the measurer of stock movement in multiple industries. The outcomes reveal that this framework produces good model predictions and can be used to help analyze the evaluation of the pre-trained model to conduct transfer learning stock prediction in different industries efficiently. The model built using the IHSG indexes can predict stock prices best in the energy, technology, and industrial sectors.

Keywords – GRU, IHSG, IDX-IC, LSTM, stock forecasting, transfer learning

I. Introduction

The Covid-19 pandemic has immensely influenced stock market volatility [1]. There are difficulties in recovering stock market conditions due to the shock caused by COVID-19. The fact that, in general, investors have a more excellent perception of risk related to a vulnerability in economic and social conditions explains this phenomenon [2]. However, the research findings suggest that stock prices in specific industries have become more predictable during the COVID-19 crisis, which implies that stock prices are heavily influenced by external factors, such as the COVID-19 crisis, and no longer reflect only available information about a company [3]. 2022 is the year when the Covid-19 pandemic begins to subside. Despite the global turmoil, the Indonesian capital market has made several positive achievements, for example, the increase in Indonesian investors. The number of investors in the Indonesian capital market increased by 37.5 percent on December 28, 2022, to 10.3 million from 7.48 million at the end of December 2021. This number has increased almost nine times compared to the last five years [4].

The number of investors in Indonesia is growing, so they must be aware of managing their financial asset portfolios. Previous research related to the behavior of the millennial generation in managing a portfolio of financial support concluded that millennials, as investors, still need to pay attention to the risks that may occur from investing in stocks. They tend to prioritize risk management less when investing in stocks [5]. Investors should better understand the changes in stock trends over time. Changes in stock trends often affect where the economy is moving. One of the factors that caused such a difference in direction is the type of industry [6]. Industry classification helps external parties such as market analysts, researchers, and investment managers conduct industry analysis. Industry classification can also serve as an industry-specific stock indicator, which can then help manage investment products [7].

One strategy investors can apply is forecasting stock prices in an industry. Stock price forecasting has become challenging and attracted many computer science and financial market analysis researchers. Accurate forecasting of stock movements can assist investors in deciding to make the decision on their assets and reduce unexpected risks [8]. Nevertheless, remember that forecasting the exact value of shares is impossible due to the complexity and uncertainty that drives the value of shares [9]. Even so, studying the previous movement patterns of stocks can be used as a reference for investors in predicting and managing their assets.

This study will try to predict stock prices using Deep Learning approaches on multi-industry stock data. Deep Learning methods, such as gated recurrent units (GRU) and long short-term memory (LSTM), have emerged as practical approaches to stock price prediction due to their capability to model complex temporal relationships and have successfully built an effective prediction model in previous studies [10]–[17]. The key difference between the GRU and LSTM models is the LSTM model uses a more complex memory mechanism that allows it to learn and remember long-term dependencies in the input data while the GRU model uses a simpler gating mechanism that allows it to learn and remember short-term dependencies more efficiently. The use of both GRU and LSTM models in this framework could provide the benefits of both models, allowing it to handle a wider range of input data and achieve higher accuracy in the predictions [11]. Therefore, this study will use a prediction model architecture combining GRU and LSTM.

To see the effectiveness of the model's performance in predicting multi-industry stock prices, in this paper, stock index data based on industry classification launched by the Indonesia stock exchange (IDX) under the name Indonesia stock exchange industry classification (IDX-IC) as a representation of the movement of shares of companies in Indonesia with different industries. The author chose IDX-IC because it is an index that measures the price performance of whole Indonesian stocks based on the company's industry as classified by the bursa efek Indonesia (BEI) [18]. However, with the amount of data still limited to IDX-IC which just launched in January 2021, it will be challenging to build an optimal prediction model. It will be better if extensive training data is used to make a deep-learning model for accurate stock price predictions. The greater the amount of training data, the model can read patterns in data effectively [8], [19].

This study used a transfer learning method to overcome the data limitation problem on IDX-IC history price data. The transfer learning approach allows the creation of a model that can work more optimally by utilizing a more significant amount of data. Prior studies found that using transfer learning methods in modeling time-series data can increase the accuracy of predictions [20]–[22]. The better results of the models created with transfer learning prove this. Transfer learning can improve prediction accuracy by properly selecting datasets as model builders [23]. Research conducted by Ozer *et al.* [24] concluded that Transfer Learning allows pre-trained models on related tasks or domains to improve the learning process and the generalization ability of new models on specific targets. Beyond addressing the problem of data limitation, the transfer learning method is also used to develop a generalized model that can accurately predict stock prices across various industrial companies.

IHSG was selected as training data for the pre-trained model since IHSG is a broad market index, it can provide a good foundation for transfer learning to predict stock prices for multi-sector industry companies. The pre-trained model can learn general patterns and trends that are common across the market, which can then be applied to predict stock prices for companies within different sectors represented by the IDX-IC stock indexes. The model's performance will then be analyzed after performing transfer learning on the different industries using IDX-IC data.

In this paper, we propose a new framework named multi-industry stock forecasting using deep transfer learning (MSF-DTL) to evaluate pre-trained models built using a combined architecture of the GRU-LSTM algorithm in predicting stocks in different industries. In short, there are some stages in this framework. The first is to build a pre-trained model using the selected dataset as training data. The author of this paper used the Composite Stock Price Index (IHSG) dataset in their study. In the second stage, the author conducts predictions on multi-datasets using the pre-trained model that could be used as a reference for evaluating model predictions with different industries. The author used ten IDX-IC indexes in this study, representing the combined stock price in each industrial sector. Finally, the author analyzed the model evaluation results in each industry.

