Harnessing Deep Learning and Technical Indicators for Enhanced Stock Predictions of Blue-Chip Stocks on the Indonesia Stock Exchange (IDX)

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ABSTRACT

Given the limitations of existing models in accurately predicting stock prices, particularly in emerging markets such as Indonesia, this study aimed to evaluate the effectiveness of deep learning models in forecasting stock prices using blue-chip company shares traded on the Indonesia Stock Exchange (IDX). The main focus lies in combining historical stock data with a series of existing technical indicators, optimizing their integration to improve prediction accuracy. The accuracy of this method is reflected in a comprehensive evaluation of model performance using robust metrics, including R^2, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Empirical results show the superiority of models integrating technical indicators compared to models relying only on historical data. The LSTM model showed the most significant improvement, with R^2 for ASII stock jumping by 14.59% after incorporating technical indicators. The prediction accuracy of the GRU model for BBCA shares increased significantly, as shown by a decrease of 45.16% in MSE. These findings underscore the critical role of feature selection in developing prediction models. Integrating technical indicators with historical stock data increases prediction accuracy and provides additional tools for informed decision-making.

Keywords-stock prediction; RNN; GRU; LSTM; technical indicator; Indonesia stock exchange

I. INTRODUCTION

Investment and finance have seen significant advances, with stock price prediction garnering significant attention. This task, recognized as challenging [1], is the key to investor success. Inaccurate predictions can lead to substantial losses, while accurate market trend forecasts are crucial for mitigating investment risks in stock markets [2]. The rapid development of computing has spurred various methodological innovations to enhance our understanding of stock market dynamics. These methods focus mainly on improving stock prediction accuracy. Historical data, long considered a crucial source for forecasting future stock prices, plays a central role in these efforts. Stock price movements are significantly influenced by a variety of factors [3-5]. These factors can be categorized into internal and external elements. Internal factors include company financial reports, while external factors encompass global macroeconomic conditions and political events [6]. A fundamental and common approach to stock analysis involves utilizing historical stock data [7]. The reliance on historical data for stock predictions stems from the premise that past trends can offer insight into future stock movements.

In the past few decades, characterized by remarkable advances in information and computing technology, stock prediction methods have evolved rapidly. Various predictive methods have been proposed for the stock market [8]. Deep learning is a prominent approach used by researchers, as it surpasses traditional methods in complexity handling [9, 10]. Architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Recurrent Neural Networks (RNNs) have gained prominence for time series predictions, including those in stock market analysis [11].

Technical indicators represent a crucial input feature frequently utilized in stock predictions [12-14]. These indicators act as analytical tools and help predict movements in stock, currency, or other asset prices based on historical data. They encompass charts, patterns, or statistical tools [15] designed to provide insight into market momentum, trends, and volatility. Examples of such indicators include the Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD), which provide additional information on stock dynamics. Although technical indicators are fundamentally derived from historical data, they offer distinct insights compared to raw historical data [16, 17].

Not all shares exhibit the same characteristics. Blue-chip shares, representing large companies with substantial market capitalization and robust liquidity, differ distinctly in dynamics from other stocks. This study focuses on blue-chip shares on the Indonesia Stock Exchange (IDX), with several compelling reasons underpinning this choice. First, blue-chip shares, representing large companies with significant market capitalization, offer enhanced stability and liquidity compared to other shares. Such stability often leads to more predictable price patterns, making them ideal for analyzing the efficacy of deep learning-based prediction techniques. Second, blue-chip stocks, frequently the focus of investors and analysts, provide a wealth of information. This includes extensive historical data and various technical indicators, potentially increasing prediction accuracy. Third, focusing on IDX blue-chip stocks offers a unique perspective, as most previous research mainly focused on stock markets in the United States, China, and India.

Thus, this study bridges a literature gap on the Indonesian stock market and contributes to a wider understanding of global stock market dynamics. Previous studies have focused primarily on developed markets, with limited exploration of emerging markets such as Indonesia, particularly in the context of integrating technical indicators with deep learning models. This study further examines the application of predictive technologies such as deep learning in emerging market contexts. By integrating technical indicators into this analysis, this study aims to reveal novel insights and develop more robust methods for predicting stock prices, particularly for blue-chip stocks on the IDX.

