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Stacked Gated Recurrent Units and Indonesian Stock Predictions: A New Approach to Financial Forecasting

Mohammad Diqi [1✉], Marselina Endah Hiswati [2], Nurhadi Wijaya [3]

[1,2,3] Dept. of Informatics, Universitas Respati Yogyakarta, Yogyakarta, Indonesia
[1]diqi@respati.ac.id✉, [2]marsel.endah@respati.ac.id, [3]nurhadi@respati.ac.id

ABSTRACT

This research paper introduces a novel approach to predicting stock prices using a Stacked Gated Recurrent Unit (GRU) model. The model was trained on historical data from the top 10 companies listed on the Indonesia Stock Exchange, covering the period from July 6, 2015, to October 14, 2021. The performance of the model was evaluated using key metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2). The results demonstrated promising performance, with average RMSE, MAE, and MAPE values of 0.00592, 0.00529, and 0.01654, respectively, indicating a high level of accuracy in the model's predictions. The average R2 value of 0.97808 further suggests a high degree of predictive power, with the model able to explain a significant proportion of the variance in the stock prices. These findings highlight the effectiveness of the Stacked GRU model in capturing stock price patterns and making accurate predictions. The practical implications of this research are significant, as the model provides a powerful tool for forecasting future stock price trends, which can be utilized in investment decision-making, financial analysis, and risk management. Future research could explore other deep learning architectures, incorporate additional features, or consider different evaluation metrics to enhance the model's performance further.

Keywords : *Stock Price Prediction, Stacked Gated Recurrent Unit (GRU), Deep Learning, Time Series Forecasting, Financial Forecasting*

I. INTRODUCTION

Stock price prediction has emerged as a critical component in the financial field, serving as a cornerstone for quantitative analysis and investment decisions [1]. The complexity and volatility of the stock market, amplified by the easy accessibility of market data, have underscored the need for accurate and reliable prediction models [2]. The advent of sophisticated deep learning methods and the proliferation of various statistical approaches have enabled the development of numerous forecasting scenarios, contributing to the significance of stock price prediction [3], [4]. The importance of stock price prediction extends beyond its role in guiding investment decisions; it also provides insights into the potential correlation between various market factors and closing prices, thereby enhancing our understanding of the intricate dynamics of the stock market [4].

The task of predicting stock prices presents many challenges, primarily due to the complex and multifaceted nature of the stock market [5]. The market is influenced by many variables and factors, making it difficult for current forecasting models to capture the intricate relationships among these factors [6]. Traditional methods, which primarily rely on time-series information for a single stock, often fall short as they lack a holistic perspective and fail to account for the linkage effect in the stock market, where those of associated stocks influence stock prices [6]. Furthermore, these traditional methods struggle to fit nonlinear data well, a characteristic inherent in stock prices [7].

The insufficiency of traditional methods has led to exploring machine learning algorithms as potential solutions for stock price prediction. These algorithms, such as Long Short-Term Memory (LSTM) networks [8], have shown promise in capturing long-term dependencies and patterns in the input data, thereby achieving promising prediction accuracy compared to traditional methods [9]. However, even with the use of machine learning strategies, the task of stock price prediction remains a challenging endeavor. The high risk associated with stocks, amplified by the unstable environment brought about by events such as the Covid-19 global pandemic, necessitates robust intelligent systems that can accurately predict stock prices and inform investment strategies [10].

The application of GRU models for stock prediction has gained traction in recent years, driven by the rapid advancement of artificial intelligence and deep learning

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techniques [2]. GRUs, as a type of recurrent neural network, have shown promise in handling the randomness, chaos, and nonlinearity of stock prices, which are often inadequately addressed by traditional methods [11]. In particular, GRUs have been employed in conjunction with other deep learning models, such as Long Short-Term Memory (LSTM) networks and convolutional neural networks (CNNs) [12], to predict stock prices using both numerical and text data, thereby providing a more comprehensive representation of the market's highly volatile and nonlinear behavior [2], [11]. In a comparative study, GRU models have demonstrated slightly lower mean squared error (MSE) and MAE than LSTM models, indicating their potential superiority in stock price prediction despite their simpler structure [13].