Furthermore, the use of the MSF-DTL framework is expected to be an option for professionals such as market analysts, researchers, or investors to help evaluate deep learning pre-trained models in conducting stock prediction and performing analysis for multi-sector industry companies. The MSF-DTL framework can help to overcome data limitation problems and facilitate the creation of a more accurate and robust stock prediction model for different industrial companies. This study also provides insights into the effectiveness of the GRU-LSTM model for predicting stock prices using transfer learning.

II. Multi-Industry Stock Forecasting using Deep Transfer Learning (MSF-DTL)

In developing this paper, there are four main steps: research introduction and background, MSF-DTL framework design process, conduct experiment on stock forecasting using MSF-DTL framework, and describing experiment result. The flow of stages in this study can be seen in Fig. 1.

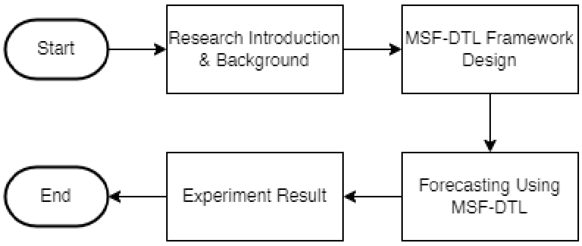


Fig. 1. Stage of research.

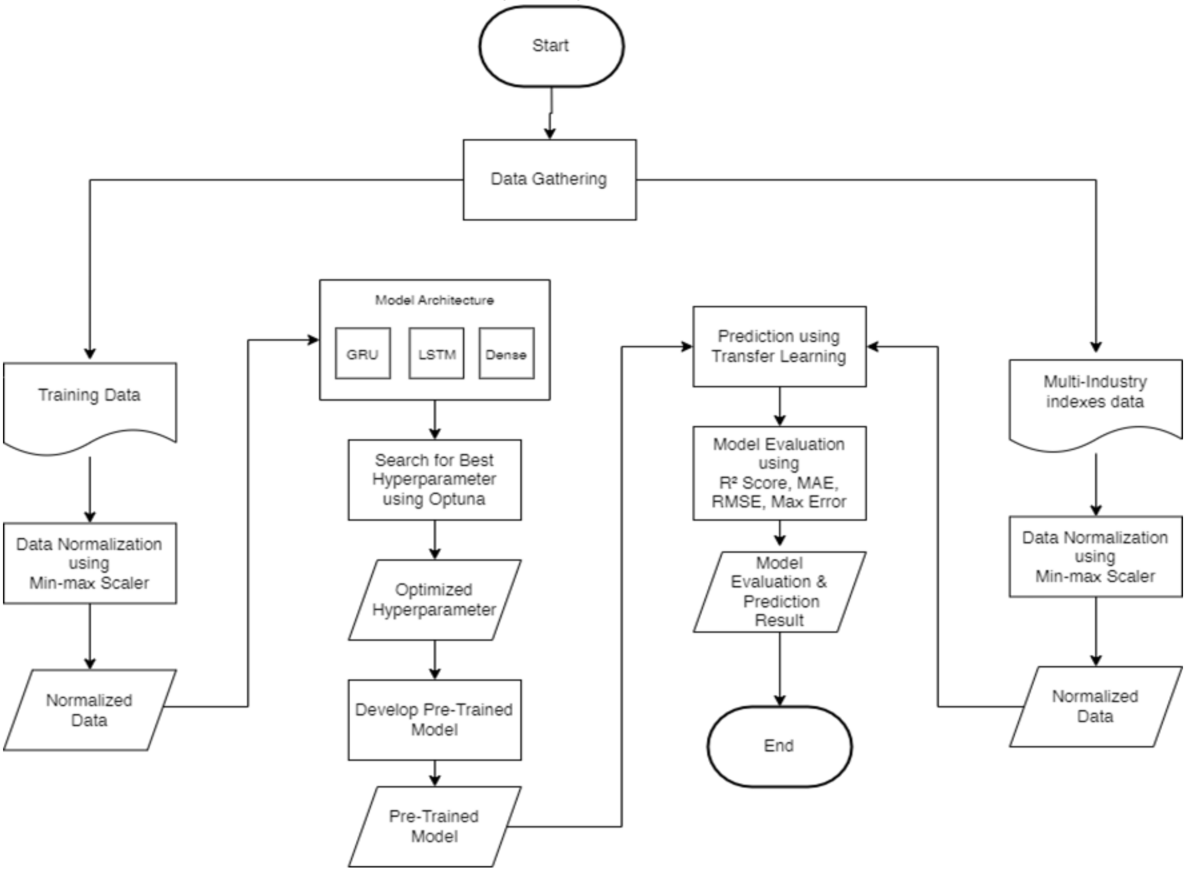


Fig. 2. Multi-industry stock forecasting-deep transfer learning.

In the stage of introduction and background of the research problem, the author describes the problems that occur in stock predictions using deep transfer learning methods in different industries, along with the proposed solution to overcome these problems. The output of this stage is a description of the research problem and the proposed solution.

