Optimization of Stock Predictions on Indonesia Stock Exchange: A New Hybrid Deep Learning Method

Bernadectus Yudi Dwiandiyanta
Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia | Department of Informatics, Universitas Atma Jaya Yogyakarta, Indonesia
yudi.dwiandiyanta@uajy.ac.id

Rudy Hartanto
Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia
rudy@ugm.ac.id (corresponding author)

Ridi Ferdiana
Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia
ridi@ugm.ac.id

Received: 21 October 2024 | Revised: 13 November 2024 | Accepted: 26 November 2024

 DOI: https://doi.org/10.48084/etasr.9363

ABSTRACT

This study presents a new method for predicting stock prices on the Indonesia Stock Exchange (IDX) using a hybrid deep learning model. The proposed model combines historical price data, consisting of open, high, low, and close values, with technical indicators such as Moving Average (MA), Simple Moving Average (SMA), and Exponential Moving Average (EMA). The proposed model offered improved accuracy and efficiency using distinct architectures of Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU) to process the datasets. The results showed that the proposed hybrid model significantly outperformed traditional single-architecture models in terms of R^2, achieving 0.98 for the BBCA stock, surpassing models using only RNN or GRU. In addition, comparable improvements were observed with additional equities, such as the PT. Bank Mandiri Tbk (BMRI) and PT. Bank Negara Indonesia Tbk (BBNI) stocks, achieving an R^2 of 0.99, demonstrating the proficiency of the proposed model in capturing the complex dynamics of the stock market. The results demonstrated the significant potential of combining historical data and technical indicators into the modeling procedure to predict stock prices. This process can benefit investors and economic forecasters in the stock market. The results could be further expanded by classifying datasets and investigating different sets of models to improve the performance of financial forecasting.

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

I. INTRODUCTION

The stock market has experienced volatility in the past decade, with fluctuations driven by macroeconomic factors, company performance, and global events [1-5]. Traditionally, stock market analysis is performed using statistic-based Auto-Regressive Integrated Moving Average (ARIMA) [6-7] and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) [8]. In some cases, these methods cannot effectively capture the nonlinear characteristics of financial time series data [9-10]. As a result, the research community explores new solutions, specifically to understand the extreme price fluctuations observed in stock prices [11]. Following this discussion, deep learning predictions represent a new avenue to improve stock price forecast accuracy [12].

Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have all proven to achieve high prediction accuracy in time series forecasting, including stock price prediction [13]. RNN-based architectures have outperformed traditional models in extracting temporal structures from sequential data to analyze market patterns over time [14]. GRU has been widely used because it addresses vanishing gradient problems and has better computational efficiency than LSTM [15]. Machine learning algorithms can improve analysis by incorporating technical indicators into deep learning structures to improve predictive models [16-18]. Technical indicators that provide an extra layer of information and uncover subliminal characteristics of volatile markets include Moving Average (MA), Relative Strength Index (RSI), and Bollinger bands. Portfolio managers can achieve a significantly better perspective by combining technical indicators into the data analysis process along with historical prices [2].

The stock market has been highly volatile during the last decade, and events such as global and macroeconomic factors played a primary role in determining its volatility. Although useful, traditional methods such as ARIMA and GARCH frequently did not adequately capture the evolving market dynamics. Some examples of studies using traditional methods are provided in [7-8, 19]. ARIMA performed poorly on non-stationary data, which is typical of stock markets characterized by frequent trend changes and volatility, indicating a need for more innovative and adaptable approaches. In the field of deep learning, RNN, LSTM, and GRU have shown far better performance in predicting time series, including stock prices. Some studies have also used simple RNN for stock price prediction [20], but the vanishing gradient problem often plagued their results, making it an inadequate tool for studying long-term dependencies in financial data. LSTM is a widely used model, and some studies used it to overcome the vanishing gradient problem [21-24]. However, these models can be complex and computationally intensive, often not accommodating large-scale or real-time data processing. Some studies relied on the GRU model [25-27] to simplify this process. However, the models used separately were not fully able to merge historical data and technical indicators.

This study presents a hybrid model that combines RNN and GRU. In addition, it combines the strengths to process historical data and technical indicators at the same time, helping to further improve the prediction accuracy in financial prediction and introducing new insights. Combining these two techniques can make the model more adaptive and accurate for studying and forecasting dynamic stock price behavior. GRU is used to manage the historical data input of stocks, and RNN is used to assess technical indicator data. Stock price predictions are obtained by combining the outputs of the RNN and GRU networks. The model was applied to blue chip stocks listed on the Indonesia Stock Exchange (IDX) to determine how the model works as a financial forecasting tool and to provide new insights into stock prediction. The primary contributions of this study include:

- The formulation of an innovative stock prediction model that combines GRU and RNN to improve the extraction of latent information in a new framework, both technically and temporally.
- A thorough analysis of the model using Mean Square Error (MSE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) to determine the benefits of the proposed model over conventional methods.
- An analysis of IDX blue chip stocks using deep learning methods and new perspectives on financial prediction.

This study addresses the issue of overloading the model with considerable information by combining both technical and historical data into a singular predictive model. This method increases accuracy and allows for more complex research that incorporates real-time data and other variables to produce more dynamic and adaptive stock market forecasts.

II. RELATED WORKS

LSTM is an effective deep-learning model for analyzing complex and unpredictable time series data. LSTM has shown its effectiveness in forecasting stock values under various market conditions, such as financial crises induced by the COVID-19 pandemic or elevated interest rates. In [28], data from multiple stocks were used to show the flexibility and resilience of LSTM in modeling financial data and accurately predicting stock prices. In [29], LSTM produced reliable predictions under volatile market conditions, showing improvements in the acquisition of temporal and spatial characteristics of financial data. In [30], LTSM was optimized with Particle Swarm Optimization (PSO), showing improvements in predictive accuracy and efficiency. In [31], LSTM was used alongside trading algorithms, demonstrating its efficacy in producing lucrative trading signals. In [32], LSTM was combined with sentiment analysis to elucidate the impact of news and public opinion on stock price fluctuations, leading to a model relating to external market influences.

