International Journal of Advances in Applied Sciences (IJAAS)
Vol. 14, No. 1, March 2025, pp. 151~163
ISSN: 2252-8814, DOI: 10.11591/ijaas.v14.i1.pp151-163

Stock's selection and trend prediction using technical analysis and artificial neural network

Ignatius Wiseto Prasetyo Agung[1,2], Toni Arifin[1,2], Erfian Junianto[1,2], Muhammad Ihsan Rabbani[1,3], Ariefa Diah Mayangsari[1,2]
[1]ARS Digital Research and Innovation (ADRI), Universitas Adhirajasa Reswara Sanjaya (ARS University), Bandung, Indonesia
[2]Informatics Study Program, Faculty of Information Technology, Universitas Adhirajasa Reswara Sanjaya (ARS University), Bandung, Indonesia
[3]Information System Study Program, Faculty of Information Technology, Universitas Adhirajasa Reswara Sanjaya (ARS University), Bandung, Indonesia

Article Info

Article history:

Received Jul 30, 2024
Revised Oct 29, 2024
Accepted Dec 26, 2024

Keywords:

Fortune 500
Long short-term memory
Stock prediction
Swing trading
Technical analysis

ABSTRACT

Stock trading offers potential profits when traders buy low and sell high. To maximize profits, accurate analysis is essential for selecting the right stocks, timing purchases, and selling at peak prices. The authors propose a new method for selecting potential stocks that are highly likely to rise in price. The method has two stages. First, technical analysis, using moving averages and stochastic oscillators, filters stocks with downward trends, anticipating a reversal and subsequent rise. Second, for selected stocks, future price trends are predicted using artificial neural networks, specifically long short-term memory (LSTM) with adaptive moment estimation (Adam) optimizer. The second step ensures that only stocks with increasing prices will be chosen for trading. This study analyzes five hundred Fortune 500 stocks over three different periods, with 250 days of data each. Simulations conducted in Python showed that technical analysis could filter 5 to 6 candidate stocks. Subsequently, the LSTM model predicted that only 4 of these stocks would have an upward trend. Validation shows that trend predictions are correct, resulting in an average profit of 5.51% within 10 working days. This profit outperforms the profits generated by other existing methods.

Corresponding Author:

Ignatius Wiseto Prasetyo Agung
ARS Digital Research and Innovation (ADRI)
Informatics Study Program, Faculty of Information Technology
Universitas Adhirajasa Reswara Sanjaya (ARS University)
Sekolah Internasional St. No. 1-2, Bandung, Indonesia
Email: wiseto.agung@ars.ac.id

1. INTRODUCTION

Stock trading involves the buying and selling of shares with the aim of generating short-term profits. Trades completed over days or weeks fall under the category of swing trading [1]. A study conducted by Gallagher *et al.* [2] indicated that engaging in short-term swing trading can be lucrative, with an average return of 2.72% observed in one swing sequence.

Nevertheless, stock traders face two challenges. The first challenge is selecting potential stocks to buy from thousands of available options. The second challenge is deciding when to buy, which involves predicting future prices, where the accuracy of the prediction directly influences the potential profit.

These challenges can be addressed by analyzing overall market conditions and examining the performance of the companies whose stocks are being traded. There are two types of analysis commonly used, namely fundamental analysis and technical analysis [3]. Fundamental analysis aims to examine the intrinsic value of the company, such as its financial, operational performance, and management. This can usually be seen in financial statements, annual reports, and news appearing in the media. Meanwhile, in technical analysis, the assessment is made based on historical data of its stock prices. Buying and selling positions are made based on the analysis of historical price behavior, trends, and the likelihood of repeating price change patterns. This technical analysis is commonly displayed in the form of charts showing prices and also several indicators calculated based on price history, which can be used in predicting future prices.

On the other hand, with the advancement of computer science, stock price predictions are facilitated with various computational algorithms, for example, machine learning. As conveyed by Syukur and Istiawan [4] and studies conducted by Li *et al.* [5] indicate the use of machine learning for stock prediction can increase efficiency by between 60 to 86% compared to previous methods. Another example, Billah *et al.* [6] presents research on stock price prediction using long short-term memory (LSTM) networks resulting in an average accuracy of 89.7%. Meanwhile, research by Ayyildiz and Iskenderoglu [7] states that artificial neural networks (ANNs), logistic regression, and support vector machine algorithms can predict the direction of stock price movement with an accuracy of more than 70%.

