Terbit *online* pada laman : http://teknosi.fti.unand.ac.id/

Jurnal Nasional Teknologi dan Sistem Informasi

| ISSN (Print) 2460-3465 | ISSN (Online) 2476-8812 |

Research Articles

Comparative Deep Learning Analysis: Unveiling the Power of LSTM, BiLSTM, GRU, and BiGRU for Agricultural Stock Price Forecasting on the Indonesian Stock Exchange

Muhammad Fadhlurrohman [a], Armin Darmawan [b,]*

[a] [b] *Department of Industrial Engineering, Faculty of Engineering, Hasanuddin University, Jl. Malino KM. 6, Romang Lompoa, Bontomarannu District, Gowa Regency, South Sulawesi, 92171, Indonesia*

ARTICLE INFORMATION

Article History:
Received : 6 December 2025
Final Revision: 27 April 2026
Published *Online* : 30 April 2026

KEYWORDS

Deep Learning,
LSTM,
BiLSTM,
GRU,
BiGRU

CORRESPONDENCE

Email: darmawanarmin@gmail.com

A B S T R A C T

This study aims to analyze the performance of *deep learning algorithms* in predicting agricultural sector stock prices on the Indonesia Stock Exchange (IDX) by comparing four models: *Long Short-Term Memory* (LSTM), *Bidirectional* LSTM (BiLSTM), *Gated Recurrent Unit* (GRU), and *Bidirectional* GRU (BiGRU). Daily historical data of six agricultural sector stock issuers (AALI, BISI, DSNG, LSIP, SIMP, SSMS) for the period 2017–2025 were used as the dataset. The research methods included data pre-processing (normalization, 80:20 training-test data split), model training with optimal *hyperparameters (unit=512, dropout rate* = 0.3, *epoch* = 50–150, *learning rate* = 0.0001), and evaluation using *Root Mean Squared Error* (RMSE), *Mean Absolute Percentage Error* (MAPE), R^2 *Score* , and computation time metrics. The results show that BiGRU is the most accurate model, with the lowest RMSE (7.43–17.20) and the highest R^2 (0.99 on BISI and SSMS), thanks to its bidirectional architecture, which processes bidirectional data to capture complex temporal patterns. However, GRU is more efficient, with a training time of 40–43 seconds, making it suitable for real-time applications. LSTM and BiLSTM have lower accuracy, especially on volatile stocks such as DSNG (RMSE LSTM = 130.51). This study provides practical recommendations: BiGRU for long-term investment strategies that prioritize accuracy, while GRU for quick decisions based on efficiency. Theoretical implications strengthen the Bidirectional architecture's effectiveness in financial time series analysis.

1. INTRODUCTION

The capital market, particularly the Indonesia Stock Exchange (IDX), plays a crucial role in the Indonesian economy by connecting companies seeking funding with investors seeking returns. With the rapid growth of the capital market, investors face challenges in managing their portfolios due to high volatility and the dependence of stock prices on external factors. [1]One sector of particular concern is agriculture, which contributes significantly to Gross Domestic Product (GDP) but is also vulnerable to fluctuations in commodity prices such as palm oil, rubber, and coffee.

The increasing number of retail investors, particularly from Generation Z, is changing market dynamics. [2]Many novice investors rely on social media as a source of information, making them vulnerable to market manipulation such as *pump-and-dump schemes [3]*. Therefore, a more objective, data-driven approach is needed to help investors make more informed decisions.

Although technology offers investors solutions to improve decision-making accuracy, its adoption in the investment world still faces challenges. Both institutional and individual investors in Indonesia continue to face obstacles in implementing artificial intelligence-based strategies and automated trading algorithms.

One major obstacle is limited technological and financial literacy, especially for investors unfamiliar with data-driven analysis and predictive models. [4]Furthermore, limited technological infrastructure, such as access to accurate data and reliable computing systems, is also a limiting factor. Capital market regulations also need to be continuously updated to accommodate developments in financial technology, thereby protecting investors and encouraging healthy innovation in the financial industry. Despite these challenges, the prospects for technology development and investment in Indonesia remain promising. A growing number of fintech startups are presenting artificial intelligence-based investment solutions, and investor interest in more objective analytical approaches is growing. The government and financial institutions have a strategic role to play in supporting the adoption of this technology through policies that encourage innovation, improve digital financial literacy, and partner with technology companies to provide broader access to advanced analytical tools [5]. With strong collaboration among regulators, investment companies, and the retail investor community, Indonesia has great potential to become a leader in Asia's technology-based investment ecosystem [6].