The second stage is the MSF-DTL framework design process, which defines the work steps and methods used to overcome the problems identified in the first stage. This includes building a pre-trained model using a selected dataset as the training data, performing transfer learning for each dataset, and evaluating the model's performance using different metrics. MSF-DTL can help researchers to analyze the evaluation of pre-trained deep learning models in predicting stocks in different industries. The output of this stage is a model of the MSF-DTL framework, which serves as the basis for conducting experiments on stock forecasting. In detail, the flow of the MSF-DTL framework can be seen in Fig. 2.

A. *Data Collection*

Data gathering is the process of collecting data for research. This study collected data on several stock indices in Indonesia. It needed two types of stock index data: training and test data. The training data used to build the model is Indeks Harga Saham Gabungan (IHSG) from 2001 to 2021 to build a model. Furthermore, the model will try to do prediction on ten stock indexes of the IDX-IC in 2022.

This study used daily closing price data on each pre-determined stock index. The data is retrieved through the site id.investing.com [25], a financial platform that provides various information about the world of stocks, including historical data on stock index prices needed to conduct stock prediction.

B. *Data Normalization*

The min-max normalization method carries out a normalization process on the collected data. Normal-

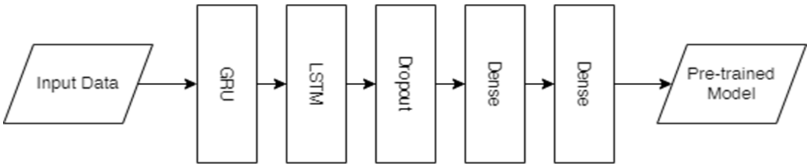


Fig. 3. MSF-DTL pre-trained model architecture.

ization converts numeric values in the data set to a standard scale without distorting the difference in the range of values [26]. Min-max normalization performs a linear transformation of the input data whose value is between the highest value being the value of 1 and the lowest data being the value of 0. The min-max normalization method carries out the calculation using (1).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X is the data to be normalized, X_{min} is the minimum value of the entire data, and X_{max} is the maximum value of the overall data.

C. Model Architecture

This research utilizes GRU and LSTM algorithms in building a pre-trained model. Previously normalized data will be trained and made a pre-trained model. Pre-trained model training will use an arrangement of layers to create a model architecture.

1) GRU

Gated recurrent unit (GRU) is a neural network architecture that can model sequential data such as stock price data [27]. The GRU has several gates, namely the reset and update gates, allowing the model to control the data flow at each time step [28]. The GRU can predict stock prices due to its ability to consider historical information in sequential data [14]. The calculation of GRU is done using (2), (3), (4), (5).

$$z_t = \sigma(w_z x_t + U_z h_{t-1} + b_z) \quad (2)$$

$$r_t = \sigma(w_r x_t + U_r h_{t-1} + b_r) \quad (3)$$

$$\tilde{h}_t = \tanh(w_h x_t + U_h(r_t * h_{t-1}) + b_h) \quad (4)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (5)$$

where, x_t is the input at the time of the step t, h_t is the output at the time of the step t, $\tilde{h}_t$ the new memory content at the time of the step t, $h_{(t-1)}$ is the previous output (or memory content) at the time step $t-1$, z_t is the activation gate update at step t time, which controls how much of the previous memory content should be stored and how much new memory content will be used, r_t is the activation of the reset gateway at the time of step t, which controls how much of the previous output should be forgotten, σ is a sigmoid function, $*$ is a symbol of multiplication, W and U is the metric weight, and b is the bias vector.

2) LSTM

Long short-term memory (LSTM) is one of the recurrent neural network architectures used to model sequential data such as stock prices [29]. LSTM has a complex network structure and can solve the problem of vanishing gradients from sequential data [30]. Using LSTM in stock price forecasting can improve accuracy compared to linear regression models. LSTM models can be optimized using ensemble, transfer learning, and unsupervised learning methods [30].

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (6)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_i) \quad (7)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_i) \quad (8)$$

$$c_t = f_t * c_{t-1} + i * \sigma(W_c x_1 + b_c) \quad (9)$$

$$h_t = o_t * \tanh(c_t) \quad (10)$$

where, x_t is the input at the time of the step t, h_t is the output at the time of the step t, c_t is the contents of the memory cell at the time of the step t, h_{t-1} and c_{t-1} is the previous output and the contents of the memory cell at the time step $t-1$, i_t, f_t, and o_t is the activation of the input gate, forget gate, and output gate at step time t, respectively, σ is a sigmoid function, $*$ is a symbol of multiplication, W and U is the metric weight, and b is the bias vector.

3) GRU-LSTM Model

MSF-DTL framework develop a pre-trained model using a combined algorithm between GRU and LSTM. The model uses GRU as the first layer and LSTM as the second layer, a dropout layer and finally two dense layers. The first Dense layer takes the output of the previous LSTM layer and applies a linear transformation to it. This layer adds more complexity to the model by introducing more non-linearity and helping the model to learn more complex patterns from the input sequence. The second Dense layer produces the final output of the model as a single scalar value that represents the predicted target value for the given input sequence.

The model architecture can be seen in Fig. 3. The implementation will use previously normalized data as training data. One of the python libraries often used to build artificial intelligence models, namely TensorFlow, will assist in the implementation. Using the Tensorflow library, users can quickly implement GRU and LSTM algorithms and perform hyperparameter tuning on individual models. The performance of models with this architecture will be compared with other models developed using Dual Layer LSTM and Dual Layer GRU.