Moreover, several studies have used both technical indicators and machine learning. For example, the study by Goutte *et al.* [8] utilized candlestick patterns and technical indicators as inputs for machine learning models to generate Bitcoin trading signals. Additionally, the work by Navarro *et al.* [9] used moving average convergence/divergence (MACD) and arnaud legoux moving average (ALMA) to identify profitable stocks, then employed the K-means algorithm to cluster stocks based on their annual rate of return and average annual risk. Then, Yin *et al.* [10] explored the use of several technical indicators to improve the random forest algorithm for stock trend prediction. Furthermore, Khodaee *et al.* [11] forecasted price turning points using 19 technical indicators, which were processed and then input into a CNN-LSTM-ResNet model. The model proposed by Khodaee *et al.* [11] generated a profit of up to 15.35%.

However, the issue remains that, so far, there has not been much comprehensive research focused on selecting potential stocks and accurately predicting their future prices to maximize profit. To address this problem, the authors propose a method for identifying potential stocks for trading, improving the accuracy of stock selection by predicting future price trends and calculating potential profits. This research employs an experimental approach that combines technical analysis (moving average and stochastic indicators) and LSTM artificial neural network simulations, implemented in Python. The main contribution of this work is the integration of conventional technical analysis used to decide what stocks to buy with an artificial intelligent (AI)-based method to predict future stock prices. Moreover, the simulation demonstrates that the profits generated by our method are approximately twice as large as those reported by Khodaee *et al.* [11].

The outline for the following sections is as follows. Section 2 explains the theoretical foundation of our work, covering the technical analysis of stock data, particularly focusing on moving averages, stochastic oscillators, and LSTM neural networks. Section 3 details the research methodology and steps of our proposed scheme. Section 4 presents the simulation results of our proposed method, and compares them with existing approaches.

2. THEORETICAL BASIS

2.1. Technical analysis in stock data

The analysis of stock market movements through technical analysis involves studying price fluctuations, with charts serving as the primary instrument [12]. The chart displays not just the historical price data but also certain indicators derived mathematically from that past data. These indicators can aid stock traders in determining optimal buying and selling times, as well as forecasting future price movements. Having knowledge of future prices allows a trader to make decisions that could be advantageous for them. If future prices rise, he has the option to purchase now and sell at a later time, thus securing a profit.

Various indicators are employed in technical analysis, two of them are moving average (MA) and stochastic oscillator, which are formulated as (1) and (2) [12].

MA,

$$MA_i = \frac{\sum_i^{i-n} Close}{n} \tag{1}$$

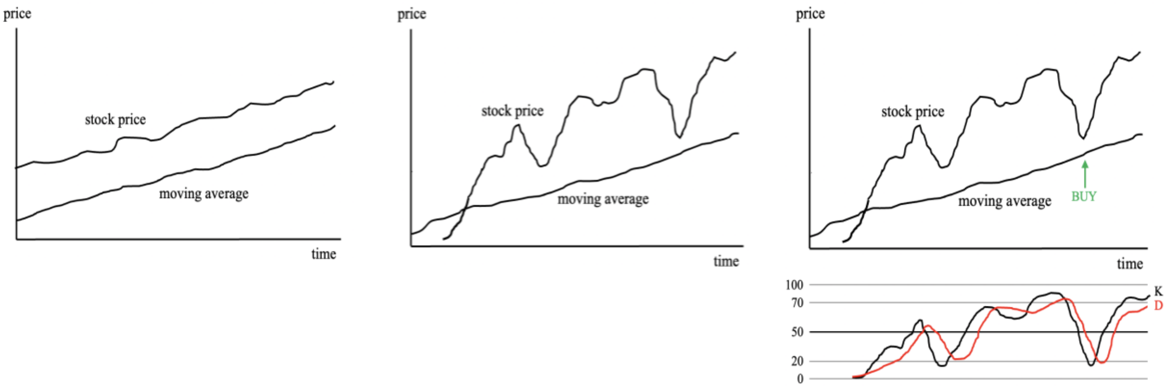
Where n is the MA period.

Stochastic oscillator,

$$\text{SchKi} = \left(\frac{Close_i - Lowest\ Low\ in\ K\ Periods}{Highest\ High\ in\ K\ Periods - Lowest\ Low\ in\ K\ Periods}\right)$$
$$SchDi = MA\ (SchKi) \tag{2}$$

Where MA uses D periods.