In the era of digital transformation, the use of intelligent technology in data processing has become a crucial aspect in various fields, including the financial sector. Data mining, as a branch of data analysis, plays a crucial role in identifying hidden patterns from large data sets [7]. The application of data mining has become increasingly effective with the advent of Artificial Intelligence (AI), which enables systems to learn and adapt strategies based on historical data. One widely used AI approach in data analysis is deep learning, a machine learning technique that leverages Artificial Neural Networks (ANNs) to recognize complex patterns. In the context of the stock market, deep learning has become a leading method for building more accurate predictive models. These models can process historical stock price data and other external factors to provide deeper insights into market movements. One category of deep learning widely used in sequential data analysis is the Recurrent Neural Network (RNN), which allows processing information in a specific time sequence. With a structure that can store historical information, RNNs form the foundation for more sophisticated algorithms in stock trend forecasting, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) [8].

LSTM is one of the most successful RNN algorithms in handling sequential data-based forecasting. The main advantage of this algorithm lies in its memory-cell structure, which replaces traditional neurons in the network's hidden layer, enabling better modeling of temporal relationships. In addition, the LSTM network can efficiently connect past information with current data, making it suitable for capturing time-flexible data structures with a high degree of predictability [9]. Meanwhile, GRU is a simpler variant of LSTM because it has fewer parameters and uses only two gates (Reset Gate and Update Gate), compared to LSTM's three gates. The main advantage of GRU lies in higher computational efficiency, because the smaller number of parameters leads to faster training times and lower memory requirements [10]. In addition to LSTM and GRU, other variants such as BiLSTM and BiGRU adopt a bidirectional approach in data processing, allowing the model to consider information from both time directions [11]. A comparative study of these four algorithms is relevant to evaluate the effectiveness of each model in stock price prediction, to provide a more accurate analysis alternative for investors [12].

In the digital era, artificial intelligence (AI) and *data mining* offer more accurate predictive solutions in stock market analysis. *Deep learning techniques*, particularly *Recurrent Neural Network* (RNN)-based models such as *Long Short-Term Memory* (LSTM) and *Gated Recurrent Unit* (GRU), have been shown to capture complex patterns in stock price data. Other variants such as *Bidirectional LSTM* (BiLSTM) and *Bidirectional GRU* (BiGRU), have also been developed to improve prediction accuracy [13].

Direct testing of deep learning algorithms is expected to yield insights and advance better approaches to stock price prediction. Overall, this research enhances the efficiency of information technology in the financial industry, potentially advancing technological development and deepening understanding of the interaction between data mining and financial markets.

2. METHOD

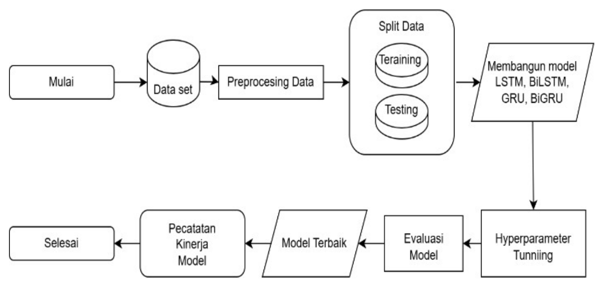

Figure 1. Research Method

In this study, the model-building stage was carried out to construct and compare the performance of four types of deep learning models: LSTM (Long Short-Term Memory), BiLSTM (Bidirectional LSTM), Gated Recurrent Unit (GRU), and BiGRU (Bidirectional GRU), in predicting stock prices taken from the Indonesia Stock Exchange. This process was carried out in a series of steps, including data collection, preprocessing, model building, training, evaluation, and result analysis.

2.1. *Data Set*

The object of this research is data from six agricultural sector stock issuers on the Indonesian Stock Exchange. The stock data was obtained from the Investing.com website, selected based on market capitalization and liquidity. These issuers are Astra Agro Lestari Tbk (AALI), Sawit Sumbermas Sarana Tbk (SSMS), Dharma Satya Nusantara Tbk (DSNG), Salim Ivomas Pratama Tbk (SIMP), London Sumatra Indonesia Tbk (LSIP), and BISI International Tbk (BISI). The data analyzed spanned from January 2017 to January 2025, with a total of 1,935 samples for the five issuers and 1,921 samples for LSIP. This daily historical data includes the opening price (*open*), highest price (*high*), lowest price (low), closing price (*close*), trading volume, and percentage price change.