GRU is a variant of RNN that has been proven to be effective in time series data for stock price prediction. The model simplifies the LSTM structure and retains its ability to handle unsolved gradient vanishing and exploding problems of highly volatile stock markets and complex financial data. As shown in [26], the GRU model based on a reconstructed dataset reduces overfitting by using data from stocks in the same industry and produces significant prediction improvements in the cross-industry. In [33], GRU was combined with Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and wavelet thresholding methods to reduce noise and improve stock index prediction performance over modified ARIMA and neural network models. In [34], StockNet was proposed, which is a data-augmented model using GRU for better stock index prediction accuracy and loss reduction. In [35], a model based on GRU and LSTM was presented for stock price prediction, showing that while GRU had competitive results, LSTM provided greater accuracy with more data.

Hybrid models combine methods from different disciplines and achieve better stock price predictions. Stock market forecasts are successfully incorporated using methods such as LSTM, CNN, GRU, sentiment analysis, and optimization to improve the accuracy of predictions. In [36], LSTM was combined with CNN. In [37], the superiority of Bi-LSTM and Transformer in capturing temporal and spatial features was demonstrated in financial data. In [38], LSTM was combined with CNN to improve the stock prediction model. For intraday stock prediction, the studies in [39] and [30] improved feature selection and parameter tuning in LSTM models using genetic algorithms and PSO, achieving better performance. In [40] Bi-LSTM was combined with CNN to improve forecasting in volatile markets by applying the advantages of each mechanism in financial data analysis. In [41], LSTM was combined with FinBERT to predict the effect of sentiments from news and social media on stock prices. The hybrid models in [42, 43] extracted important features from noisy data while increasing the accuracy of predictions, using wavelet transforms and PCA.

Although stock price prediction based on traditional and deep learning models has been significantly developed, some drawbacks still exist, especially in dealing with complex and volatile movements of stock prices. Traditional methods such as ARIMA models do not handle sudden market shocks, as this method is linear, while in periods of high volatility, nonlinear relationships are witnessed. Similarly, while GARCH provides structures for estimating volatility, it may not provide accurate real-time predictions, particularly in situations where market conditions are unpredictable. Machine learning models have been introduced to address these limitations. However, single-architecture neural networks, such as standalone RNNs or GRUs, exhibit bias toward certain types of data patterns, overfitting or underfitting the data based on their historical consistency and the model's sensitivity to parameter settings. This relates more to the IDX, which is a dynamic market, often influenced by economic policies and external global events.

In addition, although the effectiveness of GRU in alleviating vanishing gradients has been well proven, the unification with the benefits of simple RNN will not fully exploit the latent information hidden in various types of market data. To integrate technical indicators and price data, a more sophisticated method is needed to evaluate the relative importance of different inputs at different times on the market. Gaps in iterative modeling methods led to a hybrid model that combines RNN and GRU, resulting in a more robust framework capable of being modified to the multifold nature of financial datasets. These discussions underscore the importance of ongoing innovation in the development of stock prediction methods, particularly through the creation of hybrid models that integrate the most effective neural network architectures to provide a more comprehensive and precise understanding of market developments. By focusing on these particular challenges, this study can help the larger discipline of financial forecasting by providing some useful ways to more powerful predictive tools for investors and analysts.

This study extends previous work to produce a more combined and automated prediction model for blue chip IDX stocks, using a hybrid method that efficiently combines both GRU and simple RNN models. The proposed model addresses specific challenges in combining historical data inputs with technical indicators to better predict the highly complex and dynamic market conditions of the country [44]. This research adds to stock trading decisions by providing more accurate and reliable stock price predictions, providing more useful perceptions and tools for investors and analysts for decision-making.

III. METHODS

A stock price prediction model using an innovative deep learning method was developed by combining two different types of RNN, including GRU and simple RNN. Both networks were used to maximize the potential of the combination to process historical and technical stock data. For historical data showing long-term fluctuations and trends, GRU is known for the fewer parameters and the simpler structure that leads to better efficiency in managing long-term dependencies over LSTM. Consequently, basic RNN proved useful in handling technical data that required quick responses to changes in the market without ignoring historical market fluctuations. By incorporating the information from each data type, the concatenation process allowed the system to leverage the strengths of both models and generate a more comprehensive and accurate result.

A. Data Description

The data used were derived from IDX and consisted of daily trading of IDX-listed blue chip stocks, including 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). Data included the initial (Open), highest (High), lowest (Low), and closing (Close) prices, in addition to daily trading volumes. Due to the incompleteness of initial historical data, technical indicators were used, including MA, Simple Moving Average (SMA), and Exponential Moving Average (EMA), across various time frames to determine trends or momentum in stock price movements. SMA was used with intervals of 2, 3, 4, and 14 days, with 14 days for EMA. The time frames for 2, 3, 4, and 14 days are the most relevant periods to reflect current market dynamics and also represent short- and mid-term trading indicators. In addition, the Yahoo Finance website was used to obtain the trading data. Data in CSV format were made accessible at https://finance.yahoo.com from January 1, 2005, to December 31, 2022.

The data preprocessing step involved cleaning the data by removing incomplete entries and errors. An imputation technique based on the linear interpolation method, commonly used in time series analysis, was applied to address missing data and maintain temporal consistency. In addition, zero entries were removed, which typically occur on exchange holidays, to ensure that the data used reflected only active trading days. All numeric data were normalized by setting all values on the same scale to prevent bias in the model due to differing scales of variables and to accelerate convergence during training. Additionally, the data were transformed into features that were ready to be used as input to the deep learning model, after the scales were normalized on all variables using min-max scaling. The transformation of the technical data consisted of calculating various previously mentioned technical indicators that assisted in detecting vital signals from the stock market. Since the data were already in a temporal aspect, no additional transformation was needed for the historical data. Following this process, the historical data was directly normalized to preserve its original information. The purpose of this preprocessing step was to ensure that the data were clean, representative, and consistent, reducing the risk that the model was learning from noise instead of actual signals and allowing it to learn from many relevant patterns. An additional reason was to ensure that the predictive results of the model were valid and reliable.

B. Dataset Splitting

The division of data into training, validation, and testing was designed to be fair and optimizable to evaluate the performance of the deep learning model without overfitting. The collected and preprocessed data were chronologically divided to facilitate training, optimal hyperparameter tuning, and validation. By structuring the method, the model was systematically checked at every stage, improving and validating its performance before deployment for external predictions on real-world data.