In his book, Pistolese [13] suggests using the 200-period MA, which is rising, as a basis for identifying stocks to purchase. The steeper the MA, the greater the potential for capital gains, see Figure 1. Figure 1(a) displays the ideal stock price and its MA, while Figure 1(b) illustrates the acceptable stock price and its MA, tailored for a buy-and-hold or long-term investor. In addition, Ni *et al.* [14] recommend using the stochastic oscillator to indicate when traders should buy stocks, specifically when it generates oversold trading signals, where K <20. Figure 1(c) illustrates the acceptable stock to buy along with its stochastic, indicating the recommended time to buy. So, traditional traders can utilize these two indicators to identify potential stocks and determine when to purchase them. Nevertheless, aside from conventional technical analysis, AI, particularly deep learning, is increasingly utilized for predicting stock and commodity prices.



(a) (b) (c)

Figure 1. Various conditions of (a) ideal stock, (b) acceptable stock, and (c) acceptable stock and its stochastic, adopted from [13] and [14]

2.2. Long short-term memory neural network

Machine learning, a field focused on enabling systems to learn from data, includes deep learning as a subfield that uses neural networks with multiple layers to capture complex data patterns. Within deep learning, ANNs serve as the foundational structure, while recurrent neural networks (RNNs) are designed to process sequential data by retaining information from previous inputs. Further refining this approach, LSTM networks improve RNNs by addressing the vanishing gradient problem and capturing long-term dependencies, making them more effective for tasks involving sequences [15].

Ma *et al.* [15] briefly summarized the three types of neural networks as shown in Figure 2. As depicted in Figure 2(a), a conventional ANN network consists of an input layer, hidden layers, and an output layer. Typically, it includes a single input layer and a single output layer, while featuring one or more hidden layers. When dealing with time-series data modeling, conventional ANN models struggle to establish connections between information from one moment to the next. To address this limitation, researchers introduced the RNN. As shown in Figure 2(b), the output from the preceding moment serves as the input for the subsequent moment, influencing the weights at the subsequent moment. This demonstrates temporal dynamic behavior within a time sequence and enhances prediction accuracy.

However, when dealing with time series tasks, RNNs struggle to capture long-term dependencies, leading to issues like vanishing or exploding gradients. To overcome this, Hochreiter and Schmidhuber [16] introduced the LSTM network. In Figure 2(c), the distinctive green arrows depict the specialized connections among neurons. These connections regulate cell states, aiding in the retention of information over extended durations. Thus, an LSTM model is capable of managing extended sequences of data units by retaining the sequential data, which can then be utilized for subsequent inputs [17]. Moreover, it also ignores long-term vulnerability issues due to its distinctive storage unit structure and it supports predictive time series [18]. Hence, since the stock price is a long-time sequence with random and nonstationary characteristics, LSTM neural networks are more suitable [19]. A general LSTM cell structure is shown in Figure 3. Figure 3(a) shows the inputs and outputs of the cell, where the mathematical format is shown in (3) [15]. Figure 3(b) shows the LSTM architecture and the gates within it, which are mathematically depicted in (4)-(6) [17].

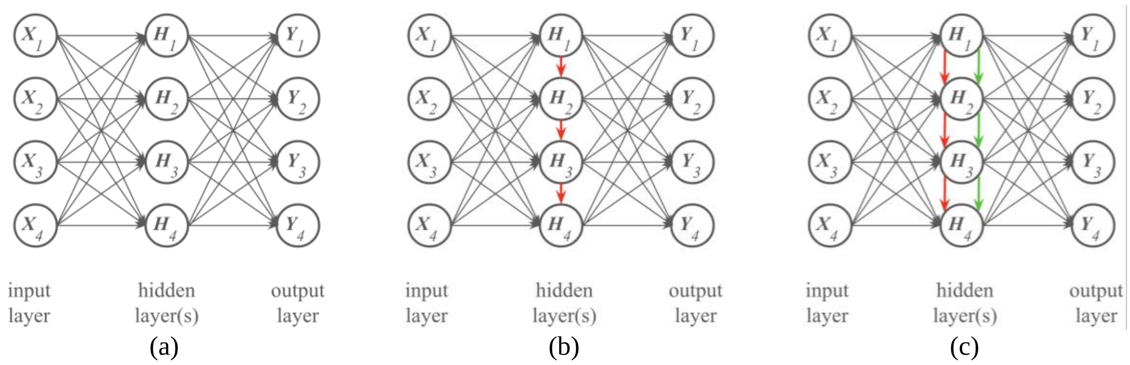


Figure 2. Typical example of (a) ANN, (b) RNN, and (c) LSTM [15]