The GRU model offers several advantages for stock price prediction. As a type of recurrent neural network, GRUs can capture long-range dependencies in time series data, which is crucial for accurately predicting stock prices [13]. Unlike traditional methods, GRUs can handle the randomness, chaos, and nonlinearity inherent in stock prices, making them more suitable for this task [11]. Furthermore, GRUs have been found to outperform other deep learning models, such as Long Short-Term Memory (LSTM) networks in some cases. Despite their simpler structure, GRUs have demonstrated lower mean squared error (MSE) and MAE than LSTM models in stock price prediction, indicating their potential superiority in this domain [13]. Additionally, GRUs can be effectively combined with other models, such as convolutional neural networks (CNNs), to create hybrid models that leverage the strengths of each model, further enhancing their predictive performance [14].

While GRU models offer several advantages in stock price prediction, they are not without limitations. One of the primary challenges is the inherent uncertainty and noise in stock market data, which can make it difficult for GRU models, or any predictive models for that matter, to make accurate predictions [13]. Furthermore, while GRUs can capture long-range dependencies in time series data, they may still struggle with highly complex and chaotic stock market data. The choice of hyperparameters can also influence the performance of GRU models, and finding the optimal set of hyperparameters can be a time-consuming process [15]. Additionally, while GRUs have been found to outperform other models, such as LSTM, in some cases, this may not always be the case, and the performance can vary depending on the specific dataset and task [16].

This research aims to leverage the capabilities of a Stacked GRU model to predict stock prices. GRUs, as a type of recurrent neural network, have been widely applied in finance for stock market prediction due to their ability to handle the randomness, chaos, and nonlinearity inherent in stock prices [2], [11]. A stacked architecture, where multiple GRU layers are stacked on each other, allows the model to learn more complex data representations, potentially leading to improved prediction accuracy [10]. Furthermore, incorporating frequency decomposition techniques can enhance the model's ability to extract discerning features from cluttered signals in the stock information flow, thereby improving its predictive performance [17]. Therefore, this research aims to explore the effectiveness of a Stacked GRU model in predicting stock prices, with the ultimate goal of providing valuable insights for investment strategies and risk management in the stock market.

The scope of this research is defined by the dataset used for the stock price prediction task. The dataset comprises explicitly the top 10 stocks listed on the Indonesia Stock Exchange, reflecting the performance of the most significant and actively traded stocks in the Indonesian market. The time frame for the data spans from July 6, 2015, to October 14, 2021. This period captures a diverse range of market conditions, including periods of growth, decline, and recovery, thereby providing a comprehensive dataset for developing and evaluating the Stacked GRU model for stock price prediction. This dataset aligns with the research objective of predicting stock prices in a complex and dynamic market environment.

II. RESEARCH METHOD

A. Stacked Gated Recurrent Unit

The GRU is a type of recurrent neural network (RNN) that has gained popularity for its efficiency in handling sequential data [18]. The architecture of a GRU consists of two gates, the update gate, and the reset gate. The update gate determines how much past information needs to be passed to the future, while the reset gate decides how much past information to forget. The GRU's hidden state is computed as a linear interpolation between the previous and candidate hidden states. The equations governing the GRU are formulated in Equations 1-4.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\widetilde{h_t} = \tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h_t} \tag{4}$$

where z_t is the update gate, r_t is the reset gate, $\widetilde{h_t}$ is the candidate's hidden state, h_t is the hidden state at time t, x_t is the input at time t, and σ is the sigmoid function.

On the other hand, a Stacked GRU is a variant of the GRU where multiple GRU layers are stacked on top of each other. This architecture allows the model to learn more complex representations of the data. In a single-layer GRU, the hidden state of the GRU is directly used for the final prediction. However, in a Stacked GRU, the hidden state of the first GRU layer is used as input to the next GRU layer, and this process is repeated for each layer in the stack. The final prediction is then made based on the hidden state of the last GRU layer. This architecture allows the model to capture more complex patterns in the data, potentially leading to improved prediction accuracy.

B. Dataset

The dataset used in this research is sourced from Yahoo Finance and comprises explicitly the top 10 stocks listed on the Indonesia Stock Exchange, reflecting the performance of the most significant and actively traded stocks in the Indonesian market. The time frame for the data spans from July 6, 2015, to October 14, 2021. This period captures a

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diverse range of market conditions, including periods of growth, decline, and recovery, thereby providing a comprehensive dataset for developing and evaluating the Stacked GRU model for stock price prediction.

The companies included in the dataset span a variety of industries, providing a broad representation of the Indonesian market. The companies and their corresponding symbols and industries are shown in Table 1.