This study used training data from January 1, 2005, to December 31, 2017. This time frame was selected for the model to fully learn the dynamics and prices of the market, covering two complete market cycles: the growth period before the 2007-2008 global financial crisis and the post-crisis recovery that lasted until around 2017. Historical data helps identify and respond to new trends in developing markets. The validation data, which covered the period from January 1, 2018, to December 31, 2020, were used to refine the method. The validation period was chosen to test the reliability and stability of the model under current market conditions during the impact and recovery after the COVID-19 pandemic. The dataset was used to calculate hyperparameters, such as the learning rate and the number of epochs. These processes were important in validating the method to optimize the model and avoid overfitting before the testing stage. The test data, which covered the period from January 1, 2021, to December 31, 2022, served as a critical test set for the final performance of the model. The testing period was chosen to assess the model's ability to cope with highly volatile market conditions influenced by the COVID-19 pandemic, which marked one of the most significant events affecting the global economy and stock markets. The predictive capabilities of the model were tested under real market conditions.

C. Model Architecture

Two separate neural network architectures were used to process technical and historical data to optimally process crucial information in each data type to develop the stock price prediction model, as shown in Figure 1. The model used an RNN consisting of each layer having 100 units, 75 units, and 50 units, with Rectified Linear Unit (ReLU) activation to provide non-linearity in each layer. Moreover, the model was used to process data at relatively short time windows, allowing it to react rapidly to volatile and changing market conditions. During the investigation, the complex dynamics of technical indicators were captured, including SMA, EMA, and MA.

The GRU architecture was applied to temporal historical data, such as Open, High, Low, and Close (OHLC) stock price data. GRU is capable of looking back at previous time steps and incorporating the information into the current data analysis. Modeling stock prices, which were mostly based on past trends and patterns, requires this process. To ensure that outputs are captured in a bounded range, a prerequisite for consistent time-series predictions, a GRU with many layers, each with a variety of sizes, and ReLU activations was used. This study employed GRU in the context of one, two, three, and multilayer architectures. Various units were tested, including [256], [256, 128], [200, 100, 75], [512, 256, 128], [200, 100, 75, 50], [200, 100, 75, 50, 50, 25, 25, 20], and [100, 75, 50, 25, 25, 20, 20, 20, 15, 15, 10, 10, 10].

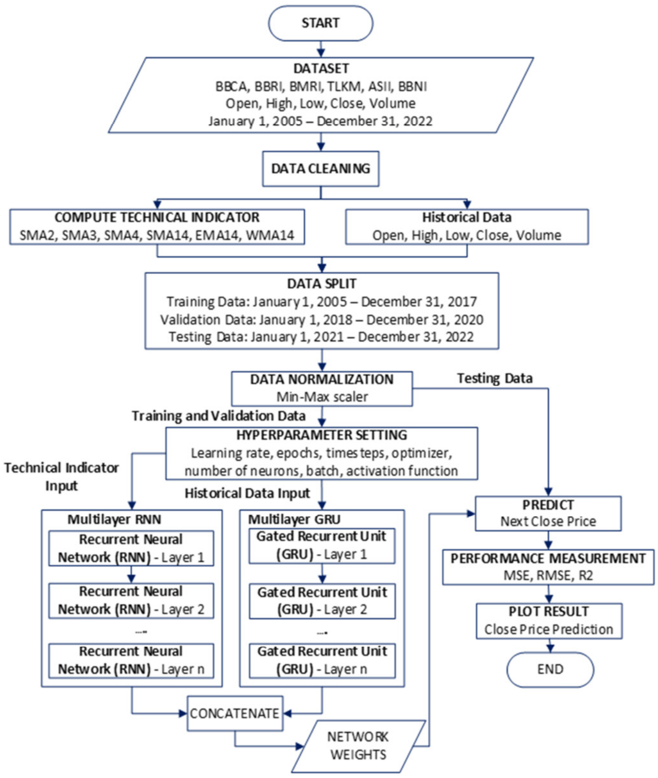

Fig. 1. The proposed method.

The outputs from both models were concatenated after each model processed historical and technical data. This step ensured that the model absorbed the information from both data domains to improve its predictive potential. A dense layer was applied to combine the outputs, further refining the information before the final prediction. In addition, the task of predicting stock prices as continuous values required a simple output layer, such as a single neuron with a linear activation function. This hybrid system collected the processed data and the subsequent stock price predictions based on the data analysis in the model.

D. Model Training

The backpropagation method was used in the training process. The training was structured in multiple phases to facilitate efficient convergence without causing overfitting. Training sessions were scheduled in epochs with a fixed batch size. The batch size was set to 64 for efficient training and proper memory use. Effectively updating the network weights was possible based on every 64 samples from the dataset. For training, a total of 400 epochs were carried out by implementing an early stopping method. Training stopped when the model did not show any improvement in the validation data over the last 80 epochs. Early stopping was based on the val_loss to avoid overfitting. The min_delta parameter was set to 0.0001, meaning that a smaller decrease is not considered a significant improvement. Patience was set to 80, allowing the model to continue training for up to 80 epochs after there was no more significant improvement in val_loss, before training was stopped if no further improvement was seen. The min mode indicates that the process will stop when there is no more decrease in val_loss, ensuring that the model does not stop training too early and stops only when there is truly no improvement in predictions. Using this method ensured the absence of overfitting.

The Adam optimizer was used, as it is a popular optimizer that automatically adjusts the learning rate during the training process. This ability facilitated faster and more stable convergence to the optimal learning minimum. Initially, the learning rate was set at 0.001 and adjusted during training to improve the model performance. The MSE was used for the loss function, as this process is a legitimate way to quantify the size of the prediction errors made by the model and handle the errors. This ability is essential in areas such as financial forecasting, where significant errors in price predictions lead to substantial costs. The model was regularly validated using the validation set during the training phase to determine the model performance.

For model training, each blue chip stock on the IDX was individually trained to understand the characteristics of the stock to adapt the model. Each stock was trained using historical data, and the model learned and internalized stock-specific patterns that may not have been captured in the broader market. On this note, each company had distinctive factors that were involved in affecting the value of its stock and shareholders, such as commercial performance, industry sector, and the subtleties of world economic situations.