$$(h_t, C_t) = H_t(x_t, h_{t-1}, C_{t-1}) \tag{3}$$

Where H_t is the whole function within the cell, h_t and C_t is the outputs, h_{t-1} and C_{t-1} is the inputs from the last cell, and x_t is the input from the last layer.

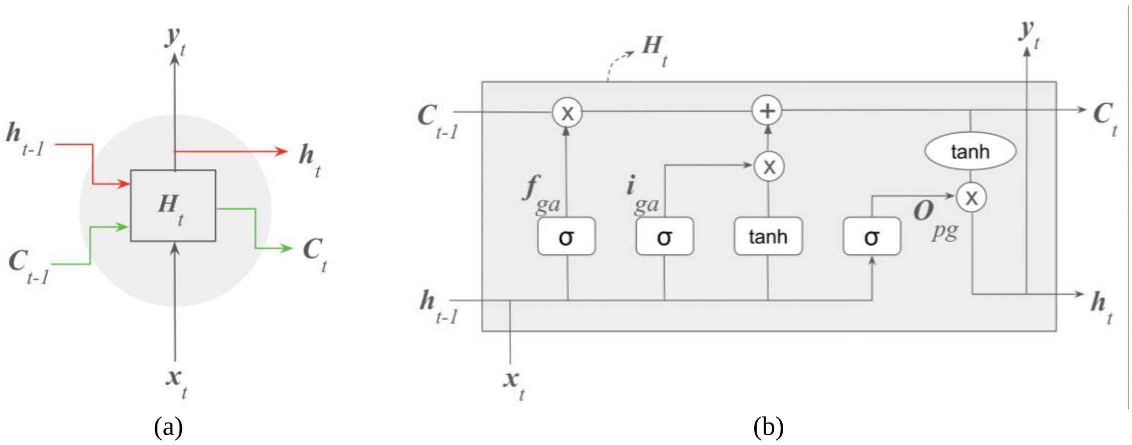


Figure 3. LSTM cell of (a) inputs and outputs of cell H_t and (b) H_t structure [15], [17]

Forget gate (useless information is eliminated),

$$f_{ga} = \sigma(W_{fg}[h_{t-1}, X_t] + b_f) \tag{4}$$

Input gate (new information in cell state),

$$i_{ga} = \sigma(W_{ip}[h_{t-1}, X_t] + b_i) \tag{5}$$

Output gate (activation to the last block of final output),

$$O_{pg} = \sigma(W_{op}[h_{t-1}, X_t] + b_o) \tag{6}$$

Where σ is sigmoid, W_x is the neuron gate *(x)* weight, h_{t-1} is the result of the preceding LSTM block, X_t is the input, and b_x is the bias.

It should be noted that in the neural network learning process, it can be challenging to determine the appropriate learning rate. Many methods have been attempted to find the optimal learning rate, including manual adjustment and automatic adaptation. One solution is the use of adaptive moment estimation (Adam), a gradient-based optimization algorithm that adaptively adjusts the learning rate based on the first and second moments of the gradients. This approach helps to address issues such as memory consumption and consistency in gradient descent, particularly in scenarios involving large datasets or numerous parameters [20].

3. METHOD

Building on the theoretical foundation outlined above, which includes technical analysis and neural networks, the authors propose a comprehensive method for selecting potential winning stocks and predicting their price trends to ensure they rise. The block representation of the entire methodology process is depicted in Figure 4. It involves four steps: data preparation, selection, prediction, and evaluation. First, the dataset used in this study consists of five hundred stocks categorized as Fortune 500 [21]. These companies' stocks have strong fundamentals, including business volume, financial strength, and operational metrics, making them suitable for trading [22]. The data for these five hundred stocks can be downloaded from the Yahoo Finance website [23].