https://doi.org/10.25077/TEKNOSI.v12i1.2026.063-070

Table 1. Descriptive Statistics

	Mean	Max	Min	StDEV	Skew	Kurt
AALI	10270.63	17175	4290	2797.06	0.18	0.94
BISI	1402.91	2080	590	311.13	0.33	0.92
DSNG	521.74	1370	310	151.12	1.74	5.11
LSIP	1165.32	1745	535	211.88	0.07	0.62
SIMP	432.64	650	177	84.42	0.18	0.15
SSMS	1169.92	1790	690	259.86	0.36	0.90

Based on Table 5, most stocks exhibit a relatively symmetric price distribution with skewness close to zero, except for DSNG, which has a high skewness (1.741), indicating a tendency for its stock price to be in the low range with occasional extreme spikes. In terms of kurtosis, only DSNG has a high value (5.112), indicating many extreme values or *outliers, while the other stocks tend to have flatter distributions (kurtosis* < 3), indicating lower volatility. Overall, stocks such as AALI and LSIP are more stable, while DSNG shows unique characteristics with high volatility.

2.2. *Data preprocessing*

Before data is used in the deep learning modeling process, it must undergo a series of preprocessing steps to ensure data quality and consistency.

2.2.1. Data Cleansing

The initial stage of preprocessing is data cleaning, where data containing errors such as empty values, outliers, or invalid values is cleaned or addressed, for example, by interpolation methods. Inappropriate elements such as quotation marks, commas, and other special characters are also removed to prevent them from interfering with the learning process [10]. Then, the data is sorted by date index to help the model better understand the time series pattern. Irrelevant features such as the opening price (open), the highest price (high), the lowest price (low), and the price change are removed to focus the modeling only on relevant features. In the volume column, the data is also redefined to make it easier for the model to understand .

Table 2. Data on AALI share movements that have gone through the *data preprocessing process*

Date	*Price* (IDR)	Volume (IDR)
2020-01-02	14025.0	79900000.0
2020-01-03	14025.0	128000000.0
2020-01-06	13500.0	111000000.0
2020-01-07	13225.0	140000000.0
2020-01-08	13200.0	86300000.0
2020-01-09	13350.0	168000000.0
2020-01-10	13650.0	78600000.0
2020-01-13	13600.0	90900000.0
2020-01-14	13200.0	162000000.0
2020-01-15	12525.0	213000000.0
2020-01-16	12525.0	139000000.0

2.2.2. Data Normalization

After the cleaning process is complete, the next step is data normalization. Normalization is used to equalize variable scales, preventing the deep learning model from being biased towards certain features. The method used is Min-Max Scaling, which scales data values to a range of 0 to 1. This process is important to ensure each feature has a balanced influence during model training. With this pre-processing stage, the data becomes cleaner, more structured, and ready to be fed into the deep learning model to produce optimal predictions [20] [14].

2.3. *Split data*

After preprocessing, the data is divided into two parts: the training set and the test set. The *training data* is used to train the model, while the test data is used to evaluate its performance after training. In this study, the *training data* comprised approximately 80% of the total data, while the testing data comprised 20%.

2.4. *Building a Model*

After pre-processing and data splitting, the next step is to build a *deep learning model to make predictions. In this study, four* popular *Recurrent Neural Network (RNN)* model architectures were used for *time series data* : *Long Short-Term Memory* (LSTM), *Bidirectional* LSTM, and LSTM. (BiLSTM), *Gated Recurrent Unit* (GRU), and *Bidirectional* GRU (BiGRU). These four models are designed to address *long-term dependencies* in time series data and mitigate the *vanishing gradient problem* that often occurs in conventional RNNs [13].

The LSTM model consists of *a memory cell* and three main *gates*: *the input gate*, *the forget gate*, and *the output gate*, which regulate which information should be stored, forgotten, or output. The BiLSTM model is an extension of the LSTM that processes data in two directions: forward *and* backward*,* allowing the model to capture context from the past and future simultaneously. Meanwhile, the GRU has a simpler structure than *the LSTM* because it only uses two main *gates, namely the update gate* and *the reset gate [15]*. Although computationally lighter, the GRU still retains long-term information quite well. [16]. The BiGRU model is a *bidirectional version* of the GRU that utilizes both processing directions to capture more complex [17]*time series patterns. These four models are built using deep learning* frameworks such as *TensorFlow* or *PyTorch*, and each is optimized through a *hyperparameter tuning process* to achieve the best prediction performance [18].

2.5. *Training and Hyperparameter Tuning*

2.5.1. Determining Loss Functions and Optimizers

A loss function measures the error between the model's prediction and the actual value in the training data. In this study, *the Mean Squared Error (MSE)* is used as the *loss function* because it can measure the extent to which the prediction differs from the actual data. *MSE* is calculated as the average of the squared differences between the model's predictions and the actual values. Optimization is performed using an algorithm such as *Adam. optimizer* because it has fast and effective performance in optimizing model weights during training [14].