E. Model Evaluation

The model was examined to predict stock prices and compare them with actual market prices. The testing phase determined how effective the model was in being truly validated under real-market scenarios. A set of widely used metrics in financial and machine learning evaluation was applied to capture different aspects of model performance, including prediction accuracy, while market dynamics captured the ability and reliability of outcomes under different market conditions. MSE, RMSE, and R^2 were used because they are widely and frequently used to evaluate stock prediction models. MSE and RMSE offer a clear measure of errors when comparing actual and predicted values, and R^2 represents how well a model predicts the dependent variable with the model itself. These metrics can be used to compare the results of this study with others in the same field that also use the same metrics [45-46]. MSE involves the average of the squares of errors, including the average squared difference between the estimated and actual values. This metric provides a clear measure of the accuracy of the model and signifies larger errors more significantly, 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 stock and $\hat{y}_i$ is the corresponding predicted result. RMSE is the square root of MSE, providing an interpretable measurement in the same units as the forecast quantity to help understand errors in the magnitude of prediction.

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

R^2 measures the extent to which the variance of the dependent variable is explained by independent variables, measuring the probability of how unseen samples were predicted.

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

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

IV. RESULTS

Using a combination of historical data and technical indicators, the proposed hybrid model was applied to stocks including BBCA, BBRI, BMRI, ASII, TLKM, and BBNI. Table I shows the prediction results for the stocks under analysis. Figures 2 and 3 are examples of loss plots for the BBRI and BMRI stocks during the model training phase. Figure 2 shows that the training loss was very consistent and steady, uniformly decreasing as the training epoch increased. In contrast, the validation loss exhibited more fluctuations and higher peaks from around 20 epochs, indicating that the model overfitted on unseen validation data. Figure 3 clearly shows a significant decrease in training loss, indicating that the model performed well on the training data. However, the validation loss remained consistent, showing fewer fluctuations, while the training loss consistently remained high, albeit not as high as in the previous example. This consistency in the difference between the training and validation losses indicates that, although the model learned the training data incredibly well, it was not as adept at predicting the validation data, leading to overfitting. Based on both loss plots, the model showed mild indications of overfitting, as indicated by the relatively small difference between training loss and validation loss, which did not significantly affect the model's predictive performance.

Fig. 2. Loss plots for the BBRI stock during model training.

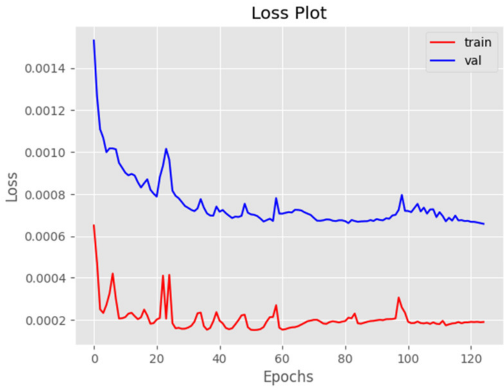

Fig. 3. Loss plots for the BMRI stock during model training.

TABLE I. RESULTS OF STOCK PREDICTION TESTING USING HYBRID MODEL

Stock	Time-steps	MSE	RMSE	R^2
BBCA	40	0.005037	0.070972	0.871525
BBCA	30	0.000947	0.030769	0.975588
BBCA	20	0.000741	0.027221	0.980643
BBCA	15	0.009964	0.099824	0.7380700
BBRI	30	0.000550	0.023456	0.937230
BBRI	25	0.000541	0.023269	0.938207
BBRI	20	0.000555	0.023560	0.936060
BMRI	30	0.000476	0.021809	0.985406
BMRI	35	0.000526	0.022926	0.983916
BMRI	20	0.000559	0.023651	0.982668
ASII	50	0.000213	0.014609	0.967222
ASII	40	0.000192	0.013865	0.970069
ASII	30	0.000202	0.014199	0.968052
ASII	21	0.000200	0.014150	0.967704
BBNI	30	0.000277	0.016635	0.988196
BBNI	40	0.000269	0.016400	0.988624
BBNI	20	0.000487	0.022077	0.978984
BBNI	50	0.000335	0.018315	0.985932
TLKM	15	0.000418	0.020450	0.972427
TLKM	20	0.000326	0.018043	0.978380
TLKM	30	0.000366	0.019124	0.975243

Figures 4, 5, and 6 show prediction examples for the BBRI, BMRI, and BBNI stocks. This study examined the model specifically for each blue chip stock instead of using a general approach, allowing for more accurate analysis and prediction according to the unique characteristics of each stock.

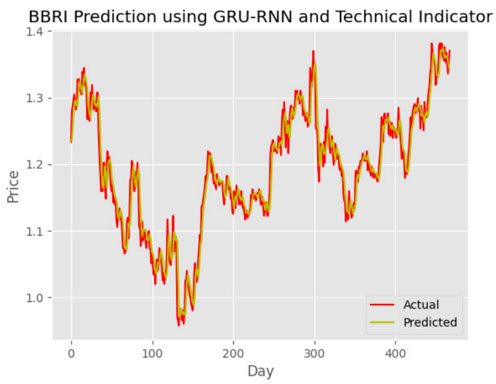

Fig. 4. BBRI stock prediction results using the hybrid model.

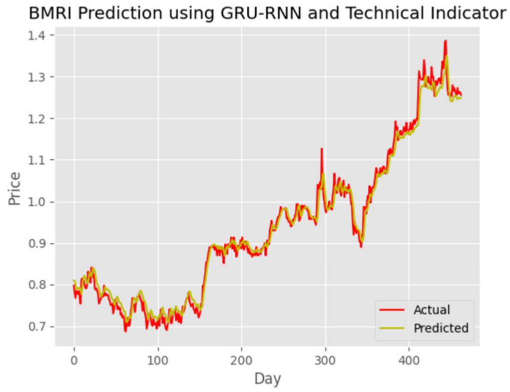

Fig. 5. BMRI stock prediction results using the proposed hybrid model.

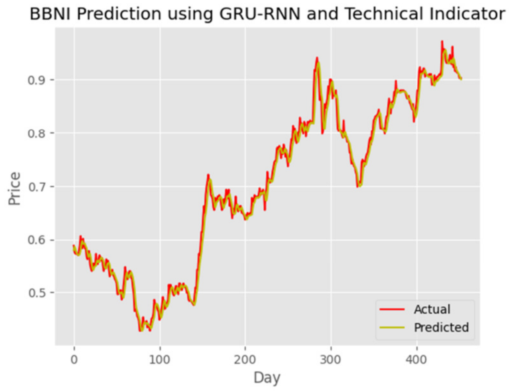

Fig. 6. BBNI stock prediction results using the proposed hybrid model.