Tabel 1. Dataset

Company Name	**Symbol**	**Industry**
Ace Hardware Indonesia	ACES	Consumer Non-Cyclicals
Aneka Tambang	ANTM	Basic Materials
JAPFA Comfeed Indonesia	JPFA	Consumer Cyclicals
Kalbe Farma	KLBF	Healthcare
Perusahaan Gas Negara	PGAS	Energy
Tambang Batubara Bukit Asam	PTBA	Energy
PP	PTPP	Infrastructures
Semen Indonesia	SMGR	Basic Materials
Telkom Indonesia	TLKM	Infrastructures
United Tractors	UNTR	Industrials

C. Data Preprocessing

Data preprocessing is vital in readying the dataset for practical examination and modeling [19]. In predicting stock prices, several preprocessing steps are typically implemented to ensure the data is of high quality and suitable for subsequent analysis. The data preprocessing methods used in this study are outlined as follows:

1) Volume Filtering

This step involves applying a volume filter to retain only significant data. It eliminates data points where the volume is zero or negative, as these values are generally considered invalid or erroneous [20].

2) Addressing Missing Values

Missing values can interfere with the analysis and negatively impact the model's performance. Therefore, any remaining missing values in the dataset are dealt with by removing the corresponding data points or using imputation techniques.

3) Normalization

This step involves scaling the numerical features within a certain range to enable fair comparisons between features [21]. This study uses the Min-Max scaler to normalize the stock price data. The equation for Min-Max normalization is provided in Equation 5.

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \quad (5)$$

where x' is the normalized value, x is the original value, $\min(X)$ is the minimum value of the feature, and $\max(X)$ is the maximum value of the feature.

4) Selection of Close Price

For this analysis, only the stocks' closing price is considered. The closing price is when a stock concludes trading for a given day. The study can concentrate on the stock's performance during trading hours by focusing solely on the closing price.

D. Data Splitting

The methodology of dividing data into training and testing sets is a fundamental procedure in machine learning and predictive modeling, assessing a model's performance on data it has not encountered before. In predicting stock prices, it's essential to strike a balance between training and evaluation data to ensure the model's effectiveness and ability to generalize.

This study utilizes data from 1269 trading days spanning from July 6, 2015, to October 14, 2021, for analysis. The dataset is partitioned into three subsets to facilitate the train-test split: training, testing, and validation.

The training set comprises 1169 trading days and forms most of the data. This extensive training set enables the model to learn from historical price patterns and trends. The model can discern underlying relationships and make accurate predictions by training on a substantial amount of data.

The testing set, which includes 50 trading days, constitutes a smaller dataset segment. The testing set's role is to evaluate the model's performance on data it has not been trained on, thereby mimicking real-world scenarios. This evaluation provides insights into the model's ability to generalize and predict new, unseen market conditions.

In addition to the training and testing sets, a validation set consisting of 50 trading days is also used. The validation set is typically employed to adjust the model's hyperparameters and optimize its performance. By assessing the model's performance on the validation set, modifications can be made to improve its predictive abilities.

In summary, this train-test split methodology, which allocates 1169 trading days for training, 50 trading days for testing, and 50 trading days for validation, ensures a sensible data distribution for model training, evaluation, and fine-tuning. This approach allows the model to learn from a significant historical context while providing comprehensive evaluation data to assess its performance on unseen market conditions and optimize its parameters.

E. Model Training Process

The process of training the model involves using a stacked GRU architecture to forecast the stock price of the following day based on the data from the preceding 50 days. The structure of the model, its hyperparameters, the optimization algorithm, and the loss function are detailed below:

1) Hyperparameters

a. n_steps: This refers to the number of preceding days taken into account as input to forecast the stock price of the following day. In this instance, n_steps is set to 50, indicating that the model uses the data from the past 50 days as input.

b. n_features: This is the number of features or variables that predict the stock price. In this case, n_features is set to 1, suggesting that only the stock price is considered the input feature.

2) Model Architecture

a. The structure of the model comprises three stacked GRU layers. The initial GRU layer, defined with 200 units, uses the ReLU activation function and returns sequences to be utilized by the following GRU layers.

b. The second GRU layer, with 200 units, employs the ReLU activation function and returns sequences.

c. The third GRU layer comprises 200 units and applies the ReLU activation function.

d. A dense layer with a single unit is added as the final output layer.

3) Optimization Algorithm

Optimization, The model uses the Adam optimizer for its training process. Adam is a widely-used optimization algorithm recognized for its adaptive learning rate and efficient convergence.