The application of LSTM networks in stock price prediction has been extensively explored, with various modifications and hybrid models developed to enhance predictive performance. In [18], data science and LSTM methods were examined in the prediction of stock prices, particularly in the short term on IDX during the COVID-19 pandemic. In [19], a model based on GRU and LSTM was used for stock price prediction. Integrating attention mechanisms with LSTM networks has received significant attention in recent years. For instance, the study in [16] focused on an Attention-based LSTM model (AttLSTM) to enhance stock price prediction performance. In [20], this field was further advanced by developing an attention mechanism-based LSTM model and achieving improved prediction accuracy across various evaluation metrics. In [21], LSTM was compared to memory-free classification methods, offering valuable insights. In [22], deep LSTM networks with embedded layers and LSTM with an automatic encoder were used to predict stock indices and individual stock prices. Similarly, in [23], an RNN was combined with Discrete Wavelet Transform (DWT) to predict stock market trends.

Various studies have focused on the GRU model for stock price prediction, achieving impressive results. In [24], the potential of GRU was investigated by developing the VMD-StackedGRU model. In [13], the Attentional GRU model was introduced to predict stock price movements, emphasizing the critical role of focusing on key segments of time series data to improve prediction accuracy. In [25], the predictive capabilities of the GRU model were expanded by integrating data from diverse sources and dimensions. The GRU model, renowned for its proficiency in managing temporal dependencies in serial data, has been acknowledged as a potent tool for stock price prediction. Through innovations such as signal decomposition and attention mechanisms, researchers continue to enhance GRU models for better predictive results. These studies lay the foundation for further advances in GRU model development and its prospective applications in stock prediction.

A hybrid approach to stock price prediction involves merging the strengths of two or more models or techniques to form a more robust and reliable predictive model. In [7], a CNN-LSTM-based model was developed to predict stock prices, showing that combining CNN's spatial characteristic convolution with LSTM's long-term memory capabilities can produce a powerful time series analysis tool. In [26], a hybrid model amalgamated RNN with Random Forests (RFs) for stock price prediction. In [27], an LSTM-CNN feature fusion model leveraged different data representations for stock price prediction. In a different vein, in [28], a hybrid ARFIMA-LSTM approach was introduced to forecast financial time series, attempting to merge the capacity of the ARFIMA model to address the long-memory nature of financial time series with the predictive capabilities of LSTM. In [29], a hybrid GRU Transformer model was based on frequency decomposition for stock price prediction.

In [15], an innovative neural network model with multifilters was used for stock price prediction. In [30], a novel method was proposed to predict stock prices by employing a deep learning approach and incorporating additional input features. In [6], a basic model using LSTM was developed to predict short-term stock price movements, utilizing a pre-trained model. In [8], a comparative analysis of RNNs was performed in stock price prediction, offering insights into the application and comparison of various RNN types. Finally, in [3] the application of deep learning, specifically LSTM, in stock market predictions was explored, indicating that it can achieve more accurate results than other models.

This research was designed to address several limitations identified in previous studies. First, although existing research has validated the effectiveness of LSTM and hybrid models in stock price prediction, there remains a potential to improve predictive performance by integrating technical indicators such as different types of MA, OBV, and AD. A novel approach is proposed, which merges historical stock data with carefully selected technical indicators to refine prediction accuracy, focusing on blue-chip stocks on the IDX. The integration of technical indicators with historical data enables the proposed model to capture trends, momentum, and volume dynamics more effectively. These indicators provide complementary information that enhances the model's ability to identify complex temporal patterns and market behaviors, ultimately improving prediction accuracy. Second, this study aims to broaden the application of deep learning techniques in stock markets in developing countries, a domain that needs to be explored. By focusing on this area, this study contributes to the theoretical understanding of deep learning's application in stock prediction, providing pertinent practical insights for investors and analysts in emerging markets. Finally, this study explores how the RNN, LSTM, and GRU models, when augmented with appropriate technical indicators, can effectively address the unique challenges posed by the volatility and dynamics of the IDX. This exploration aims to develop a more robust and reliable method for stock price prediction, providing significant value to the field.