The proposed model showed an important improvement in accuracy, as evidenced by the very high R^2 values for several stocks. For example, in the case of BBCA, reducing the time steps from 40 to 30 led to an increase in R^2 from 0.8715 to 0.9756, while MSE and RMSE decreased from 0.0050 to 0.000947 and from 0.070972 to 0.030769, respectively. These results show a significant improvement in the model's ability to explain stock price variability. For the BBRI stock, R^2 was in a relatively stable range, from 0.9360 to 0.9382, showing that the model captured the stable market dynamics of the stock and performed well under less volatile market conditions. Changes in time steps did not significantly affect the stock, implying that the model was well-optimized for the stock on a variety of time-step configurations. The R^2 for the BMRI stock increased considerably with changing time steps, with the maximum at 0.9854 at 30 time steps. This result shows that BMRI market dynamics were more complicated and could be adequately predicted by classical model adjustments on a finer scale.

The performance of the model was continuously high in the case of the ASII stock. This result signifies the good stability and reliability of the model in estimating and predicting stock price movements, regardless of the tested configuration. The consistency of the model showed that it successfully captured the main market patterns affecting ASII stock, considering the factors that influence its price, while minimally affected by short-term fluctuations. The model achieved impressive performance on the BBNI stock, with an R^2 of 0.9886 at 40 time steps, showing that it nearly captured all variability in the stock price movements of BBNI. Although the result for R^2 slightly decreased to 0.9789 when reducing the time steps to 20, the process still reflected a perfect result considering the information given to the model at each prediction. This process shows that the model closely mirrored the market trends that affected BBNI. However, higher RMSE values in some configurations could help improve the performance of correctly predicting prices.

The model produced consistent and strong results on the TLKM stock with R^2 of 0.9724 after 15 time steps and 0.9784 after 20 time steps. The performance of the model improved with increasing time steps, indicating that more historical information helped the model better predict stock price movements. The model showed the ability to understand and analyze the market dynamics of TLKM with consistently high R^2 at each time step, which is a stock with highly predictable prices through exhaustive technical analysis.

These results imply that the hybrid model was superior to financial modeling. A comparison of model accuracy showed that combining the model with technical indicators and historical data produced a significant increase in prediction accuracy. These results allow careful adjustments of time steps and layer depth relative to the exceptional characteristics of each stock. This process shows the significance of an adjustable and custom hybrid model in an ever-changing and frequently unforeseeable universe of stock markets.

Table II provides the R^2 values for the BBNI stock with 30 time steps and 100 RNN units. The analysis of various GRU unit configurations on BBNI stock prediction reveals that models with larger GRU units in the initial layer, such as the configuration [512, 256, 128], performed better, yielding the highest R^2 of 0.9882. This suggests that the model can capture complex information in the data more effectively. On the contrary, configurations with smaller units and a higher number of layers, such as [100, 75, 50, 25, 25, 20, 20, 20, 15, 15, 10, 10, 10], had lower R^2. This suggests that the model might be underfitting or lacking generalization power. With three or four layers ([200, 100, 75] and [200, 100, 75, 50] respectively), the results were very competitive and can be considered an efficient choice in terms of balancing model complexity and predictive performance. The conclusion from these results is that having several layers with large units at the beginning is more appropriate for the prediction of stock data with high accuracy and low computational efficiency.

TABLE II. GRU CONFIGURATION AND R^2-SCORES FOR PREDICTION PERFORMANCE ON THE BBNI STOCK

GRU Units	R^2
[200, 100, 75, 50, 50, 25, 25, 20]	0.9853
[100, 75, 50, 25, 25, 20, 20, 20, 15, 15, 10, 10, 10]	0.9805
[200, 100, 75]	0.9876
[200, 100, 75, 50]	0.9859
[256, 128]	0.9864
[512, 256, 128]	0.9882

This study used historical data and technical indicators to analyze the performance of stock price prediction of IDX blue chip stocks. The hybrid model performed better than the GRU, LSTM, and RNN models, achieving a higher R^2, as shown in Table III. Several blue-chip stocks were compared in Table III based on GRU, LSTM, RNN, and hybrid models. Furthermore, the hybrid method provided better predictions, revealing the complex dynamics of financial markets compared to single-model methods.

TABLE III. COMPARISON OF R^2 VALUES ON BLUE-CHIP STOCKS

Model	Input	BBCA	BBRI	BMRI	TLKM	ASII	BBNI
GRU	Historical	0.8803	0.8451	0.9574	0.8350	0.9300	0.9155
GRU	Combined	0.9314	0.8716	0.9267	0.9087	0.9474	0.9467
LSTM	Historical	0.8380	0.7778	0.8803	0.8130	0.8270	0.8908
LSTM	Combined	0.9359	0.8830	0.9372	0.8845	0.9477	0.9402
RNN	Historical	0.9008	0.7931	0.9369	0.9025	0.8925	0.8652
RNN	Combined	0.9384	0.8854	0.9678	0.9126	0.9151	0.9445
Hybrid model	Combined	0.9806	0.9382	0.9854	0.9784	0.9701	0.9886

The hybrid model surpassed both the LSTM and the GRU models using only historical data on all stocks. For example, the hybrid model achieved an R^2 of 0.9806 for BBCA, outperforming GRU (0.8803) and LSTM (0.8380). Similarly, the hybrid model reached an R^2 of 0.9854 for BMRI compared to 0.9574 for GRU and 0.8803 for LSTM. The model was successful due to the hybrid linkages of the technical indicators that worked to improve its ability to change with market movements rapidly and clearly. The technical indicator data show an additional layer of data prediction that effectively reduces noise and improves the reliability of the generated signals. These variables are important in addressing the frequently unstable and unpredictable dynamics of the stock market, proving that the inclusion of technical data in stock prediction models places the models in a good position for financial analysis.