4) Loss Function

The mean squared error (MSE) loss function is used to measure the difference between the predicted and actual stock prices. The MSE loss function computes the average of the squared differences between the predicted and actual values.

The model is adjusted to the data and trained over 100 epochs using the Adam optimizer and the MSE loss function. By defining the model's architecture, hyperparameters, optimization algorithm, and loss function, the model is trained to recognize patterns and relationships in the historical stock price data, thereby enabling it to make predictions for future stock prices based on the input sequence of the previous 50 days.

F. Evaluation Metrics

The performance of the model is evaluated using four metrics: RMSE, MAE, MAPE, and R2. These metrics provide different perspectives on the model's prediction accuracy and are defined as follows.

1) Root Mean Square Error (RMSE)

RMSE is a commonly used metric that measures the average magnitude of the error. It does this by squaring the errors, averaging them, and then taking the square root [22]. The RMSE is particularly useful when significant errors are particularly undesirable. The equation for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of observations.

2) Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions without considering their direction [23]. It's the average of the absolute differences between prediction and actual observation over the test sample. The equation for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

3) Mean Absolute Percentage Error (MAPE)

MAPE measures the prediction accuracy of a forecasting method in statistics [24]. It expresses accuracy as a percentage and is defined by the formula:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

4) R-squared (R2)

R2, also known as the coefficient of determination, is a statistical measure representing the proportion of the variance for a dependent variable explained by an independent variable or variables in a regression model [25]. The equation for R2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

where $\bar{y}$ is the mean of the observed data.

These metrics collectively provide a comprehensive evaluation of the model's performance.

III. RESULTS AND ANALYSIS

A. Performance *Metrics*

This study utilized the Stacked GRU model to predict the stock prices for the next 50 days. The model's performance was evaluated using key metrics, including RMSE, MAE, MAPE, and R2. These metrics provide insights into the accuracy and reliability of the predictions, as shown in Table 2.

Tabel 2. Performance Metrics

Symbol	RMSE	MAE	MAPE	R2
ACES	0,00754	0,00704	0,01134	0,97388
ANTM	0,00688	0,00588	0,00841	0,92854
JPFA	0,00108	0,00091	0,00167	0,99921
KLBF	0,00422	0,00299	0,00541	0,99630
PGAS	0,00673	0,00639	0,04580	0,97657
PTBA	0,00328	0,00299	0,00794	0,99705
PTPP	0,00150	0,00116	0,00917	0,99760
SMGR	0,01346	0,01258	0,03920	0,93615
TLKM	0,01033	0,00941	0,02488	0,97750
UNTR	0,00420	0,00353	0,01156	0,99804
Average	0,00592	0,00529	0,01654	0,97808

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A figure was generated to illustrate the performance visually, showcasing the actual and predicted values for the next 50 days, as shown in Figures 1-10. This graphical representation clearly compares the predicted (red line) and observed (blue line) stock prices, highlighting any significant trends or deviations. The figure provides a visual confirmation of the model's ability to capture the general patterns and movements in the stock prices, further supporting the effectiveness of the Stacked GRU model in predicting future stock price trends.