II. MATERIAL AND METHODS

A. Dataset

This study utilized a dataset comprising IDX blue-chip stocks. This dataset includes six prominent blue-chip stocks: PT. Bank Central Asia Tbk. (BBCA), PT. Bank Rakyat Indonesia Tbk. (BBRI), PT. Bank Mandiri Tbk. (BMRI), PT. Bank Negara Indonesia Tbk (BBNI), PT Telekomunikasi Indonesia Tbk. (TLKM), and PT Astra International Tbk (ASII). These blue-chip stocks were chosen for their significant market capitalization, high liquidity, and substantial weight in key indices, such as LQ45, which makes them representative of broader market trends in Indonesia. The stock trading data was sourced from the Yahoo Finance website and covers from January 1, 2016, to December 31, 2022.

B. Input Features

Input features are crucial to enhance the accuracy of predictive models. This study selected input features that include historical prices and various technical indicators, which have been demonstrated to be effective in stock price prediction.

1) Historical Data

Historical stock data provides foundational insights into market behavior and is a critical starting point for predictive analysis. This study incorporated Open, High, Low, Close, and Volume values.

2) Technical Indicators

To augment the historical data used for stock prediction, technical indicators were incorporated to provide deeper insights into market momentum, trends, and volume. These indicators are instrumental in helping models identify patterns or trends that may take time to discern from historical data alone. The selected technical indicators include:

- The Simple Moving Average (SMA) is a fundamental tool in technical indicator analysis and is widely utilized in stock trading and other financial markets. The SMA can be calculated by averaging the closing prices of a stock over a designated period [31]. This study used SMA with periods of 2, 3, 4, and 14 days.
- The Exponential Moving Average (EMA) is a moving average that places greater emphasis on recent price data [32]. It differs from the WMA in its approach to weighting recent prices. EMA is designed to respond more rapidly to recent price changes, making it a preferred indicator for traders to identify market trends. This study employed an EMA with 14 days.
- The Weighted Moving Average (WMA) is a variation of the moving average that prioritizes the most recent data in a price series [33]. Its primary objective is to smooth out price data, facilitating the emergence of more precise and discernible trends, particularly in volatile markets. This study utilized a WMA for 14 days.
- The On-Balance Volume (OBV) is a critical tool in technical analysis, employing volume flow to predict stock price movements [32]. This indicator operates on the principle that volume shifts often precede price changes, asserting that volume is a fundamental companion to price trends.
- The Accumulation/Distribution (AD) indicator is a technical analysis tool to assess volume flow in stocks [32]. This indicator is primarily used to discern whether a stock is in an accumulation (buying) or a distribution (selling) phase by examining the interaction between price and volume movements. The fundamental principle of AD is the confirmation of the trend by volume.

These technical indicators were selected based on their proven effectiveness in capturing key market aspects such as trends, momentum, and volume dynamics, as demonstrated in previous studies. Their combination provides complementary insights, enhancing the model's ability to identify complex stock price patterns.

To capture different market behaviors across short- and medium-term market trends, a selection of 2, 3, 4, and 14-day technical indicator periods was tested. Common period lengths used to detect immediate short-term price fluctuations are periods of 2, 3, and 4 days, where the model can maintain sensitivity to recent market movements. The 14-day period strikes a balance between medium-term trend analysis and smoothing short-term volatility, while still responding to price changes. The timeframes used in the financial literature and trading practice are widely used, and the chosen indicators can provide both short-term momentum and represent wider market trends. This combination helps improve the model's ability to understand stock price dynamics on various time horizons.

C. Data Preprocessing

Several preprocessing steps are necessary to ensure that the data is optimally prepared for training and evaluation. Data preprocessing is crucial not just for enhancing data quality but also for significantly improving model performance.

1) Data Cleaning

The initial step in the preprocessing phase involves data cleaning to verify that the dataset is devoid of missing or inconsistent values. To maintain the integrity of the dataset, rows containing missing data were eliminated. Additionally, the dataset was scrutinized for anomalies or outliers, which were addressed as required to ensure the accuracy and reliability of the data.

2) Data Normalization

As neural networks typically exhibit superior performance when dealing with values within a standardized range, all numerical features in the dataset were normalized to fall within [0, 1] using the min-max scaling technique.

3) Data Splitting

The dataset was partitioned into three sets: training, validation, and testing. This tripartite division is crucial to ensure the model is trained, validated, and tested on different data segments, mitigating the risk of overfitting and assessing the model's generalization capabilities.