TABLE IV. PERFORMANCE COMPARISON IN STOCK PREDICTION IN EMERGING MARKETS

Authors	Model	Market	Performance Measurement
[29]	LSTM	Indonesia	Accuracy=94.57%
[47]	LSTM	Indonesia	Accuracy=94.59%
[48]	LSTM	India	MSE=1.034, RMSE=1.002
[49]	RNN	Indonesia	RMSE=0.148, MAE=0.109, MAPE=28.97
	GRU		RMSE=0.140, MAE=0.103, MAPE=26.36
	LSTM		RMSE=0.141, MAE=0.103, MAPE=27.81
[50]	LSTM	India	MAPE=0.0028, MAE=0.0058, RMSE=0.0069, R^2-Score=0.9740
[35]	LSTM GRU	Tanzania	RMSE= 4.7524 RMSE= 8.7162
Proposed model	Hybrid GRU-RNN	Indonesia	MSE=0.000269, RMSE=0.016400, R^2-score=0.9886

Table IV compares the performance of LSTM, GRU, and hybrid GRU-RNN models in stock prediction across several emerging markets. The performance of model variants in Indonesia, India, and Tanzania showed significant variation, with GRU and LSTM being used frequently. The proposed hybrid GRU-RNN model performed very well with a high R^2, confirming its effectiveness in a market like Indonesia. This table highlights the ability of different models to capture stock market dynamics and supports the superiority of the proposed hybrid approach in similar contexts.

The achievement of the hybrid model was due to the types of financial analysis used. The hybrid model helped to increase prediction accuracy and instill confidence in its performance under different market conditions by harnessing the strengths of diverse inputs. In addition, the model considerably decreases the risks included and substantially accelerates the return on investment in stock market decision-making. For investors and analysts who work in a fast-moving and often unpredictable market environment, the hybrid model has proven excellent, as shown by its success in predicting stock prices more accurately. Moreover, the model was flexible to adapt to new and unexpected market conditions, allowing it to be highly relevant and valuable.

The results show that the hybrid model, combining historical data with technical indicators, presents a more stable and quick method for stock price prediction, confirming its technical superiority and its added value for financial predictions when combining different data. Improvements to the proposed model would allow the development of more complex and adaptive predictive tools that could address complex opportunities across global financial markets.

V. DISCUSSION

This study showed the ability to predict stock prices using a hybrid deep learning model on IDX blue chip stocks. The investigation employed different architectural configurations to examine how the depth of the hidden layers and changes in time steps affect the predictive accuracy of the model. The results showed that the appropriate configurations were able to significantly improve model performance (R^2 and RMSE). Based on the results, the model was able to reproduce the dynamics of the stock market to some extent. The results indicate that the model was susceptible to unpredictable market fluctuations. Low-performing models showed higher accuracy in predicting prices as the market was stable but performed less accurately when the output was exogenous (such as extreme market volatility). This raises questions about the stability and reliability of models in many possible unstable market scenarios, underlining the need to develop systems useful in normal and also strong in unstable conditions.

Discussions should continue to determine that while deep learning technology has presented significant opportunities for predictive analysis, the examination is still progressing. Adding more public data sources from macroeconomic indicators to market sentiment data could expand the dimensional range of the model to acquire sensitivity and dynamism in reaction to the external circumstances that influence the market. In addition, there is a need to address the risk of overfitting, which occurs when a model becomes overly trained to specific historical data, limiting its ability to generalize to new data or adapt to changing market conditions. This analysis serves as a stepping stone to the use of more severe regularization methods and cross-validation in training the model to avoid risk and improve its generalization ability.

Stock prediction models are required to become more general and interpretable. This process includes how the predictions of the model could be transformed into profitable trading strategies that produce actual economic benefits in real markets, rather than pure theoretical performance when testing. This study intensifies the discourse on the aspects and provides a stronger understanding of the predictive capabilities of these models, establishing a solid foundation for the future development of more complex and adaptive predictive technology in finance.

VI. CONCLUSION

This study proposed a hybrid model to predict the stock prices of IDX blue chip companies. The proposed model achieved a very high accuracy when a proper architectural configuration was established. The configuration included depths of the hidden layers and time step settings, achieving high R^2 and low RMSE values. These results highlight the need for models capable of optimizing performance under stable regimes that are sufficiently flexible and adaptable to respond to fluctuations in market dynamics. The inability of models to respond to sharp economic shifts and adjust their internal parameters has led to recommendations for further research, aimed at developing predictive models that could proactively adapt the parameters, ensuring accuracy in a changing market. This study validated the application of hybrid deep learning models in financial analysis, building a foundation for the continuation of model refinement. Future research should develop dynamic and responsive methods to advance the reliability and effectiveness of financial predictive models to provide investors and analysts with the resources needed for informed data-driven decisions.

ACKNOWLEDGMENT

The author acknowledges the Universitas Atma Jaya Yogyakarta and the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada Yogyakarta, for funding this research. This work was funded by the Final Project Recognition Grant Universitas Gadjah Mada Number 5286/UN1.P1/PT.01.03/2024.

REFERENCES

[1] Y. Gu, T. Shibukawa, Y. Kondo, S. Nagao, and S. Kamijo, "Prediction of Stock Performance Using Deep Neural Networks," *Applied Sciences*, vol. 10, no. 22, Jan. 2020, Art. no. 8142, https://doi.org/10.3390/app10228142.

[2] A. Thakkar and K. Chaudhari, "A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions," *Expert Systems with Applications*, vol. 177, Sep. 2021, Art. no. 114800, https://doi.org/10.1016/j.eswa.2021.114800.

[3] M. Nabipour, P. Nayyeri, H. Jabani, S. S., and A. Mosavi, "Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis," *IEEE Access*, vol. 8, pp. 150199–150212, 2020, https://doi.org/10.1109/ACCESS.2020.3015966.

[4] Y. Gao, R. Wang, and E. Zhou, "Stock Prediction Based on Optimized LSTM and GRU Models," *Scientific Programming*, vol. 2021, no. 1, 2021, Art. no. 4055281, https://doi.org/10.1155/2021/4055281.

[5] N. Deepika and M. Nirupamabhat, "An Optimized Machine Learning Model for Stock Trend Anticipation," *Ingénierie des systèmes d information*, vol. 25, no. 6, pp. 783–792, Dec. 2020, https://doi.org/10.18280/isi.250608.

[6] S. Deepan, P. S. Reddy, M. Vyshnevy, K. Tejasri, B. Akshaya, and P. Nikhil, "Prediction and Analysis of Stock Markets Using ARIMA Models," in *2024 3rd International Conference on Computational Modelling, Simulation and Optimization (ICCMSO)*, Phuket, Thailand, Jun. 2024, pp. 268–271, https://doi.org/10.1109/ICCMSO61761.2024.00061.