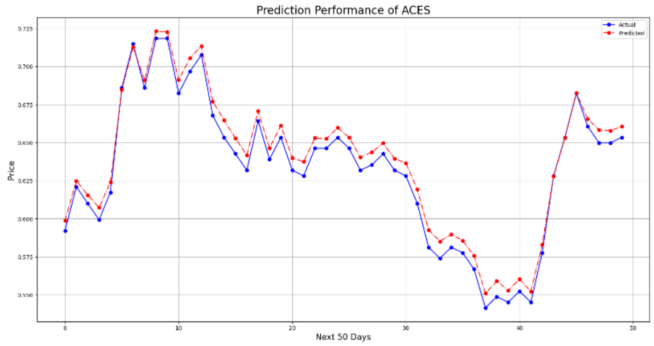

Fig. 1. Performance of ACES

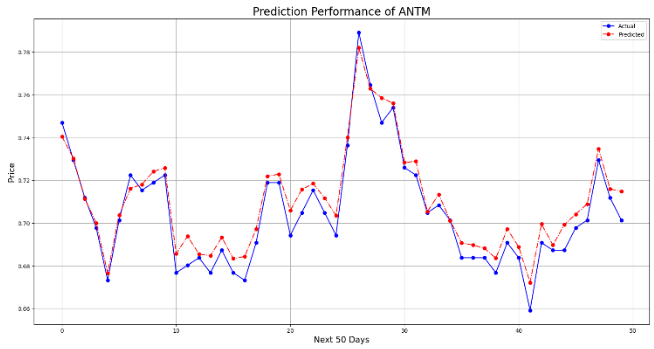

Fig. 2. Performance of ANTM

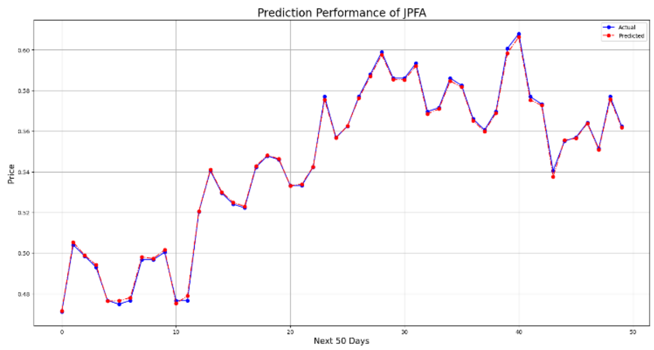

Fig. 3. Performance of JPFA

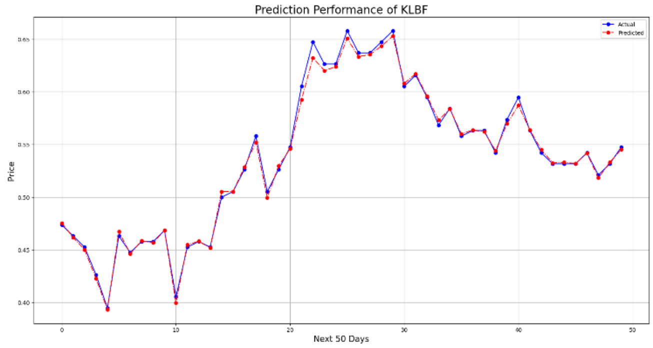

Fig. 4. Performance of KLBF

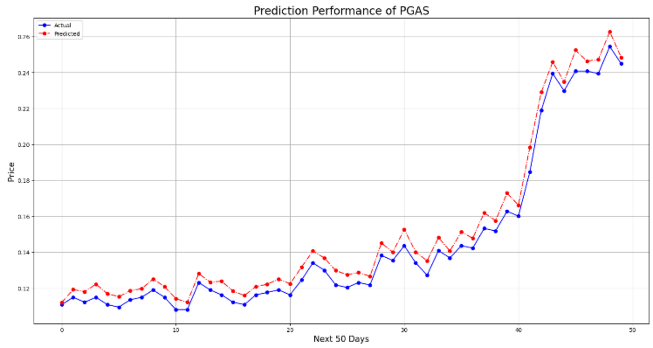

Fig. 5. Performance of PGAS

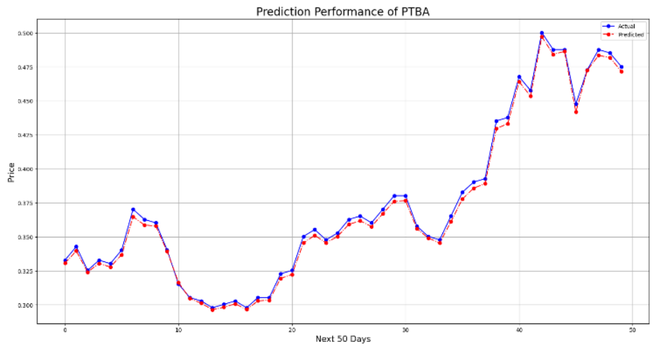

Fig. 6. Performance of PTBA

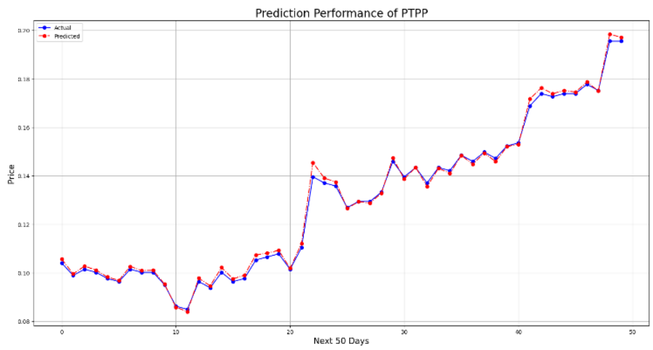

Fig. 7. Performance of PTPP

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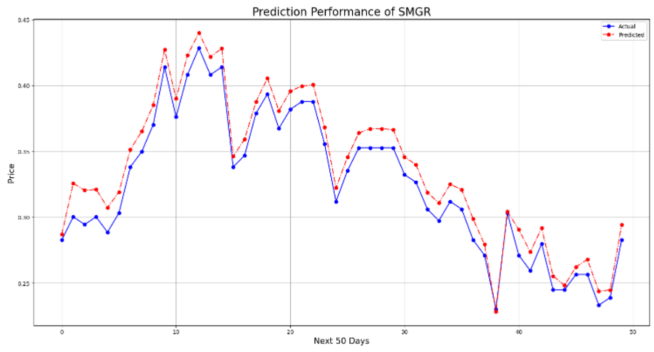

Fig. 8. Performance of SMGR

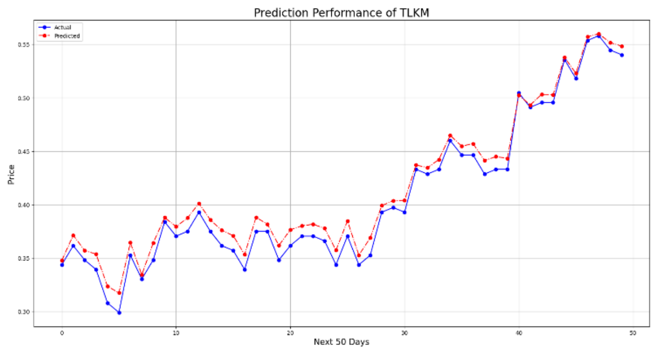

Fig. 9. Performance of TLKM

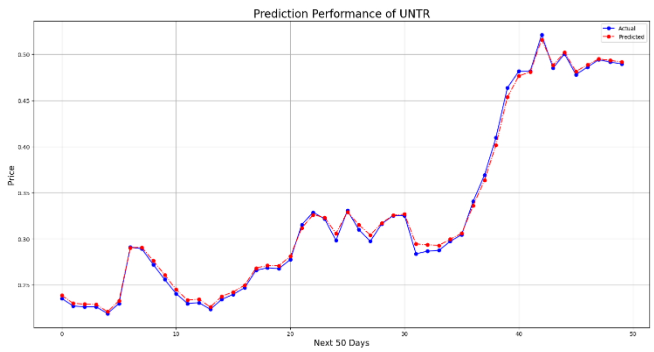

Fig. 10. Performance of UNTR

B. *Performance Analysis*

The results obtained from the Stacked GRU model demonstrate its effectiveness in predicting stock prices for the top 10 companies listed on the Indonesia Stock Exchange.

The RMSE values range from 0.00108 to 0.01346, with an average of 0.00592. Lower RMSE values indicate better fit, as they represent the standard deviation of the residuals. The low RMSE values suggest that the model's predictions are close to the actual values, indicating high accuracy.

The MAE values, which measure the average magnitude of the prediction errors, range from 0.00091 to 0.01258, with an average of 0.00529. These low MAE values confirm the model's accuracy, indicating that the average difference between the predicted and actual stock prices is small.

The MAPE values, which express the error as a percentage, range from 0.00167 to 0.04580, with an average of 0.01654. These values suggest that the model's predictions are generally within a reasonable percentage of the actual values, further supporting the model's accuracy.

The R2 values, which represent the proportion of the variance in the dependent variable that is predictable from the independent variable(s), range from 0.92854 to 0.99921, with an average of 0.97808. These high R2 values indicate that the model can explain a large proportion of the variance in the stock prices, suggesting a high level of predictive power.

In summary, the Stacked GRU model demonstrates promising performance in predicting stock prices, with high levels of accuracy and predictive power across all evaluated companies. The low RMSE, MAE, and MAPE values, along with the high R2 values, suggest that the model can accurately predict future stock price trends based on historical data.

C. *Strengths and Limitations*

The Stacked GRU model exhibits several strengths in capturing stock price patterns and making accurate predictions.

Firstly, the model's architecture, which includes multiple GRU layers stacked on each other, allows it to learn more complex data representations. This is particularly useful in the context of stock price prediction, where a multitude of factors can influence price movements and can exhibit complex patterns.