Training data encompassed the trading period from January 1, 2016, to December 31, 2020. This dataset provides the model with comprehensive insights into historical trends and trading patterns, which are essential for effective learning and weight adjustment. Data spanning January 1, 2021, to December 31, 2021, was utilized for the validation phase. This dataset is crucial to optimize the model and verify its ability to generalize learned patterns to new data while avoiding overfitting. Finally, the test data, covering the period from January 1, 2022, to December 31, 2022, were employed to evaluate the model against entirely new and previously unseen data. This step is vital for a realistic assessment of the model's performance under market conditions. The selected periods for training from 2016 to 2020, validation in 2021, and testing in 2022 were chosen to ensure a balanced representation of different market conditions, including periods of stability and volatility. This approach allows the model to learn from diverse patterns, effectively optimize its parameters, and evaluate its performance on unseen data in realistic market scenarios.

D. Evaluation Metrics

The models were evaluated by comparing the resulting predictions with the actual values using the following metrics:

- Mean Squared Error (MSE) quantifies the average of the squared differences between the predicted and actual values. It is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

where y_i represents the actual value of the shares and $\hat{y}_i$ denotes the corresponding predicted result. This metric is particularly useful for identifying the extent to which the model's predictions deviate from the actual observed values.

- Root Mean Squared Error (RMSE) is a standard evaluation metric derived as the square root of MSE. RMSE transforms the MSE back to the original data scale, offering a more intuitive understanding of the model's predictive accuracy.

$$RMSE = \sqrt{MSE} \quad (2)$$

- R^2, also known as the coefficient of determination, is a crucial metric that assesses the proportion of variance in the dependent variable that is predictable from the independent variable(s). A higher R^2 indicates a greater explanatory power of the model, which means that it accounts for more variation in the data. This metric is instrumental in evaluating the model's effectiveness in capturing the underlying patterns and relationships within the dataset.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

where $\bar{y}$ is the average of the target data.

E. Proposed Methods

This research applied the methods described in the previous sections following a systematic process as shown in Figure 1. Table I details the specific architecture of the model employed. The selection of hyperparameters, including the number of layers, learning rates, and batch sizes, was guided by findings from previous studies and empirical experimentation to balance model complexity, training stability, and generalization performance. The selected configurations aimed to optimize the learning process, prevent overfitting, and ensure convergence during training across the LSTM, GRU, and RNN models. This approach ensured a structured and consistent application of the models, facilitating a comprehensive evaluation of their effectiveness in predicting stock prices.

TABLE I. MODEL ARCHITECTURE

Model	Parameter	Value
LSTM	Number of hidden layers	2
	Number of neurons per layer	64 and 64
	Learning rate	0.01, 0.001, 0.0001
	Optimizer	Adam
	Batches	64
GRU	Number of hidden layers	2
	Number of neurons per layer	64 and 64
	Learning rate	0.1, 0.01, 0.001, 0.0001
	Optimizer	Adam
	Batches	64
RNN	Number of hidden layers	2
	Number of neurons per layer	64 and 64
	Learning rate	0.1, 0.01, 0.001, 0.0001
	Optimizer	Adam
	Batches	64