[7] A. A. Ariyo, A. O. Adewumi, and C. K. Ayo, "Stock Price Prediction Using the ARIMA Model," in *2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation*, Cambridge, UK, Mar. 2014, pp. 106–112, https://doi.org/10.1109/UKSim.2014.67.

[8] H. Herwartz, "Stock return prediction under GARCH — An empirical assessment," *International Journal of Forecasting*, vol. 33, no. 3, pp. 569–580, Jul. 2017, https://doi.org/10.1016/j.ijforecast.2017.01.002.

[9] T. S. Mian, "Evaluation of Stock Closing Prices using Transformer Learning," *Engineering, Technologsty & Applied Science Research*, vol. 13, no. 5, pp. 11635–11642, Oct. 2023, https://doi.org/10.48084/etasr.6017.

[10] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, and H. Zhang, "Deep Learning with Long Short-Term Memory for Time Series Prediction," *IEEE Communications Magazine*, vol. 57, no. 6, pp. 114–119, Jun. 2019, https://doi.org/10.1109/MCOM.2019.1800155.

[11] A. A. Adebiyi, A. O. Adewumi, and C. K. Ayo, "Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction," *Journal of Applied Mathematics*, vol. 2014, no. 1, 2014, Art. no. 614342, https://doi.org/10.1155/2014/614342.

[12] W. Jiang, "Applications of deep learning in stock market prediction: Recent progress," *Expert Systems with Applications*, vol. 184, Dec. 2021, Art. no. 115537, https://doi.org/10.1016/j.eswa.2021.115537.

[13] V. D. Ta, C. M. Liu, and D. A. Tadesse, "Portfolio Optimization-Based Stock Prediction Using Long-Short Term Memory Network in Quantitative Trading," *Applied Sciences*, vol. 10, no. 2, Jan. 2020, Art. no. 437, https://doi.org/10.3390/app10020437.

[14] M. A. Haq *et al.*, "Analysis of environmental factors using AI and ML methods," *Scientific Reports*, vol. 12, no. 1, Aug. 2022, Art. no. 13267, https://doi.org/10.1038/s41598-022-16665-7.

[15] T. B. Shahi, A. Shrestha, A. Neupane, and W. Guo, "Stock Price Forecasting with Deep Learning: A Comparative Study," *Mathematics*, vol. 8, no. 9, Aug. 2020, Art. no. 1441, https://doi.org/10.3390/math8091441.

[16] N. Y. Vanguri, S. Pazhanirajan, and T. A. Kumar, "Competitive feedback particle swarm optimization enabled deep recurrent neural network with technical indicators for forecasting stock trends," *International Journal of Intelligent Robotics and Applications*, vol. 7, no. 2, pp. 385–405, Jun. 2023, https://doi.org/10.1007/s41315-022-00250-2.

[17] M. C. Lee, "Research on the Feasibility of Applying GRU and Attention Mechanism Combined with Technical Indicators in Stock Trading Strategies," *Applied Sciences*, vol. 12, no. 3, Jan. 2022, Art. no. 1007, https://doi.org/10.3390/app12031007.

[18] S. Borovkova and I. Tsiamas, "An ensemble of LSTM neural networks for high-frequency stock market classification," *Journal of Forecasting*, vol. 38, no. 6, pp. 600–619, 2019, https://doi.org/10.1002/for.2585.

[19] K. Albeladi, B. Zafar, and A. Mueen, "Time Series Forecasting using LSTM and ARIMA," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 1, 2023, https://doi.org/10.14569/IJACSA.2023.0140133.

[20] Y. F. Lin, T. M. Huang, W. H. Chung, and Y. L. Ueng, "Forecasting Fluctuations in the Financial Index Using a Recurrent Neural Network Based on Price Features," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 5, no. 5, pp. 780–791, Jul. 2021, https://doi.org/10.1109/TETCI.2020.2971218.

[21] R. Zhang, "LSTM-based Stock Prediction Modeling and Analysis," presented at the 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022), Mar. 2022, pp. 2537–2542, https://doi.org/10.2991/aebmr.k.220307.414.

[22] C. Ma, Y. Liang, S. Wang, and S. Lu, "Stock linkage prediction based on optimized LSTM model," *Multimedia Tools and Applications*, vol. 81, no. 9, pp. 12599–12617, Apr. 2022, https://doi.org/10.1007/s11042-022-12381-6.

[23] P. Ahire, H. Lad, S. Parekh, and S. Kabrawala, "LSTM Based Stock Price Prediction," *International Advanced Research Journal in Science, Engineering and Technology*, vol. 8, no. 5, 2021.

[24] I. Kalbandi, A. Jare, O. Kale, H. Borole, and S. Navsare, "Stock Market Prediction Using LSTM," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 123–128, 2021.

[25] U. Gupta, V. Bhattacharjee, and P. S. Bishnu, "StockNet—GRU based stock index prediction," *Expert Systems with Applications*, vol. 207, Nov. 2022, Art. no. 117986, https://doi.org/10.1016/j.eswa.2022.117986.

[26] C. Chen, L. Xue, and W. Xing, "Research on Improved GRU-Based Stock Price Prediction Method," *Applied Sciences*, vol. 13, no. 15, Jan. 2023, Art. no. 8813, https://doi.org/10.3390/app13158813.

[27] H. Xu, L. Chai, Z. Luo, and S. Li, "Stock movement prediction via gated recurrent unit network based on reinforcement learning with incorporated attention mechanisms," *Neurocomputing*, vol. 467, pp. 214–228, Jan. 2022, https://doi.org/10.1016/j.neucom.2021.09.072.

[28] G. Ding and L. Qin, "Study on the prediction of stock price based on the associated network model of LSTM," *International Journal of Machine Learning and Cybernetics*, vol. 11, no. 6, pp. 1307–1317, Jun. 2020, https://doi.org/10.1007/s13042-019-01041-1.

[29] W. Budiharto, "Data science approach to stock prices forecasting in Indonesia during Covid-19 using Long Short-Term Memory (LSTM)," *Journal of Big Data*, vol. 8, no. 1, Mar. 2021, Art. no. 47, https://doi.org/10.1186/s40537-021-00430-0.