2.5.2. Hyperparameter Tuning

Although *deep learning* (DL) algorithms have significant capabilities for forecasting time series data, they (like other neural networks) have drawbacks related to the complexity of hyperparameter settings and their dependence on various factors. DL parameter tuning is generally done through *a trial-and-error approach*. This is mainly due to the limitations of DL algorithms that cannot be easily applied universally to other case studies [19]. A parameter set that is effective on one dataset may not yield the same results on another, even within a similar research field [20].

In this study, we conducted a series of *trial-and-error tests* to determine the optimal parameters for the four DL algorithms used. Model performance metrics were systematically examined and recorded. A thorough analysis of these performance indicators helped tune the optimal DL parameters. Since the primary focus of this study was to compare the performance of the four DL algorithms in predicting stock prices, model parameters were kept consistent to ensure the validity and reliability of the comparison [21]. The optimal parameters used are presented in the following table.

Table 1*Optimal hyperparameters* used in *the deep learning algorithms LSTM, BiLSTM,* GRU*,* and BiGRU in this study.

Parameter	Mark	Meaning
Units	512	Number of cells in a *deep learning structure*
Learning Rate	0.0001	The value that controls the weight *updates* during training.
Batch Size	5	The number of samples to be processed in one iteration.
Epoch	50, 150	The number of "iterations" during the training phase
Dropout Rate	0.3	The unit's probability level is ignored at random.
Learning Rate	0.0001	The value that controls the model weight update rate.
Scaler	Min-Max	Allows to scale data in the interval [-1,1]
Optimizer	Adam	Adaptive moment estimation (Adam) is an improved adaptive gradient descent algorithm for training *deep learning networks.*

2.6. Analysis and Comparison

When analyzing the performance of a stock price prediction model, three key metrics can provide a comprehensive overview. First, *the Root Mean Squared Error (RMSE)* measures the magnitude of the prediction error in terms of a unit of the stock price. *RMSE* imposes a larger penalty on larger errors, which is particularly useful when benchmarking a model against highly volatile stocks. Second, *the Mean Absolute Percentage Error (MAPE)* allows for model comparisons between stocks with significantly different prices. Because *MAPE* is measured as a percentage, it's easy to see how large the model's error is relative to the actual price. The R² Score measures how well a model captures patterns and variability in the data, indicating how accurately it explains stock price changes relative to the average. The combination of these three metrics provides a deeper understanding of the model's predictive accuracy, both in terms of absolute error and relative error, as well as its ability to represent the data [14].

3. RESULTS

Table 5. Comparison of *RMSE, MAPE, R2* values, and training time for the proposed model.

Model	AALI			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	19.82	13.63	0.96	137
BiLSTM	15.98	13.34	0.97	195
GRU	16.54	13.58	0.97	125
BiGRU	12.43	13.24	0.98	173
Model	LSIP			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	20.14	13.66	0.96	44
BiLSTM	13.88	13.31	0.98	58
GRU	17.81	13.61	0.97	40
BiGRU	12.78	13.25	0.98	52
Model	BISI			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	28.47	13.79	0.97	45
BiLSTM	18.87	13.94	0.99	61
GRU	29.19	13.80	0.97	43
BiGRU	17.20	14.01	0.99	57
Model	DSNG			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	130.51	18.79	0.53	48
BiLSTM	87.48	21.38	0.79	66
GRU	126.49	19.02	0.56	43
BiGRU	90.04	21.21	0.77	60
Model	SIMP			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	1.81	5.66	0.99	47
BiLSTM	0.75	5.58	0.99	65
GRU	3.64	5.68	0.96	42
BiGRU	0.73	5.57	0.99	59
Model	SSMS			
	RMSE (IDR)	MAPE (%)	R2(%)	TIME(s)
LTSM	19.82	13.63	0.96	137
BiLSTM	15.98	13.34	0.97	195
GRU	16.54	13.58	0.97	125
BiGRU	12.43	13.24	0.98	173

Based on the evaluation results, the BiGRU model achieved the best performance in predicting agricultural stock prices on the Indonesia Stock Exchange (IDX). The Root Mean Square Error value indicates this. A lower *RMSE (Reliability Mean Regression) compared to other models, as well as a coefficient of determination (R²) value* reaching 0.99 for several stocks, such as BISI and SSMS. This nearly perfect R² value indicates that BiGRU captures

https://doi.org/10.25077/TEKNOSI.v12i1.2026.063-070

price movement patterns very well. The main advantage of BiGRU lies in its *bidirectional architecture, which allows the model to understand temporal relationships in both* directions. Thus, BiGRU is more effective at capturing both short- and long-term data dependencies than unidirectional models such as LSTM and GRU, which process data in only one direction. However, despite its superior accuracy, BiGRU requires longer training time than other models.