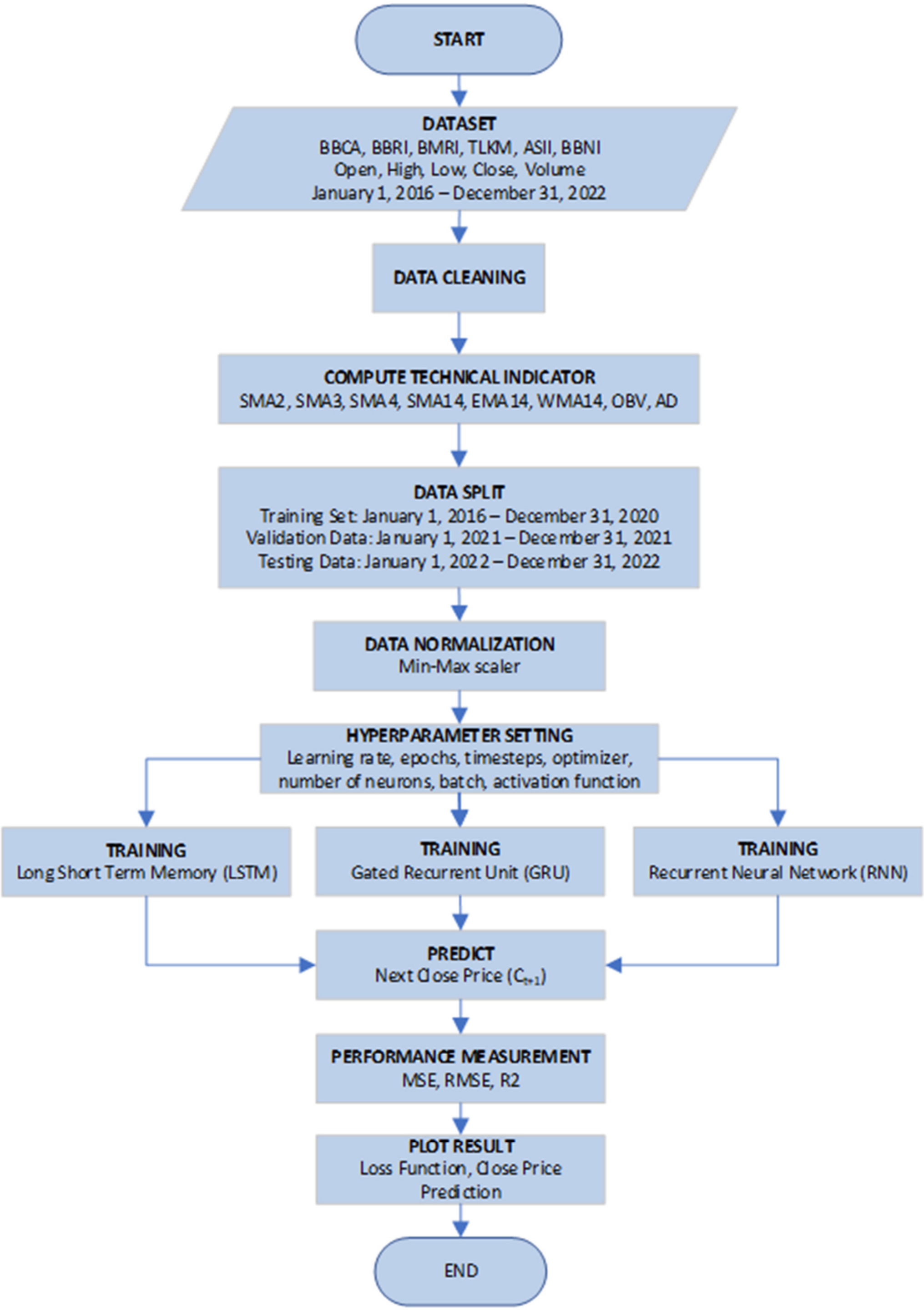

Fig. 1. Proposed method.

III. RESULTS AND DISCUSSION

A. *Dataset Characteristics*

The dataset spans a timeframe marked by significant global economic events, including the impact of the COVID-19 pandemic. Models rely on sufficient training data to learn complex patterns, reduce overfitting, and improve generalization. However, beyond a certain point, additional data offers minimal benefits. The data period (2016–2022) was carefully selected to balance noise reduction and computational efficiency. This period was characterized by considerable fluctuations in the global stock markets, mainly driven by the economic repercussions of the pandemic. These effects manifested as pronounced stock price volatility in IDX. This period was marked by sharp price changes, reflecting market uncertainty and investor reactions to varying government policies and global economic trends. Such conditions provide a critical backdrop for this analysis, influencing trading patterns and investor behavior that directly affected stock prices. Including these turbulent periods in the dataset allows us to evaluate how these models adapt and perform in unstable, unpredictable, and highly volatile market scenarios. This analysis is crucial to understanding stock market dynamics during crisis periods and gaining insight into the calibration and application of predictive models under dynamic and volatile market conditions.

The dataset underwent additional processing to extract technical features such as the SMA, EMA, WMA, OBV, and AD. These features are integral to technical analysis in stock markets. The data were normalized to ensure uniform scaling of all features, a critical step for effective optimization during the model training process.

B. Model Testing Results

This subsection describes the testing outcomes of three machine learning models: RNN, LSTM, and GRU. Testing was carried out using two distinct types of input: solely historical stock data, and a combination of historical data with technical indicators. The primary objective was to determine the relative efficacy of each model in stock price prediction and to assess the influence of incorporating technical indicators on prediction accuracy. Tables II to VII display the test results for each model, encompassing both input types across the six blue-chip stocks under examination. Additionally, Figures 2 and 3 illustrate the graphs representing the most accurate prediction results of the stocks.