[30] K. Kumar and Md. T. U. Haider, "Enhanced Prediction of Intra-day Stock Market Using Metaheuristic Optimization on RNN–LSTM Network," *New Generation Computing*, vol. 39, no. 1, pp. 231–272, Apr. 2021, https://doi.org/10.1007/s00354-020-00104-0.

[31] C. Yang, J. Zhai, and G. Tao, "Deep Learning for Price Movement Prediction Using Convolutional Neural Network and Long Short-Term Memory," *Mathematical Problems in Engineering*, vol. 2020, no. 1, 2020, Art. no. 2746845, https://doi.org/10.1155/2020/2746845.

[32] X. Ji, J. Wang, and Z. Yan, "A stock price prediction method based on deep learning technology," *International Journal of Crowd Science*, vol. 5, no. 1, pp. 55–72, Mar. 2021, https://doi.org/10.1108/IJCS-05-2020-0012.

[33] C. Qi, J. Ren, and J. Su, "GRU Neural Network Based on CEEMDAN–Wavelet for Stock Price Prediction," *Applied Sciences*, vol. 13, no. 12, Jun. 2023, Art. no. 7104, https://doi.org/10.3390/app13127104.

[34] U. Gupta, V. Bhattacharjee, and P. S. Bishnu, "StockNet—GRU based stock index prediction," *Expert Systems with Applications*, vol. 207, Nov. 2022, Art. no. 117986, https://doi.org/10.1016/j.eswa.2022.117986.

[35] S. Joseph, N. Mduma, and D. Nyambo, "A Deep Learning Model for Predicting Stock Prices in Tanzania," *Engineering, Technology & Applied Science Research*, vol. 13, no. 2, pp. 10517–10522, Apr. 2023, https://doi.org/10.48084/etasr.5710.

[36] A. Kelotra and P. Pandey, "Stock Market Prediction Using Optimized Deep-ConvLSTM Model," *Big Data*, vol. 8, no. 1, pp. 5–24, Feb. 2020, https://doi.org/10.1089/big.2018.0143.

[37] S. Wang, "A Stock Price Prediction Method Based on BiLSTM and Improved Transformer," *IEEE Access*, vol. 11, pp. 104211–104223, 2023, https://doi.org/10.1109/ACCESS.2023.3296308.

[38] A. Kanwal, M. F. Lau, S. P. H. Ng, K. Y. Sim, and S. Chandrasekaran, "BiCuDNNLSTM-1dCNN — A hybrid deep learning-based predictive model for stock price prediction," *Expert Systems with Applications*, vol. 202, Sep. 2022, Art. no. 117123, https://doi.org/10.1016/j.eswa.2022.117123.

[39] S. Chen and C. Zhou, "Stock Prediction Based on Genetic Algorithm Feature Selection and Long Short-Term Memory Neural Network," *IEEE Access*, vol. 9, pp. 9066–9072, 2021, https://doi.org/10.1109/ACCESS.2020.3047109.

[40] J. Zhang, L. Ye, and Y. Lai, "Stock Price Prediction Using CNN-BiLSTM-Attention Model," *Mathematics*, vol. 11, no. 9, Apr. 2023, Art. no. 1985, https://doi.org/10.3390/math11091985.

[41] J. Kim, H. S. Kim, and S. Y. Choi, "Forecasting the S&P 500 Index Using Mathematical-Based Sentiment Analysis and Deep Learning Models: A FinBERT Transformer Model and LSTM," *Axioms*, vol. 12, no. 9, Sep. 2023, Art. no. 835, https://doi.org/10.3390/axioms12090835.

[42] Y. Chen, J. Wu, and Z. Wu, "China's commercial bank stock price prediction using a novel K-means-LSTM hybrid approach," *Expert Systems with Applications*, vol. 202, Sep. 2022, Art. no. 117370, https://doi.org/10.1016/j.eswa.2022.117370.

[43] Z. K. Mansoor and A. Y. Al-Sultan, "Enhancing Stock Price Prediction Using Mutual Information, PCA, and LSTM: A Deep Learning Approach," *Fusion: Practice and Applications*, no. Issue 1, pp. 196–208, Jan. 2025, https://doi.org/10.54216/FPA.170114.

[44] B. Y. Dwiandiyanta, R. Hartanto, and R. Ferdiana, "Deep Learning in Stock Market Prediction: A Five-Year Literature Review on Developments, Challenges, and Future Directions," *Journal of Theoretical and Applied Information Technology*, vol. 101, no. 21, pp. 7033–7051, 2023.

[45] M. Li, Y. Zhu, Y. Shen, and M. Angelova, "Clustering-enhanced stock price prediction using deep learning," *World Wide Web*, vol. 26, no. 1, pp. 207–232, Jan. 2023, https://doi.org/10.1007/s11280-021-01003-0.

[46] Z. Fathali, Z. Kodia, and L. Ben Said, "Stock Market Prediction of NIFTY 50 Index Applying Machine Learning Techniques," *Applied Artificial Intelligence*, vol. 36, no. 1, Dec. 2022, Art. no. 2111134, https://doi.org/10.1080/08839514.2022.2111134.

[47] A. H. Manurung, W. Budiharto, and H. Prabowo, "Algorithm and Modeling of Stock Prices Forecasting Based on Long Short-Term Memory (LSTM)," *ICIC Express Letters*, vol. 12, no. 12, pp. 1277–1283, 2018, https://doi.org/10.24507/icicel.12.12.1277.

[48] K. Kumar and D. P. Gandhmal, "An intelligent indian stock market forecasting system using LSTM deep learning," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 2, pp. 1082–1089, Feb. 2021, https://doi.org/10.11591/ijeecs.v21.i2.pp1082-1089.

[49] D. Satria, "Predicting Banking Stock Prices Using RNN, LSTM, and GRU Approach," *Applied Computer Science*, vol. 19, no. 1, pp. 82–94, Mar. 2023, https://doi.org/10.35784/acs-2023-06.

[50] J. Nayak, P. B. Dash, B. Naik, S. Mohapatra, and A. R. Routray, "Deep Learning-Based Trend Analysis on Indian Stock Market in COVID-19 Pandemic Scenario and Forecasting Future Financial Drift," *Journal of The Institution of Engineers (India): Series B*, vol. 103, no. 5, pp. 1459–1478, Oct. 2022, https://doi.org/10.1007/s40031-022-00762-2.