D. Hyperparameter Optimization

In designing this model architecture, it is necessary to consider factors such as the number of neurons, learning rate, dropout rate, batch size, and the most optimal epoch. The most optimal hyperparameter search method in this framework used Optuna. Optuna is a Python library that can optimize model hyperparameters using bayesian optimization techniques [31]. This bayesian optimization technique has been used in many previous studies and provides effective results [32]–[34].

In this framework, the output of running hyperparameter optimization using Optuna generates the number of neurons, learning rate, dropout rate, batch size, and the best epoch for later data training in making prediction models.

E. Pre-trained Model Development

After determining the best hyperparameters, the training process for IHSG data is carried out. This framework used the Adam optimization algorithm to optimize the model's performance in the data training process. Adam's optimization algorithm is commonly used in deep learning to optimize models, including in predictions using deep learning [35]. Adam stands for Adaptive Moment Estimation. This algorithm combines the concepts of the stochastic algorithm gradient descent and the momentum algorithm [26]. Previous studies have shown that Adam's algorithm performs well predicting time series [37]–[39]. The model that has been compiled and developed is then stored for model evaluation of the test data with different datasets.

F. Transfer Learning

Transfer Learning is one of the techniques in Machine Learning. Transfer Learning aims to perform modeling using one or more data sources that will later be used to make predictions in the target data [40]. In this framework, Transfer Learning was used to overcome the problem of limited data on the IDX-IC stock index. The prediction model, which was developed using IHSG as training data with daily stock data for twenty years, will be transferred to the data of ten IDX-IC stock indices within one year.

G. Model Evaluation

The evaluation of the model in this framework uses three metrics, namely R2 Score, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), to be able to determine the level of model accuracy in predictions made on ten stock indices based on the IDX-IC industrial sector. In this study, all model evaluation results are calculated on normalized data.

1) R^2 Score (Coefficient of Determination)

R^2 Score is a measure of the performance of a regression model that measures how well the model can explain the variance in the target variable. The R^2 Score ranges between 0 and 1, where a higher value indicates a better model. R^2 Score is obtained using (11).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \tag{11}$$

where, y is the actual value, $\bar{y}$ is the average value of y, and $\hat{y}$ is the predicted value of y.

2) Mean Absolute Error (MAE)

MAE is the average of the absolute errors of each prediction. MAE measures the average absolute error of the model and is used to understand how close the prediction is to the actual value. MAE is obtained using (12).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{12}$$

where, y is the actual value and $\hat{y}$ is the predicted value of y.

3) Root Mean Squared Error (RMSE)

RMSE is the root of the squared error mean of each prediction. RMSE measures the variance of errors and is commonly used to compare the performance of regression models. RMSE is obtained using (13).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{13}$$

where, y is the actual value and $\hat{y}$ is the predicted value of y.

Working through this framework results in the value of R^2 Score, MAE, and RMSE from evaluating the model in each of the existing industrial datasets. The third stage of this study involves conducting experiments on stock forecasting using the MSF-DTL framework. This involves gathering the necessary data, building the pre-trained model, performing transfer learning for each dataset, and obtaining model evaluation results for each test data. The final output of this stage is the model evaluation result for each test dataset, which will be used in the next stage. In the final stage, the author analyzes the model evaluation results obtained from the MSF-DTL framework in each industry. The author compares the model's performance with the metrics used in the MSF-DTL framework and presents and discusses the results. Based on the findings, conclusions are drawn.

Overall, this research methodology follows a systematic approach, starting from defining the research problem and proposing a solution to overcome it, designing a framework to implement the proposed solution, conducting experiments to test the framework's effectiveness, and analyzing the results to draw conclusions and make recommendations.

Table 1. Information and Data Allocation

No.	Indexes Code	Description	Year Range	Amount of Data	Data Usage
1	IHSG	An index that measure the price performance of all stocks listed on both the Main Board and Development Board of the Indonesia Stock Exchange	2001 – 2021	5096	Train Data
2	IDXENERGY	Index that measure the price performance of stock prices in Indonesia in the energy industry sector	2022	246	Test Data
3	IDXBASIC	Index that measure the price performance of stock prices in Indonesia in the raw goods industry sector	2022	246	Test Data
4	IDXINDUST	Index that measure the price performance of stock prices in Indonesia in the industrial industry sector	2022	246	Test Data
5	IDXNONCYC	Index that measure the price performance of stock prices in Indonesia in the primary consumer goods industry sector	2022	246	Test Data
6	IDXCYCLIC	Index that measure the price performance of stock prices in Indonesia in the non-primary consumer goods industry sector	2022	246	Test Data
7	IDXHEALTH	Index that measure the price performance of stock prices in Indonesia in the health industry sector	2022	246	Test Data
8	IDXFINANCE	Index that measure the price performance of stock prices in Indonesia in the financial industry sector	2022	246	Test Data
9	IDXTECHNO	Index that measure the price performance of stock prices in Indonesia in the technology industry sector	2022	246	Test Data
10	IDXINFRA	Index that measure the price performance of stock prices in Indonesia in the infrastructure industry sector	2022	246	Test Data
11	IDXTRANS	Index that measure the price performance of stock prices in Indonesia in the transportation & logistics industry sector	2022	246	Test Data

III. Result

The data collected is price data from eleven stock indices according to the Indonesia Stock Exchange through the id.investing.com website with the information listed in Table 1.