TABLE II. PERFORMANCE METRICS FOR BBCA

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.880292	0.001696	0.041179
GRU	Combined	0.931407	0.00093	0.030497
LSTM	Historical data	0.837972	0.002295	0.047908
LSTM	Combined	0.935948	0.000868	0.02947
RNN	Historical data	0.900848	0.001405	0.037477
RNN	Combined	**0.93841**	0.000835	0.028898

TABLE III. PERFORMANCE METRICS FOR BBRI

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.845087	0.000919	0.03032
GRU	Combined	0.871593	0.000866	0.029423
LSTM	Historical data	0.777786	0.001319	0.036314
LSTM	Combined	0.882965	0.000772	0.027777
RNN	Historical data	0.79308	0.001228	0.035042
RNN	Combined	**0.885407**	0.000755	0.027486

TABLE IV. PERFORMANCE METRICS FOR BMRI

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.957402	0.001455	0.038146
GRU	Combined	0.926659	0.002711	0.052069
LSTM	Historical data	0.880307	0.004088	0.063941
LSTM	Combined	0.937236	0.00232	0.048168
RNN	Historical data	0.936895	0.002156	0.046428
RNN	Combined	**0.967768**	0.001192	0.034518

TABLE V. PERFORMANCE METRICS FOR TLKM

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.835037	0.002351	0.048489
GRU	Combined	0.908716	0.00122	0.034933
LSTM	Historical data	0.813014	0.002665	0.051624
LSTM	Combined	0.884521	0.001544	0.03929
RNN	Historical data	0.902542	0.001389	0.03727
RNN	Combined	**0.912624**	0.001168	0.034177

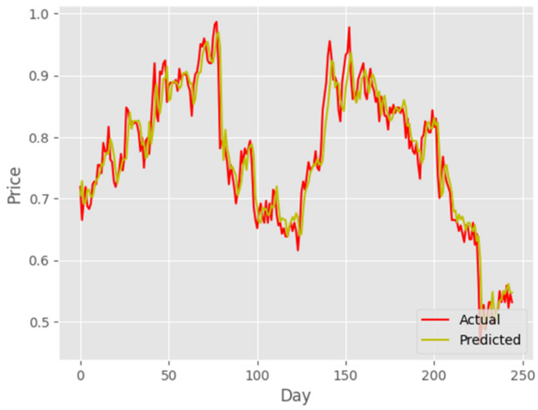

Fig. 2. TLKM stock prediction using RNN and technical indicators.

TABLE VI. PERFORMANCE METRICS FOR ASII

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.929962	0.000557	0.0236
GRU	Combined	0.9474	0.000468	0.021623
LSTM	Historical data	0.827026	0.001376	0.037088
LSTM	Combined	**0.947715**	0.000465	0.021558
RNN	Historical data	0.892458	0.000855	0.029244
RNN	Combined	0.915121	0.000754	0.027467

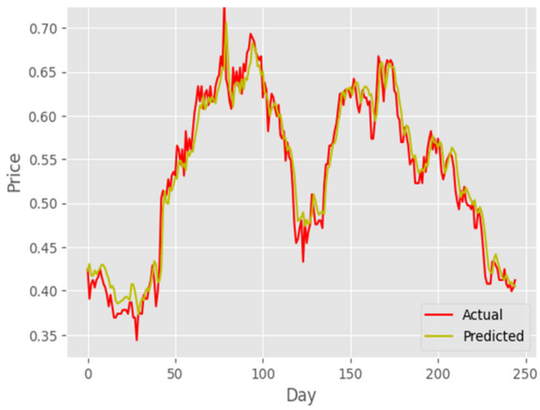

Fig. 3. ASII stock prediction results using LSTM and technical indicators.

TABLE VII. PERFORMANCE METRICS FOR BBNI

Model	Inputs	R^2	MSE	RMSE
GRU	Historical data	0.915524	0.000718	0.026787
GRU	Combined	**0.946707**	0.000589	0.024261
LSTM	Historical data	0.890835	0.000927	0.030451
LSTM	Combined	0.940245	0.00066	0.02569
RNN	Historical data	0.865215	0.001145	0.033837
RNN	Combined	0.944547	0.000612	0.024748

An analysis of the results reveals that all models experienced an increase in R^2 when technical indicators were integrated with historical data. This enhancement underscores the value of combining technical data with historical records in improving the models' capacity to account for variations in stock prices. Notably, the LSTM model employing both data types demonstrated the most considerable improvement in R^2, highlighting its superior ability to leverage the combined dataset for predictions.