Secondly, the model's gating mechanisms in the GRU layers allow it to capture long-term dependencies in the data effectively. This is crucial in stock price prediction, where historical price movements can significantly impact future prices.

Thirdly, the model's performance metrics, including low RMSE, MAE, and MAPE values and high R2 values, indicate high accuracy and predictive power. This suggests that the model can make accurate predictions on unseen data, which is crucial for practical applications in stock price prediction.

However, the model also has certain limitations. One limitation is that it assumes that future stock prices depend solely on historical prices. In reality, stock prices are influenced by various factors, including economic indicators, company performance, and market sentiment, which the model does not consider.

Another limitation is that the model may not perform well when the stock price movements are highly volatile or influenced by unexpected events. In such situations, the patterns learned by the model from historical data may not accurately reflect future price movements.

Lastly, while the model's performance metrics are generally high, there is still room for improvement. For example, the MAPE values, while relatively low, indicate that there is still a certain percentage of error in the predictions. Further research and model tuning could potentially improve these metrics.

In conclusion, while the Stacked GRU model shows promising performance in predicting stock prices, it is important to be aware of its limitations and to consider these when interpreting the model's predictions.

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IV. CONCLUSION

This research has demonstrated the effectiveness of the Stacked GRU model in predicting stock prices. The model was trained on historical stock price data from the top 10 companies listed on the Indonesia Stock Exchange, and its performance was evaluated using key metrics such as RMSE, MAE, MAPE, and R2. The results showed promising performance, with low error rates and high predictive power, indicating the model's capability to capture stock price patterns and make reliable predictions accurately. These findings have practical implications for investors, financial analysts, and other stakeholders in the financial industry, as they provide a powerful tool for forecasting future stock price trends. For future research, it would be worthwhile to explore other deep learning architectures, incorporate additional features that may influence stock prices, or consider different evaluation metrics further to enhance the accuracy and reliability of stock price predictions.

REFERENCES

[1] R. Li, "New Energy Vehicles Industry Stock Price Prediction Based on ARIMA: Tesla, NIO and BAIC BluePark," *BCPBM*, vol. 38, pp. 3375–3382, Mar. 2023, doi: 10.54691/bcpbm.v38i.4310.

[2] K. R. Dahal *et al.*, "A comparative study on effect of news sentiment on stock price prediction with deep learning architecture," *PLOS ONE*, vol. 18, no. 4, p. e0284695, Apr. 2023, doi: 10.1371/journal.pone.0284695.

[3] T. Hu, "Stock Price Prediction of the TMT Industry Based on Machine-Learning," *HSET*, vol. 49, pp. 250–255, May 2023, doi: 10.54097/hset.v49i.8514.

[4] Y. Fu and H. Xiao, "Stock Price Prediction Model based on Dual Attention and TCN," in *Signal, Image Processing and Embedded Systems Trends*, Academy and Industry Research Collaboration Center (AIRCC), Nov. 2022, pp. 99–114. doi: 10.5121/csit.2022.122007.

[5] M. Kabir Ahmed, G. Maksha Wajiga, N. Vachaku Blamah, and B. Modi, "Stock Market Forecasting Using ant Colony Optimization Based Algorithm," *AJMCM*, vol. 4, no. 3, p. 52, 2019, doi: 10.11648/j.ajmcm.20190403.11.

[6] C. Zhao, P. Hu, X. Liu, X. Lan, and H. Zhang, "Stock Market Analysis Using Time Series Relational Models for Stock Price Prediction," *Mathematics*, vol. 11, no. 5, 2023, doi: 10.3390/math11051130.

[7] Wenqing Yao, Yuting Gu, Sanfei Chang, Jing Li, Qingbo Zhao, and Fangli Ge, "Stock price analysis and forecasting based on machine learning," presented at the Proc.SPIE, Dec. 2022, p. 1250660. doi: 10.1117/12.2662176.

[8] M. Diqi, A. Sahal, and F. N. Aini, "Multi-Step Vector Output Prediction of Time Series Using EMA LSTM," *Jurnal Online Informatika*, vol. 8, no. 1.

[9] W. Chen, H. Zhang, M. K. Mehlawat, and L. Jia, "Mean–variance portfolio optimization using machine learning-based stock price prediction," *Applied Soft Computing*, vol. 100, 2021, doi: 10.1016/j.asoc.2020.106943.