Of the eleven data, the IHSG index will be used as data that will be used as training data in developing prediction models. The data used as training data is daily data on stock index close prices throughout 2001-2021 with a total of twenty years and totaling 5096 data.

Fig. 4 shows the trend from IHSG history price data which is used as training data to build the model. It can be seen that the IHSG price strengthened year on year from 1991 to 2021 and only experienced a slight decline in certain periods. With this pattern, IHSG is relatively stable. This stability can make the pre-trained model more robust, reducing the risk of overfitting or underfitting the data.

As for the test data, there are ten IDX-IC stock indexes. Each test data used is daily data on the closing price of the IDX-IC index throughout 2022, which amounts to 246 data.

Fig. 5 shows the trend from ten indexes of normalized IDX-IC history price data on each industry. The trend for each industry has different patterns. It indicates that the stock prices of companies within each industry are influenced by different factors, and therefore exhibit unique patterns and trends. Therefore, it becomes a challenge to build a model that can predict the different patterns that exist in each industrial sector.

There are three models to be developed: the combined model between GRU-LSTM as the main model used in MSF-DTL and then Dual Layer LSTM and Dual Layer GRU as the comparison. Each model has five layers, with the details shown in Table 2.

Table 2. Model Details

Model	Layer Arrangement	Number of Trainable Parameters
GRU-LSTM	GRU, LSTM, Dropout, Dense, Dense	30751
Dual Layer LSTM	LSTM, LSTM, Dropout, Dense, Dense	33201
Dual Layer GRU	GRU, GRU, Dropout, Dense, Dense	25851

The Dual Layer GRU model has the least trainable parameters, and the LSTM Dual Layer has the most trainable parameters. The GRU-LSTM model that will be used as a focus of this study has fewer trainable parameters than Dual Layer LSTM but still more than Dual Layer GRU.

Each model uses the same data input. Before being fitted into the model, the data that has been collected is normalized with the Min-Max Scaler. Once normalized, data is fed into the model to proceed to the

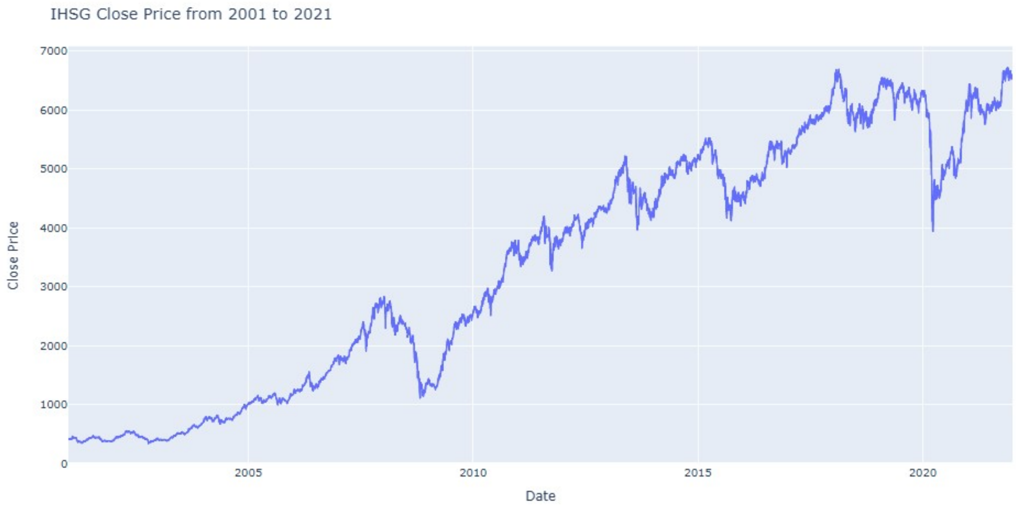


Fig. 4. IHSG close price from 2001 to 2021.

Fig. 5. Normalized 10 IDX-IC indexes close price in 2022.

process of searching for the most optimal hyperparameters.

To determine the most optimal hyperparameter configuration, bayesian optimization techniques are used, assisted by the Optuna library in Python by iterating 100 times. From searching and analyzing the hyperparameter results in each model, a combination of hyperparameters was found that will be applied to each model with the details in Table 3.

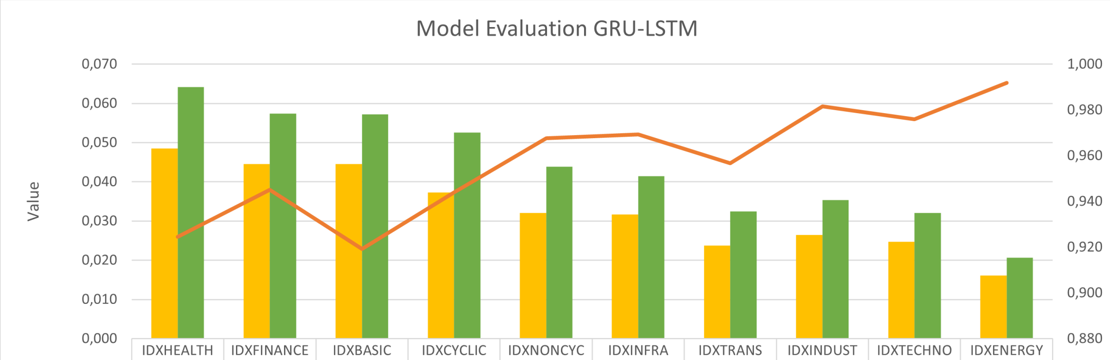
Table 3. Hyperparameter of the Model

Types of Hyperparameter	**Value**
Number of Neurons	50
Dropout Rate	0.01
Learning Rate	0.001
Batch Size	32
Amount of Epoch	50

Each model has 50 neurons in a hidden layer and a dropout rate of 0.01. The optimizer used is Adam, with a learning rate of 0.001 and a batch size of 32. The model is trained for 50 epochs. The built model was then stored for transfer learning to the data of ten IDX-IC stock indices as test data which can be seen in detail in Table 1.