Moreover, the observation of lower MSE and RMSE values for models using combined inputs corroborates that incorporating technical indicators increases the precision of predictions and decreases the error margin in stock price forecasting. Among the models, the LSTM with combined inputs showed the most notable reduction in error rates compared to the GRU and RNN models. This finding indicates the enhanced ability of LSTM to assimilate and interpret more complex information, offering a more accurate and reliable predictive model.

C. Analysis

1) Model Performance Analysis

The results show that models incorporating historical data and technical indicators generally outperform those relying solely on historical data. This finding underscores the crucial role of technical indicators in enhancing the ability of machine learning models to interpret and predict the dynamics of the stock market accurately. The notable improvement in model performance with the inclusion of technical indicators can be attributed to several factors. First, technical indicators such as SMA, EMA, WMA, OBV, and AD provide additional insights into market momentum, trends, and trading volume, aspects not captured entirely by historical stock price data alone. Incorporating these indicators enables the models to grasp finer market nuances and dynamics, which might need to be considered when focusing exclusively on historical prices. Second, merging historical data with technical indicators broadens the information spectrum available to the model, improving its ability to identify complex patterns and long-term dependencies crucial to understanding stock price movements. Third, as IDX is characterized by volatility and sensitivity to economic news, the integration of technical indicators is invaluable for generating more timely and accurate trading signals. This underscores the importance of considering technical aspects for more precise and reliable predictions. In summary, this study shows that a comprehensive approach combining diverse data types yields superior results in stock prediction models, particularly in markets subject to rapid changes and unpredictability.

2) R^2 Analysis

Analyzing the test results, a significant disparity in R^2 scores is evident between models using only historical stock data and those incorporating technical indicators. For instance, the GRU model's R^2 score for predicting TLKM share prices increased from 0.835036 with historical data alone to 0.908715 when adding technical indicators, marking an 8.82% improvement. This demonstrates that technical indicators contribute meaningful data, enabling the model to capture market dynamics not entirely reflected by historical prices.

The most pronounced enhancement in R^2 was observed in the LSTM model for the ASII stock, which soared from 0.827026 to 0.947715, a notable increase of 14.59% after the integration of technical indicators. This highlights the considerable value of additional information from technical indicators, particularly in understanding the behavior of ASII share prices.

3) Evaluation of MSE and RMSE

In terms of MSE and RMSE, the LSTM model using combined data demonstrated the most substantial improvement for ASII shares. MSE decreased significantly from 0.0013755 (with only historical data) to 0.0004647 (with combined data), indicating a marked reduction in predictive error. Consequently, RMSE decreased from 0.037088174 to 0.021557792, confirming an increase in the model accuracy. Comparatively, when supplemented with technical indicators, the GRU model exhibited more modest improvements in MSE and RMSE values. For BBCA shares, MSE reduced from 0.0016957 to 0.00093. This result suggests that the GRU model might benefit from more meticulous parameter tuning or, potentially, the inclusion of additional technical indicators to enhance its predictive accuracy.

D. Discussion

In quantitative evaluation, significant differences in performance were detected among the models examined. Using R^2, MSE, and RMSE as benchmarks [11], models integrating historical data with technical indicators were found to consistently outperform the use of only historical data. Incorporating technical indicators, the LSTM model applied to six blue-chip stocks had an average increase of 10.10% in R^2, indicating a significant improvement in stock price prediction. Similarly, the RNN model showed a substantial reduction in MSE by 32.99%, indicating a decrease in prediction error. The RMSE analysis is in line with these observations, which showed that models using aggregated data consistently had lower RMSE values compared to their historical data-only counterparts. These results strongly affirm the effectiveness of the adopted approach, stating the importance of incorporating technical indicators into predictive models. The integration of multiple technical indicators significantly enhanced the model's performance by capturing trends, momentum, and volume dynamics [34]. Although isolating each indicator's contribution was beyond the scope of this study, their combined use allowed the model to interpret stock price patterns more effectively, improving predictive accuracy and robustness.