Next, in the second step, the downloaded data is preprocessed. The data consists of open, high, low, and close prices, but only the close price data is used. Then, technical indicators i.e. the 200-period MA and the stochastic oscillator are calculated based on the close price data. Afterward, the data is examined, and only the stocks that meet the following filtering criteria of (1) and (2) are chosen: i) prices (at least within the last 2 months) are above their 200-period MA and ii) the K of the last day meets the condition of K <20%.

The selected stocks are then prepared for the third step, which is price trend prediction. Please note that in the experiment, there are two scenarios of using the data as prediction input, namely: close-only and close plus its MA plus its stochastic value. In the latter scenario, data normalization is employed to refine precision, leading to substantial enhancements in prediction accuracy [24]. Therefore, the input data is normalized using the formula recommended by [25], as presented in the subsequent (7).

$$x_{normal} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{7}$$

Where x is the value to be normalized, x_{normal} is the normalized value, x_{min} is the minimum value of the entire value to be normalized, and x_{max} is the maximum value of the entire value to be normalized.

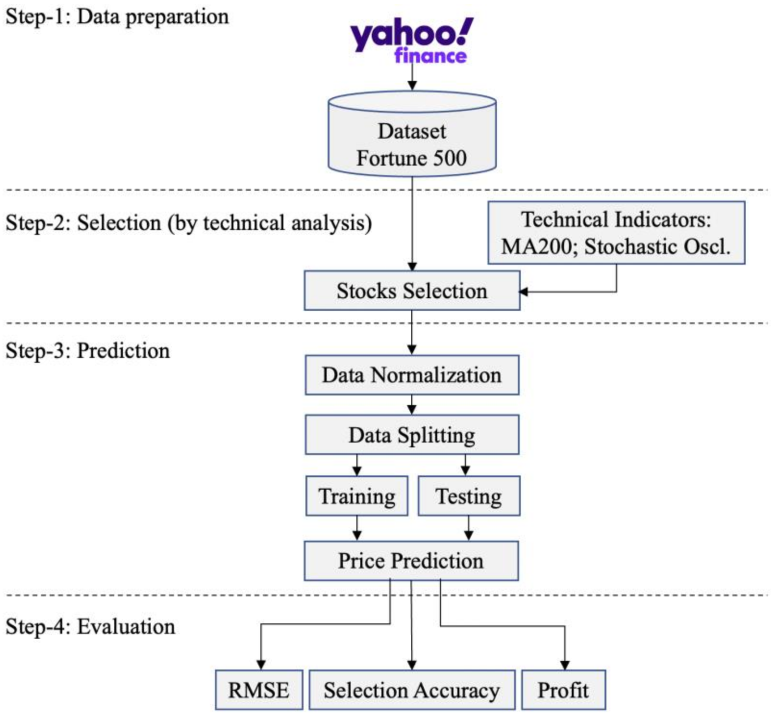


Figure 4. Experimental procedure

Then, the data for each selected stock is split into 96% for training and 4% for testing. Next, LSTM and LSTM with Adam optimizer are employed for making predictions for the next 2 weeks or 10 working days. Finally, a performance evaluation is conducted, where three points are checked, namely root mean square error (RMSE), stock selection accuracy, and profit. First, RMSE is used to measure the deviation between predicted and actual values, which is sensitive to outliers [26]. RMSE is defined as (8) [27].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (8)$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted output value of the model's i^{th} observation in the model and n is the number of samples [27]. Note that the best result for RMSE metrics is the smallest value [28]. The second performance evaluation assesses the accuracy of the stock filtering criteria used in the second step, the technical analysis processes [13], [14]. It is expected that a significant number of the filtered stocks will experience an uptrend price reversal. The accuracy [29] of the price trend selection is calculated by (9).

$$Acc = \frac{U}{A} \times 100\% \quad (9)$$

Where Acc represents the selection accuracy, U is the number of predicted trends recognized as uptrend, and A is the number of all selected stocks based on the technical analysis in the second step.

Thirdly, the profits, which represent the difference between the buy and sell prices, are calculated as (10).

$$AP = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{C_{i_{rh}} - C_{i_{p1}}}{C_{i_1}} \times 100\%\right) \quad (10)$$

Where AP is the average profit of n predicted stocks, $C_{i_{p1}}$ and $C_{i_{rh}}$ represent the predicted closing prices of the stock on day 1 and the highest closing price of the real data within a 10-day prediction period, respectively.