In addition to BiGRU, the BiLSTM model also demonstrated relatively high accuracy, though it required longer training time, making it less computationally efficient. On the other hand, the GRU model offers a balance between accuracy and training time efficiency. Although GRU's RMSE value is slightly higher than BiGRU's, it has a significantly faster training time. For example, when predicting the stock prices of LSIP and SSMS, GRU required only about 40 seconds to train, making it an attractive choice for analyses with limited processing time. Meanwhile, LSTM, which is designed to capture long-term patterns in time-series data, actually performed worse in this study. This model struggled to predict stock prices with high volatility, as reflected in its higher RMSE value and lower R^2 value compared to the other models. The following is a visualization of the prediction results for six issuers across the compared models.

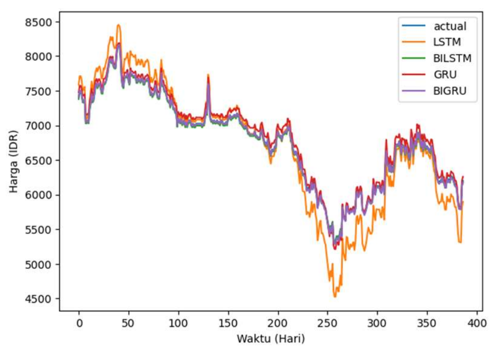

Figure 2. Astra Agro Lestari Tbk.(AALI)

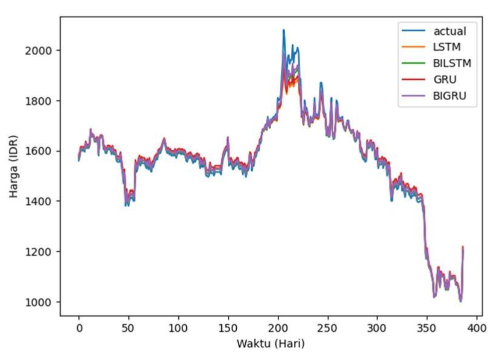

Figure 3. Bisi International Tbk. (BISI)

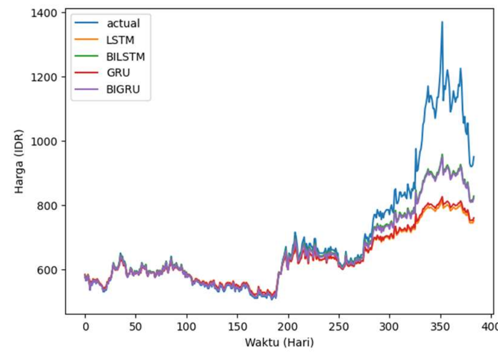

Figure 4. Dharma Satya Nusantara Tbk. (DSNG)

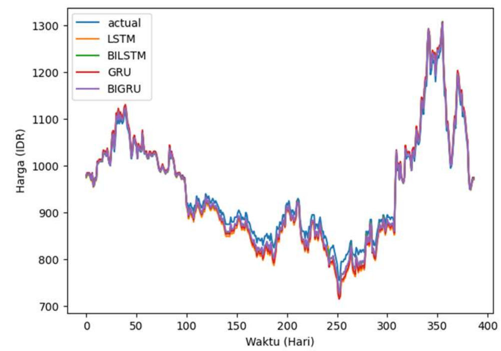

Figure 4. London Sumatra Indonesia Tbk. (LSIP)

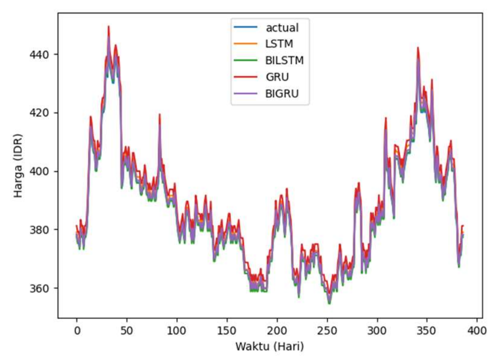

Figure 5. Salim Ivomas Pratama Tbk

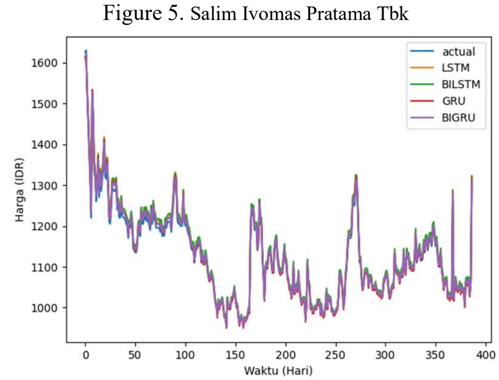

Figure 6. Sawit Sumbermas Sarana Tbk. (SSMS)