RNN, which is hindered by vanishing gradient while capturing long-term dependencies [35, 36], showed significant performance improvements when incorporating technical indicators. This implies that technical indicators provide essential information that aids basic RNNs and reduces some of their limitations. The GRU and LSTM models, known for their proficiency in handling long-term dependencies, showed an enhanced ability to predict complex price movements when integrated with technical indicators. This improvement was attributed to the capacity of these models to effectively use information from technical indicators and the temporal context derived from historical data. The results obtained imply that, in general, RNN models outperformed the more complex LSTM and GRU models. This implies that the basic RNN architecture is in line with the data characteristics and eliminates the need for sophisticated long-term memory capabilities of LSTM and GRU. The effective use of technical indicators, which represent long-term calculations, also played a crucial role in these results.

These indicators focused on the importance of feature selection in stock price prediction models. Appropriate selection of features addresses specific architectural limitations of a model, potentially facilitating the use of more resource-efficient models, particularly in scenarios with limited computing resources. The results obtained are significant for investors and financial analysts, suggesting the potential value of integrating similar predictive models into the development of trading strategies. The limitations of this research, particularly the scope, are due to the limited number of IDX stocks. Therefore, the results obtained are not universally applicable to stocks or markets with different characteristics.

Integrating technical indicators with historical data improved the accuracy of the stock prediction model and offered a valuable tool for more informed decision-making [12-14, 37]. This approach is critical to the navigation of the volatile stock market and can empower market participants to anticipate price movements and manage investment risks more effectively. Its results can provide investors with essential information to refine buy, sell, and hold strategies. Furthermore, these results can be used by financial analysts to explain emerging trends more deeply and subsequently identify profitable opportunities and manage risk more effectively in dynamic market situations. Future research should focus on testing the model's effectiveness across various market conditions and with a broader dataset to validate the reliability and generalizability of the results.

This research primarily contributes through the innovative amalgamation of technical indicators with historical stock data to significantly enhance the predictive accuracy of deep learning models within the IDX environment. In contrast to previous studies that focused mainly on developed markets, often marginalizing emerging markets such as Indonesia [38], this one provides novel insight into the dynamics of blue-chip stocks in a developing market context. The marked enhancement in prediction accuracy, as evidenced by the superior performance of the LSTM and GRU models, highlights the critical importance of integrating multifaceted data within predictive modeling frameworks. This investigation not only augments the academic literature on stock price prediction but also provides practical implications for investors and financial analysts who seek refined tools for informed decision-making in inherently volatile market environments. By addressing the deficiencies in current research and empirically validating the efficacy of incorporating technical indicators, this work establishes a foundational basis for future studies to further examine these findings across varied market conditions and diverse stock typologies.

IV. CONCLUSION

This study applied deep learning models for stock price prediction on the IDX, focusing on blue chip stocks. Through meticulous analysis, it was established that the integration of technical indicators, such as SMA, EMA, WMA, OBV, and AD, with historical stock data significantly increases the precision of prediction models. In particular, the RNN and LSTM models demonstrated more pronounced performance enhancements compared to the GRU. These advances hold substantial implications for developing trading strategies in the stock market and provide investors and analysts with sharper tools for accurate predictions. Furthermore, this study addressed a critical literature gap by focusing on the application of deep learning techniques in stock markets of developing countries, an area often overlooked in previous research. The findings provide valuable insights into how these models combining historical data and technical indicators can effectively handle the volatility and unique characteristics of emerging markets such as Indonesia.

In light of these findings, this study advocates the incorporation of optimized deep learning models combined with technical indicators to improve investment decision-making processes. However, investors and analysts must recognize the limitations of these models, particularly regarding their generalizability beyond the tested samples and market conditions. These models should ideally be employed alongside fundamental analysis and a comprehensive understanding of the market context. Additionally, this research highlights the importance of aligning predictive frameworks with the specific dynamics of emerging markets, offering both methodological contributions and practical insights to improve decision-making processes in financial analysis. Future research should expand the application of these models to a broader spectrum of market conditions and a more diverse range of stock types. Integrating cross-validation methods is also suggested to further enhance the models' reliability and accuracy. Future investigations could also explore alternative machine learning or deep learning techniques and develop models suitable for real-time trading simulations. Additionally, it is imperative to examine the models' performance in actual market scenarios to validate their practical applicability and effectiveness.

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