[10] X. Chen, "Stock Price Prediction Using Machine Learning Strategies," *BCPBM*, vol. 36, pp. 488–497, Jan. 2023, doi: 10.54691/bcpbm.v36i.3507.

[11] H. Song and H. Choi, "Forecasting Stock Market Indices Using the Recurrent Neural Network Based Hybrid Models: CNN-LSTM, GRU-CNN, and Ensemble Models," *Applied Sciences*, vol. 13, no. 7, 2023, doi: 10.3390/app13074644.

[12] M. Diqi, S. H. Mulyani, and R. Pradila, "DeepCov: Effective Prediction Model of COVID-19 Using CNN Algorithm," *SN Computer Science*, vol. 4, no. 4, p. 396, May 2023, doi: 10.1007/s42979-023-01834-w.

[13] M. Ghadimpour and S. babak Ebrahimi, "Forecasting Financial Time Series Using Deep Learning Networks: Evidence from Long-Short Term Memory and Gated Recurrent Unit," *Iranian Journal of Finance*, vol. 6, no. 4, pp. 81–94, 2022, doi: 10.30699/ijf.2022.313164.1286.

[14] C. Y. Kang, C. P. Lee, and K. M. Lim, "Cryptocurrency Price Prediction with Convolutional Neural Network and Stacked Gated Recurrent Unit," *Data*, vol. 7, no. 11, 2022, doi: 10.3390/data7110149.

[15] S. Wang, C. Shao, J. Zhang, Y. Zheng, and M. Meng, "Traffic flow prediction using bi-directional gated recurrent unit method," *Urban Informatics*, vol. 1, no. 1, p. 16, Dec. 2022, doi: 10.1007/s44212-022-00015-z.

[16] D. Endalie, G. Haile, and W. Taye, "Bi-directional long short term memory-gated recurrent unit model for Amharic next word prediction," *PLOS ONE*, vol. 17, no. 8, p. e0273156, Aug. 2022, doi: 10.1371/journal.pone.0273156.

[17] C. Li and G. Qian, "Stock Price Prediction Using a Frequency Decomposition Based GRU Transformer Neural Network," *Applied Sciences*, vol. 13, no. 1, 2023, doi: 10.3390/app13010222.

[18] Y. Wang, J. Tang, V. P. Vimal, J. R. Lackner, P. DiZio, and P. Hong, "Crash Prediction Using Deep Learning in a Disorienting Spaceflight Analog Balancing Task," *Front. Physiol.*, vol. 13, p. 806357, Jan. 2022, doi: 10.3389/fphys.2022.806357.

[19] C. Fan, M. Chen, X. Wang, J. Wang, and B. Huang, "A Review on Data Preprocessing Techniques Toward Efficient and Reliable Knowledge Discovery From Building Operational Data," *Front. Energy Res.*, vol. 9, p. 652801, Mar. 2021, doi: 10.3389/fenrg.2021.652801.

[20] R. Ballester-Ripoll, D. Steiner, and R. Pajarola, "Multiresolution Volume Filtering in the Tensor Compressed Domain," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 10, pp. 2714–2727, Oct. 2018, doi: 10.1109/TVCG.2017.2771282.

[21] D. Singh and B. Singh, "Investigating the impact of data normalization on classification performance," *Applied Soft Computing*, vol. 97, p. 105524, Dec. 2020, doi: 10.1016/j.asoc.2019.105524.

[22] S. Yuan, "Review of Root-Mean-Square Error Calculation Methods for Large Deployable Mesh Reflectors," *International Journal of Aerospace Engineering*, vol. 2022, p. 5352146, Aug. 2022, doi: 10.1155/2022/5352146.

[23] F. Yang, X. Yao, W. Zhang, and Y. Su, "Research and analysis of performance evaluation metrics for estimation algorithms," in *2016 35th Chinese Control Conference (CCC)*, Jul. 2016, pp. 5195–5199. doi: 10.1109/ChiCC.2016.7554162.

[24] A. de Myttenaere, B. Golden, B. Le Grand, and F. Rossi, "Mean Absolute Percentage Error for regression models," *Neurocomputing*, vol. 192, pp. 38–48, Jun. 2016, doi: 10.1016/j.neucom.2015.12.114.

[25] D. Zhang, "A Coefficient of Determination for Generalized Linear Models," *The American Statistician*, vol. 71, no. 4, pp. 310–316, Oct. 2017, doi: 10.1080/00031305.2016.1256839.