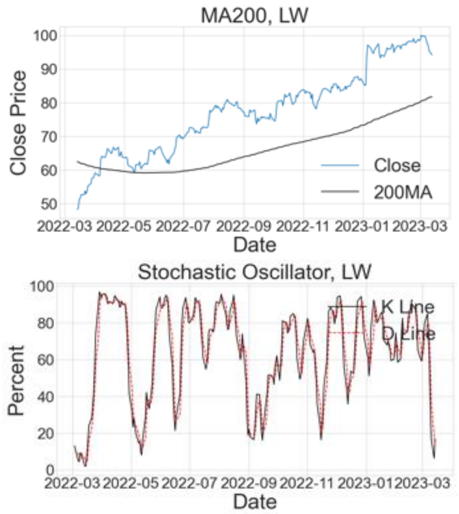
4. RESULTS AND DISCUSSION

4.1. Results

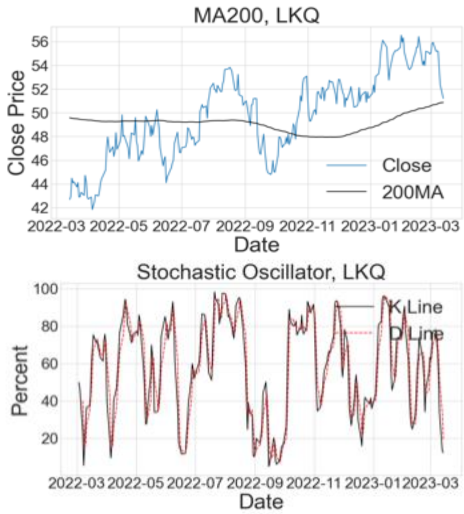
This work utilized price data for 500 stocks from 3 different time periods: March 14, 2023 and 249 days prior; August 22, 2023 and 249 days prior; and December 9, 2023 and 249 days prior. For March 14, 2023, after applying the selecting criteria (step 2) based on the MA and stochastic oscillator, 6 stocks have been selected as candidates as shown in Figure 5. As shown in Figure 5(a), Lamb Weston (LW) stock prices have remained above their MA200 since May 2022, and on the last day, the K value of the stochastic oscillator dropped under 20%. Similarly, Figure 5(b) illustrates that since October 2022, LKQ Corporation (LKQ) stock prices have been above their MA200, with the K value of the stochastic oscillator also falling under 20% on the last day. In Figure 5(c), Interpublic Group (IPG) stock prices have stayed above their MA200 since November 2022, with the last K value falling under 20%. Figure 5(d) shows MGM Resorts International Common Stock (MGM) stock prices above their MA200 since January 2023, with its last K value also dropping under 20%. Likewise, Figure 5(e) shows Ralph Lauren (RL) stock prices have been above their MA200 since November 2022, with the last K value under 20%. Lastly, Figure 5(f) displays Conagra Brands (CAG) stock prices staying above their MA200 since October 2022, with the last K value under 20%. Despite the downtrend in the last few days for LW, LKQ, IPG, MGM, RL, and CAG stocks, they are expected to reverse and continue increasing.

Next, in step 3, LSTM models with 1-3 layers and varying epochs (10, 20, 50, and 100) were employed to predict the prices of these 6 stocks for the subsequent 10 days. The models were tested under two input conditions: one with only the close price and another with three inputs including the close price, its MA, and stochastic value. The models were run 10 times, and the averages of the RMSE results are displayed in Table 1, with the lowest RMSEs highlighted in bold.

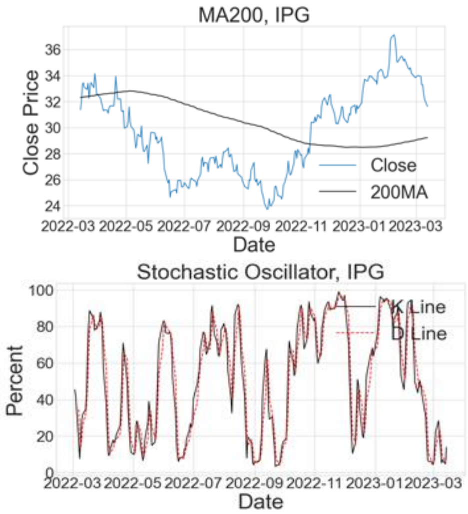
From Table 1, for the prediction of 6 stocks using LSTM, it can be observed that the lowest RMSE values range between 0.45 and 1.54. These numbers are quite similar to the RMSE reported by Sharma *et al.* [30], who utilized a three-layer LSTM model to predict Apple (AAPL) stock, with an RMSE of 0.85. Moreover, it can also be seen that the LSTM model using one input has the lowest RMSE for four stocks (LW, LKQ, MGM, RL), while the LSTM model using three inputs has the lowest RMSE for two stocks (IPG, CAG).