The results of the analysis of the actual and predicted price comparison charts show that *bidirectional models* , such as BiGRU and BiLSTM, can follow price patterns more accurately than the *non-directional model* . For AALI stock, for example, the BiGRU prediction almost completely overlaps the actual price line, even during a significant price spike. In contrast, the LSTM model experiences larger deviations, especially when faced with sharp price changes. This indicates that the *bidirectional model* better captures complex patterns and temporal dependencies in stock data. Furthermore, the BiGRU model produces a smoother prediction line, demonstrating its ability to filter out noise and maintain stable predictions.

For DSNG stock, all models struggled to predict prices during the fourth quarter due to high volatility. However, the *bidirectional model* still outperformed the others, with predictions closer to the actual price line. The scatterplot also confirmed BiGRU's superiority, with the model's predictions clustering around a perfect diagonal (y = x), indicating very high accuracy. In contrast, the LSTM and GRU models showed greater scatter, indicating they were less able to capture the relationship between predicted and actual prices consistently.

Furthermore, a comparison between GRU and LSTM shows that GRU often outperforms LSTM in stock price prediction despite its simpler architecture. This is due to the efficient structure of GRU, which has only two main gates (reset and update gates), in contrast to LSTM, which has three gates (input, forget, and output*)*. This simplicity makes GRU training faster and more computationally efficient, with minimal loss of accuracy. Several previous studies have also confirmed that GRU tends to outperform LSTM across various time-series applications, especially in financial contexts that require high processing speed.

4. DISCUSSION.

Based on the experimental results presented in Table 5, the Gated Recurrent Unit (GRU) model outperforms the Long Short-Term Memory (LSTM) model in predicting stock prices. In theory, an LSTM with a more complex architecture should be able to capture patterns in stock price movements better. However, in practice, GRUs often outperform LSTMs, and several main reasons can explain this. One of the main factors is the model's architecture. GRU has a simpler structure with only two main gates, namely *the Reset Gate* and *the update gate, while LSTM has three gates (Input Gate, Forget Gate, and Output Gate), which results in more parameters in LSTM than in* GRU. [22]stated that, because of fewer parameters, GRU has faster training speed and faster convergence than LSTM. This simplicity allows GRU to adjust weights more efficiently without requiring long training times, thereby improving computational efficiency and prediction accuracy in financial applications [23].

In addition, when dealing with time series data, although LSTM is designed to address the vanishing gradient problem Gradient, GRU, with its simpler architecture, is still able to retain long-term information effectively. [24]found that GRU achieves higher accuracy than LSTM in stock price forecasting due to its update gate mechanism, which can choose which information to keep or discard without requiring additional complexity. Furthermore, in terms of computational efficiency, GRU requires fewer computing resources and shorter training time than LSTM, making it a better choice for large datasets or for stock trading systems that require *real-time decisions.* [25]. In addition, research by [26]shows that, in a comparison of stock price prediction accuracy, GRU has lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) than LSTM, indicating that GRU is superior at capturing data patterns without overfitting.

bidirectional models (BiLSTM and BiGRU) outperform unidirectional models (LSTM and GRU) because they can capture data patterns from both directions simultaneously. *Unidirectional models* use only information from the previous time step to the current time step, while bidirectional models can consider the relationship between past and future data when making predictions. In the context of stock price prediction, this *bidirectional approach* is more effective at recognizing complex, non-linear trend patterns. [27]found that *bidirectional models* can capture both long- and short-term dependency patterns simultaneously, making them more accurate than unidirectional models across various time-series prediction tasks, including in the financial sector. This finding is reinforced by[28] which shows that the *bidirectional model* achieves lower error rates in S&P 500 predictions than the traditional model because it better captures market variability.

In addition to the advantages of the *bidirectional model* , BiGRU also shows superior performance compared to BiLSTM, even though both use a bidirectional approach. This is due to the simpler architecture of GRU, with only two main gates (Reset *Gate* and *Update Gate)*, compared to LSTM, which has three gates (*Input Gate* , *Forget Gate* , and *Output Gate*) [29]. This simplicity makes GRU more computationally efficient, reduces the number of parameters to train, and reduces the risk of overfitting on high-volatility financial datasets. found that GRU can achieve equal or better performance than LSTM across various time-series prediction tasks, with higher training speed. [10]In addition, it also stated that BiGRU can provide an optimal balance between accuracy and efficiency in stock price prediction, making it a better choice than BiLSTM in certain cases [30]. Thus, the phenomenon in which BiGRU outperforms BiLSTM in this study can be explained by the GRU's efficiency, which allows the model to capture stock price patterns more quickly without sacrificing accuracy.