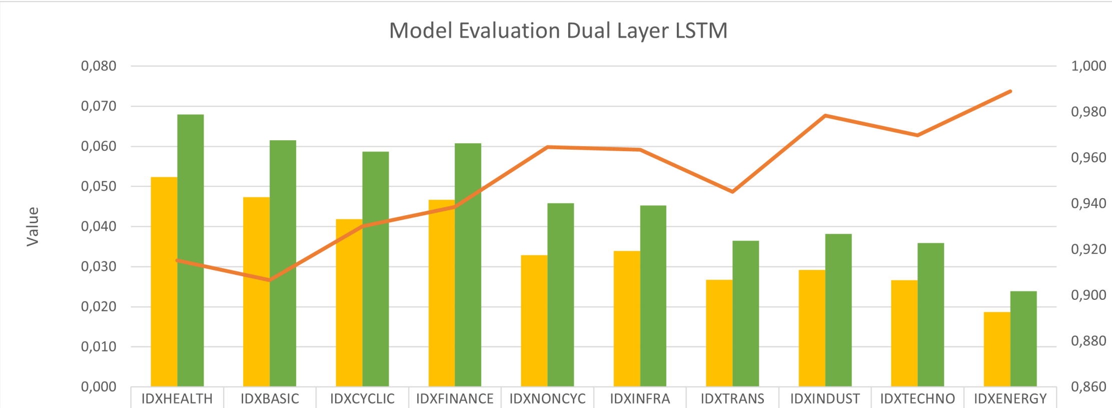
Fig. 6, Fig. 7, and Fig. 8 show the results of the prediction evaluation of the three models on all ten IDX-IC indices displayed using a mixed chart between the bar chart and the line chart. The yellow bar chart shows the MAE value, the green bar chart shows the RMSE value, and the red line chart shows the R^2 score.

Fig. 6 shows the results of the evaluation of the GRU-LSTM model on each IDX-IC stock index. The model showed promising results in predicting stock prices for the evaluated sectors. The GRU-LSTM model achieved an R^2 score above 0.9 for all sectors, indicating that it could explain the high percentage of variance in the data. The MAE and RMSE for the GRU-LSTM model are also relatively low, indicating that the model can predict stock prices with high accuracy. The GRU-LSTM model performs best in the



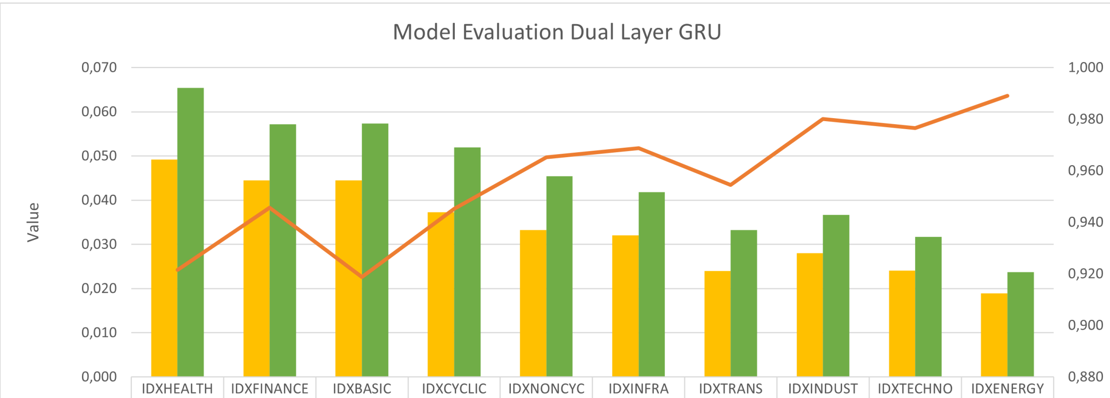
	IDXHEALTH	IDXFINANCE	IDXBASIC	IDXCYCLIC	IDXNONCYC	IDXINFRA	IDXTRANS	IDXINDUST	IDXTECHNO	IDXENERGY
MAE	0,048	0,045	0,045	0,037	0,032	0,032	0,024	0,026	0,025	0,016
RMSE	0,064	0,057	0,057	0,053	0,044	0,041	0,032	0,035	0,032	0,021
R2 Score	0,924	0,945	0,919	0,944	0,968	0,969	0,957	0,982	0,976	0,992

Fig. 6. GRU-LSTM model evaluation results graph.