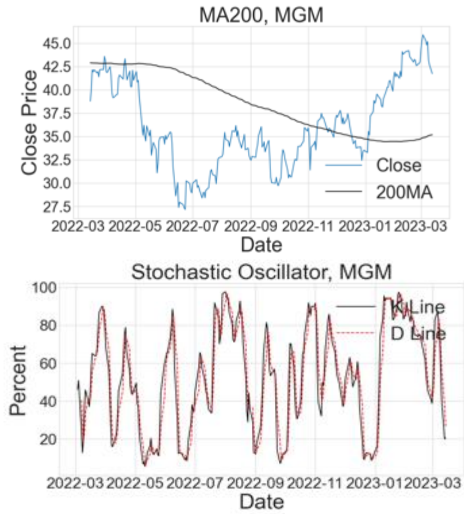
(a)



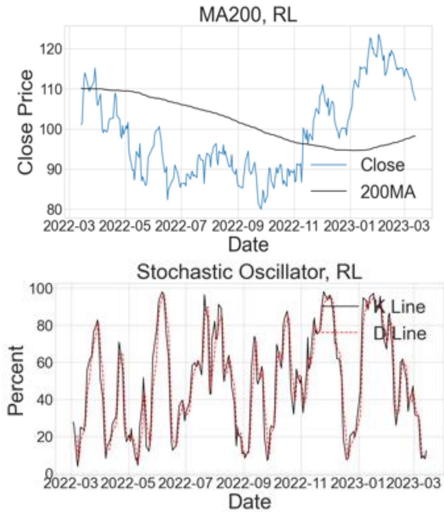
(b)



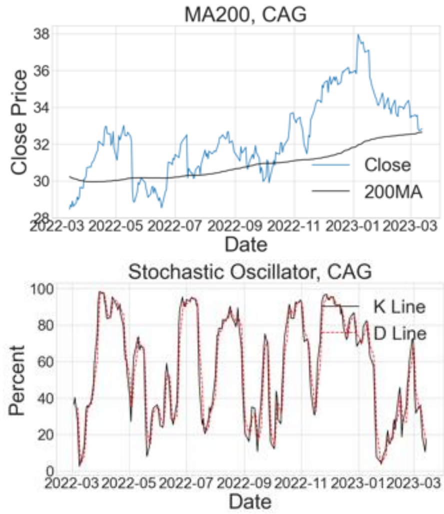
(c)



(d)



(e)



(f)

Figure 5. MA200 and stochastic oscillator (March 2023) of (a) MA 200 and stochastic of LW, (b) MA 200 and stochastic of LKQ, (c) MA 200 and stochastic of IPG, (d) MA 200 and stochastic of MGM, (e) MA 200 and stochastic of RL, and (f) MA 200 and stochastic of CAG

Table 1. RMSE of LSTM (stocks in March 2023)