5. CONCLUSION

This study develops a stock price prediction model for the agricultural sector on the Indonesia Stock Exchange (IDX) using data mining and deep learning techniques. Four tested models—LSTM, BiLSTM, GRU, and BiGRU—were compared based on accuracy and time efficiency using RMSE, MAPE, and R^2 metrics. The results showed that BiGRU was the most accurate model, with lower RMSE and MAPE values across most stocks, especially those with complex price patterns such as AALI and BISI. However, in terms of time efficiency, GRU was a better choice because it offered a balance between accuracy and execution speed, making it more suitable for real-time applications. The deep learning model successfully captured stock price movement patterns, despite challenges posed by high volatility, as seen in DSNG shares.

The implications of this research are significant for investment strategies and stock management in the agricultural sector. BiGRU, with its higher accuracy, is suitable for long-term investors who prioritize accuracy in price forecasting. At the same time, GRU is more efficient for investors who require rapid

https://doi.org/10.25077/TEKNOSI.v12i1.2026.063-070

analysis for real-time decision-making. Furthermore, this model can help companies understand market trends, adjust business strategies, and increase competitiveness in the agricultural industry. Overall, this study's results indicate that deep learning can improve the quality of market analysis and enable smarter, data-driven investment decisions.

BIBLIOGRAPHY

[1] Galih Adhi Putratama, Satya Maulana Fahreza, and Yudhistira Rakha Ramandhani, “Comparative Evaluation of Machine Learning Methods for Predicting Stock Price Changes,” *Antivirus: Scientific Journal of Informatics Engineering* , vol. 17, no. 2, pp. 278–285, May 2024, doi: 10.35457/antivirus.v17i2.2871.

[2] G. Budiprasetyo, M. Hani'ah, and DZ Aflah, “Sharia stock price prediction using long short- term memory (LSTM) algorithm,” *National Journal of Technology and Information Systems* , vol. 8, no. 3, pp. 164–172, 2023.

[3] A. Holly, R. Jao, A. Limang, U. Atma Jaya Makassar, and S. Selatan, “Muhammadiyah Riau Accounting and Business Journal Emotional Bias And Risk Tolerance Behavior In Investment Decision Making,” 2022. [Online]. Available: http://ejurnal.umri.ac.id/index.php/MRABJ

[4] A. Rosyd, AI Purnamasari, and I. Ali, “Application Of The Long Short-Term Memory (LSTM) Method In Predicting PT Bank Central Asia Stock Prices,” *JATI (Informatics Engineering Student Journal)* , vol. 8, no. 1, pp. 501–506, 2024.

[5] F. Risyda, MM Purba, and Y. Gardenia, “Application Of Machine Learning With Naive Bayes Model For Evaluation Of Student Satisfaction Case Study: UNSURYA Campus Library,” *JSI (Journal of Information Systems) Suryadarma University,* vol. 11, no. 2, pp. 237–248, 2024.

[6] AA Aprilia, SR Handayani, and RR Hidayat, “Investment Decision Analysis Based on Stock Price Assessment (Study Using Fundamental Analysis with Price Earning Ratio (PER) Approach on Mining Sector Stocks Listed on the IDX 2012-2014 Period),” *Journal of Business Administration (JAB) Vol* . 32, pp. 58–65, 2016.

[7] N. Hafizah, E. Noviani, and H. Perdana Abstract, “Technical Analysis Of LQ-45 Stocks Using The Bollinger Bands Indicator,” 2019.

[8] T. Phuoc, PTK Anh, PH Tam, and CV Nguyen, “Applying machine learning algorithms to predict the stock price trend in the stock market – The case of Vietnam,” *Humanit Soc Sci Commun* , vol. 11, no. 1, Dec. 2024, doi: 10.1057/s41599-024-02807-x.

[9] J. Qiu, B. Wang, and C. Zhou, “Forecasting stock prices with long-short term memory neural network based on attention mechanisms,” *PLoS One* , vol. 15, no. 1, Jan. 2020, doi: 10.1371/journal.pone.0227222.

[10] A. Zhang, Z.C. Lipton, M.U. Li, and A.J. Smola, “Dive into Deep Learning,” 2022.

[11] M. Bi, Z. Liu, and X. Yang, “A Hybrid Prediction Model for International Crude Oil Price Based on Variational Mode Decomposition with BiTCN-BiGRU-Attention Deep Learning Techniques,” 2024.