	IDXHEALTH	IDXBASIC	IDXCYCLIC	IDXFINANCE	IDXNONCYC	IDXINFRA	IDXTRANS	IDXINDUST	IDXTECHNO	IDXENERGY
MAE	0,052	0,047	0,042	0,047	0,033	0,034	0,027	0,029	0,027	0,019
RMSE	0,068	0,062	0,059	0,061	0,046	0,045	0,036	0,038	0,036	0,024
R2 Score	0,915	0,907	0,930	0,939	0,965	0,963	0,945	0,978	0,970	0,989

Fig. 7. Graph of LSTM dual layer model evaluation results.



	IDXHEALTH	IDXFINANCE	IDXBASIC	IDXCYCLIC	IDXNONCYC	IDXINFRA	IDXTRANS	IDXINDUST	IDXTECHNO	IDXENERGY
MAE	0,049	0,044	0,044	0,037	0,033	0,032	0,024	0,028	0,024	0,019
RMSE	0,065	0,057	0,057	0,052	0,045	0,042	0,033	0,037	0,032	0,024
R2 Score	0,922	0,946	0,919	0,945	0,965	0,969	0,954	0,980	0,977	0,989

Fig. 8. Graph of GRU dual layer model evaluation results.

energy, technology, and industrial sectors.

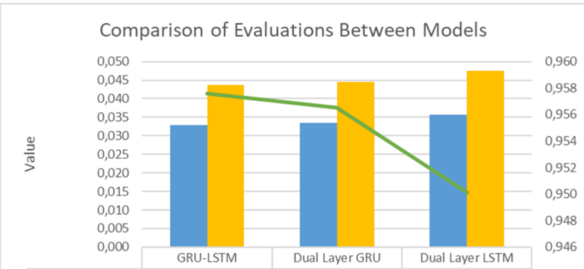
Not much different from the GRU-LSTM model, the Dual Layer LSTM model also has an R^2 score above 0.9, and low MAE and RMSE values can also be seen in Fig. 7. This indicates that the Dual Layer LSTM model performs well, although the GRU-LSTM model is slightly better.

The evaluation of the GRU model in Fig. 8 shows results that are also similar to the performance of the GRU-LSTM and Dual Layer LSTM models. With an R^2 score above 0.9 and a low error rate in MAE and RMSE values, it can be seen that GRU performance works very well, considering that GRU has a smaller number of trainable parameters. However, regarding data accuracy, the GRU-LSTM model is still slightly better than the Dual Layer GRU.

Overall, each model works well in predicting the price of each stock index and bears similarities in the performance of making predictions. The high R^2 score above 0.9 indicates that stock price volatility is mainly recorded in the model, and low error are evidenced by low MAE and RMS. The GRU-LSTM model performs slightly better at predicting most indices, with the highest R^2 score and MAE and RMSE lowest on most indices.

Each model can predict the IDXENERGY, IDX-TECHNO, and IDXINDUST stock indices, as evidenced by the three indices having a combination of the best R^2 score, MAE, and RMSE values. This indicates that the IHSG training data model can better predict energy, technology, and industrial stock prices.

As for the IDXHEALTH, IDXBASIC, IDXFI-NANCE, and IDXCYCLIC indices have performed less well than other stock indices. This indicates that the model is less good at predicting stocks in the health industry sector, raw material industry, financial industry, and non-primary consumer goods industry.



	GRU-LSTM	Dual Layer GRU	Dual Layer LSTM
MAE Avg	0,033	0,034	0,036
RMSE Avg	0,044	0,044	0,047
R2 Score Avg	0,958	0,957	0,950

Fig. 9. Comparison of evaluations between models.

The results of the comparative analysis by calculating the average of the model evaluation results in Fig. 9 shows that the model selection affects the accuracy of the stock price prediction. The GRU-LSTM model performed better than the Dual Layer LSTM and Dual Layer GRU models in this examination. However, it is worth noting that model performance may vary for stock indices and periods.

The experiment result that compares between predicted values and actual values can be seen in Fig. 10 to Fig. 19.

It can be seen from the experiment results that the model's predictive capabilities have revealed promising results. The analysis indicates that the model is able to generate accurate predictions, with minimal deviation from the actual values. It is noteworthy that the largest error of each ten indexes occurred during the long holiday period in Indonesia, in early May 2022. This occurrence highlights the model's potential weakness in making accurate predictions when there are large gaps in the time sequence. But overall, our study suggests that the model show high predictive accuracy and can be a valuable tool for forecasting on various industries stocks.

IV. Discussion

The experimental results demonstrated the effectiveness of the proposed MSF-DTL framework in predicting the stock prices of different industrial sectors. Comparing the results with the metrics used in the framework shows that the proposed framework effectively evaluates the performance of pre-trained models for different industries. The model evaluation results show that the GRU-LSTM model, which is used in the framework, is also a promising approach to making a pre-trained prediction model and performs slightly better than the Dual Layer LSTM and Dual Layer GRU.

Analysis of the prediction results of each industry shows that the model built using the IHSG index can better predict stock prices in the energy, technology, and industrial sectors and less good in the health, raw material, and financial sectors. But overall, the model is able to do predictions on each industry's sector with a relatively small margin of error.

V. Conclusion

In conclusion, this study proposed Multi-Industry Stock Forecasting using Deep Transfer Learning (MSF-DTL) framework to evaluate pre-trained models built using a combined architecture of the GRU-LSTM algorithm in predicting stocks in different industries. This designed framework can be considered for future researchers to evaluate pre-trained models on stock predictions in multiple industries.