[12] DI Puteri, G. Darmawan, and BN Ruchjana, “Sharia Stock Price Prediction using Bidirectional Long Short Term Memory (BiLSTM) and Grid Search Algorithm,” *Jambura Journal of Mathematics* , vol. 6, no. 1, pp. 39–45, Feb. 2024, doi: 10.37905/jjom.v6i1.23297.

[13] S. Zargar, “Introduction to sequence learning models: RNN, LSTM, GRU,” *Department of Mechanical and Aerospace Engineering, North Carolina State University* , 2021.

[14] Z. Han, C. Gao, J. Liu, J. Zhang, and S. Q. Zhang, “Parameter-efficient fine-tuning for large models: A comprehensive survey,” *arXiv preprint arXiv:2403.14608* , 2024.

[15] Christopher Olah, “Understanding LSTM Networks. Retrieved from,” http://colah.github.io/posts/2015-08-Understanding-LSTMs/. Accessed: 19 December 2024. [Online]. Available: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

[16] A. Arwansyah, S. Suryani, SY Hasyrif, U. Usman, A. Ahyuna, and S. Alam, “Time Series Forecasting Using Deep Gated Recurrent Units,” *Digital Transformation Technology* , vol. 4, no. 1, pp. 410–416, 2024.

[17] Y. Gao, D. Glowacka, R.J. Durrant, and K.-E. Kim, “Deep Gate Recurrent Neural Network,” 2016.

[18] RC Staudemeyer and ER Morris, “Understanding LSTM--a tutorial into long short-term memory recurrent neural networks,” *arXiv preprint arXiv:1909.09586* , 2019.

[19] H. Ben Ameur, S. Boubaker, Z. Ftiti, W. Louhichi, and K. Tissaoui, “Forecasting commodity prices: empirical evidence using deep learning tools,” *Ann Oper Res* , vol. 339, no. 1–2, pp. 349–367, Aug. 2024, doi: 10.1007/s10479-022-05076-6.

[20] Q. Tan *et al.* , “Data-gru: Dual-attention time-aware gated recurrent unit for irregular multivariate time series,” in *Proceedings of the AAAI conference on artificial intelligence* , 2020, pp. 930–937.

[21] B. Shachi and R. Gor, “Stock Price Prediction Using Grid Hyper Parameter Tuning In Gated Recurrent Units,” 2022.

[22] J. Wang, J. Yan, C. Li, R. X. Gao, and R. Zhao, “Deep heterogeneous GRU model for predictive analytics in smart manufacturing: Application to tool wear prediction,” *Comput Ind* , vol. 111, pp. 1–14, 2019.

[23] N. Elsayed, A.S. Maida, and M. Bayoumi, “Deep gated recurrent and convolutional network hybrid model for univariate time series classification,” *arXiv preprint arXiv:1812.07683* , 2018.

[24] T. B. Shahi, A. Shrestha, A. Neupane, and W. Guo, “Stock price forecasting with deep learning: A comparative study,” *Mathematics* , vol. 8, no. 9, p. 1441, 2020.

[25] S. Kumar, L. Hussain, S. Banarjee, and M. Reza, “Energy load forecasting using deep learning approach-LSTM and GRU in spark cluster,” in *2018 fifth international conference on emerging applications of information technology (EAIT)* , IEEE, 2018, pp. 1–4.

[26] Y. *Deng* , L. Wang, H. Jia , 15, no. 8, pp. 4481–4493, 2019.

[27] Z. Wang, Y. Guo, Z. Li, M. Tang, T. Qi, and J. Wang, “Research on microblog rumor events detection via dynamic time series based GRU model,” in *ICC 2019-*

2019 IEEE International Conference on Communications (ICC) , IEEE, 2019, pp. 1–6.

[28] KA Althelaya, E.-SM El-Alfy, and S. Mohammed, “Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU),” in *2018 21st Saudi Computer Society National Computer Conference (NCC)* , IEEE, 2018, pp. 1–7.

[29] M. Haris, T. Pustaka, MH Diponegoro, S. Kusumawardani, and I. Hidayah, “Systematic Literature Review: Implementation of Deep Learning Methods in Predicting Student Performance: A Systematic Literature Review,” 2021.

[30] S. Siami-Namini, N. Tavakoli, and AS Namin, “The performance of LSTM and BiLSTM in forecasting time series,” in *2019 IEEE International conference on big data (Big Data)* , IEEE, 2019, pp. 3285–3292.

 https://doi.org/10.25077/TEKNOSI.v12i1.2026.063-070