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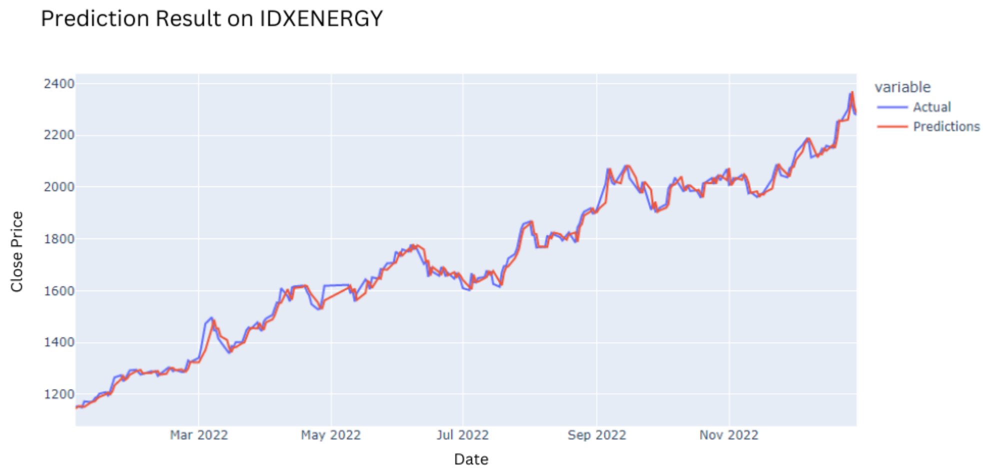

Fig. 10. Comparison of predicted and actual prices for IDXENERGY.

Fig. 11. Comparison of Predicted and Actual Prices for IDXBASIC.

Fig. 12. Comparison of Predicted and Actual Prices for IDXINDUST.

Fig. 13. Comparison of Predicted and Actual Prices for IDXNONCYC.

Fig. 14. Comparison of Predicted and Actual Prices for IDXCYCLIC.

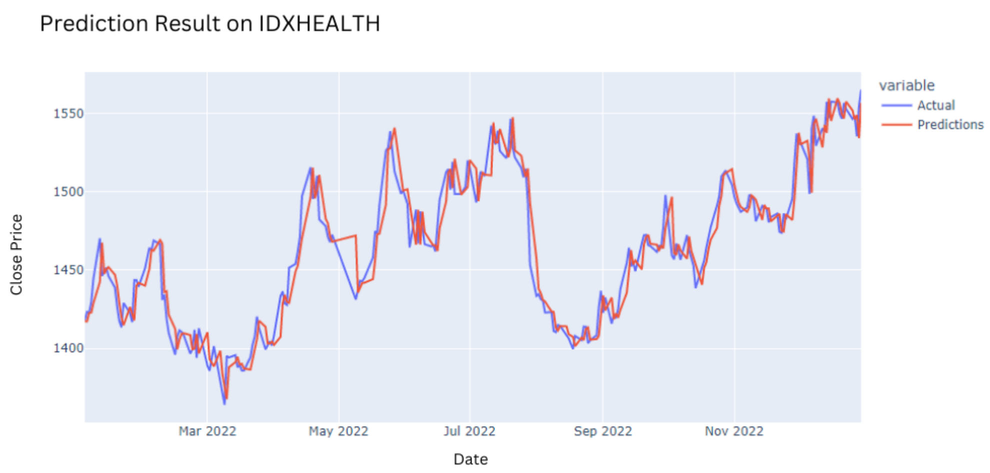

Fig. 15. Comparison of Predicted and Actual Prices for IDXHEALTH.

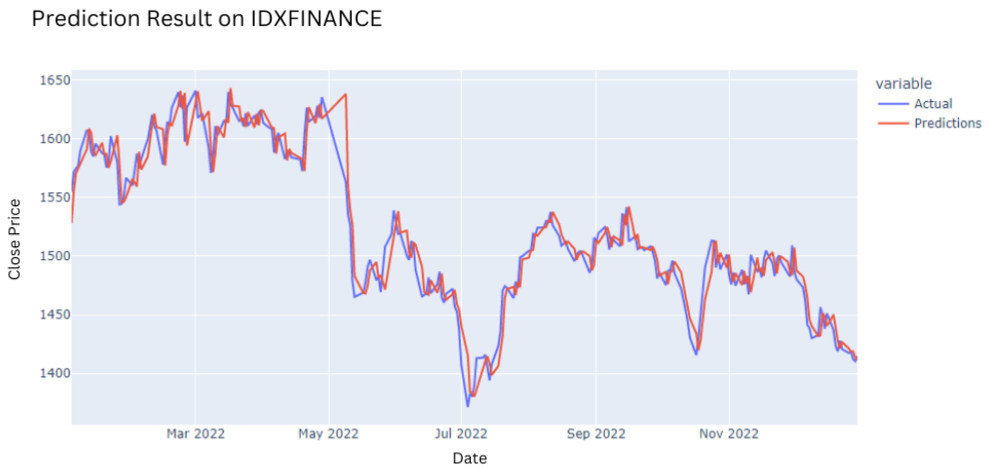

Fig. 16. Comparison of Predicted and Actual Prices for IDXFINANCE.

Fig. 17. Comparison of Predicted and Actual Prices for IDXTECHNO.

Fig. 18. Comparison of Predicted and Actual Prices for IDXINFRA.

Fig. 19. Comparison of Predicted and Actual Prices for IDXTRANS.

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