Inputs	LSTM	Layers	Epoch	STOCKS					
				LW	LKQ	IPG	MGM	RL	CAG
Close price	Without Optimizer	1	10	**1.18**	0.82	0.72	1.00	1.83	0.37
			20	1.37	0.96	0.76	0.88	1.76	0.41
			50	1.47	0.88	0.76	0.85	1.82	0.39
			100	1.48	0.83	0.77	**0.841**	**1.544**	0.34
		2	10	2.38	0.92	0.67	0.94	1.67	0.49
			20	1.71	0.93	0.67	0.95	2.68	0.44
			50	1.40	0.86	0.80	0.86	1.54	0.339
			100	1.62	0.80	0.81	0.99	1.88	0.41
		3	10	1.38	0.90	0.62	0.91	2.23	0.48
			20	2.30	1.00	0.72	1.00	1.98	0.38
			50	1.86	0.83	0.78	0.91	1.70	0.39
			100	1.85	0.98	0.77	0.86	1.63	0.34
	Adam Optimizer	1	10	1.50	**0.70**	0.63	0.92	1.72	0.46
			20	1.70	0.84	0.72	0.95	1.72	0.34
			50	1.76	0.80	0.80	0.90	1.61	0.37
			100	1.66	0.85	0.73	0.92	1.548	0.37
		2	10	1.74	0.94	0.67	1.03	1.89	0.43
			20	1.82	0.92	0.90	1.04	1.94	0.54
			50	1.74	0.81	0.81	0.94	1.70	0.42
			100	1.64	0.79	0.79	0.843	1.74	0.37
		3	10	1.40	0.86	0.71	1.11	1.67	0.48
			20	2.20	1.03	0.95	1.06	2.15	0.337
			50	1.60	0.83	0.88	0.95	2.09	0.37
			100	1.65	0.88	0.75	1.14	1.88	0.37
Close price, MA 200, stochastic	Without Optimizer	1	10	1.48	1.02	0.50	1.13	3.30	0.15
			20	1.60	1.07	0.51	1.08	3.01	0.21
			50	1.79	1.24	0.46	1.16	2.70	0.13
			100	1.53	1.03	0.45	1.04	3.44	0.15
		2	10	1.30	1.27	0.67	1.45	3.63	0.16
			20	1.48	1.19	0.73	0.89	3.25	**0.130**
			50	1.28	1.021	0.70	1.50	3.42	0.15
			100	1.68	1.08	0.84	1.22	2.94	0.15
		3	10	1.88	1.13	0.99	1.61	3.68	0.15
			20	1.84	1.31	0.89	1.22	4.15	0.22
			50	1.84	1.25	1.00	1.54	3.71	0.18
			100	1.99	1.15	0.88	1.36	2.62	0.20
	Adam Optimizer	1	10	1.39	1.22	0.66	1.15	2.64	0.19
			20	1.40	1.025	0.72	1.04	3.62	0.17
			50	1.44	1.33	0.71	1.36	2.25	0.15
			100	2.07	1.08	**0.45**	0.96	3.02	0.15
		2	10	1.31	1.14	0.84	1.66	4.27	0.16
			20	1.44	1.48	0.96	1.24	2.84	0.15
			50	1.61	1.33	0.87	1.04	3.96	0.14
			100	2.07	1.19	0.71	0.95	2.96	0.134
		3	10	1.78	1.59	0.79	1.12	3.96	0.21
			20	1.48	1.57	0.71	1.25	2.88	0.26
			50	1.60	1.31	0.84	1.38	3.97	0.14
			100	1.79	1.37	0.77	0.96	3.73	0.20

Then, in step 4, for each stock, the scenario with the lowest RMSE was selected, and the corresponding stock price data are presented in Figure 6. Training, prediction, and validation phases are indicated in blue, orange, and green respectively. From these graphs of the 6 stocks, it is evident that the predictions (in orange) follow a similar trend to the validations (in green). Furthermore, it can also be observed that 4 stocks, LW (Figure 6(a)), LKQ (Figure 6(b)), IPG (Figure 6(c)), and CAG (Figure 6(f)), show trend reversals, whereas 2 other stocks, MGM (Figure 6(d)) and RL (Figure 6(e)) do not; instead, they experience sideways movement. Therefore, it can be inferred that the technical analysis criteria using the MA and stochastic oscillator, as suggested by Pistolese [13] and Ni *et al.* [14] to predict trend reversals, have an accuracy rate of 4 out of 6, or 66.66%, as calculated by (9).

Next, for the 4 stocks experiencing a price reversal and continuing to increase in price, the profits can be calculated using (10), and the results are shown in Table 2. It can be seen that for 2 weeks or 10 working days, the profits range between 2.7 and 4.5%, with an average of 3.62%. The same steps were followed for August 22, 2023, and the details of the simulation results can be found in the online supplement 1 *(https://zenodo.org/records/14615357)*. After applying the filtering criteria based on the MA and stochastic oscillator, 5 stocks were selected as candidates: Hubbell Incorporated (HUBB), Ametek Inc. (AME), Cintas Corporation (CTAS), W.W. Grainger Inc. (GWW), and Cardinal Health, Inc. (CAH). Then, LSTM models with varying layers, epochs, and inputs were employed to predict stock price trends for the subsequent 10 days. Four of these stocks are experiencing trend reversals, while CAH is not. The profits of the four stocks, displayed in Table 3, range from 3.6 to 7%, with an average of 4.57%.

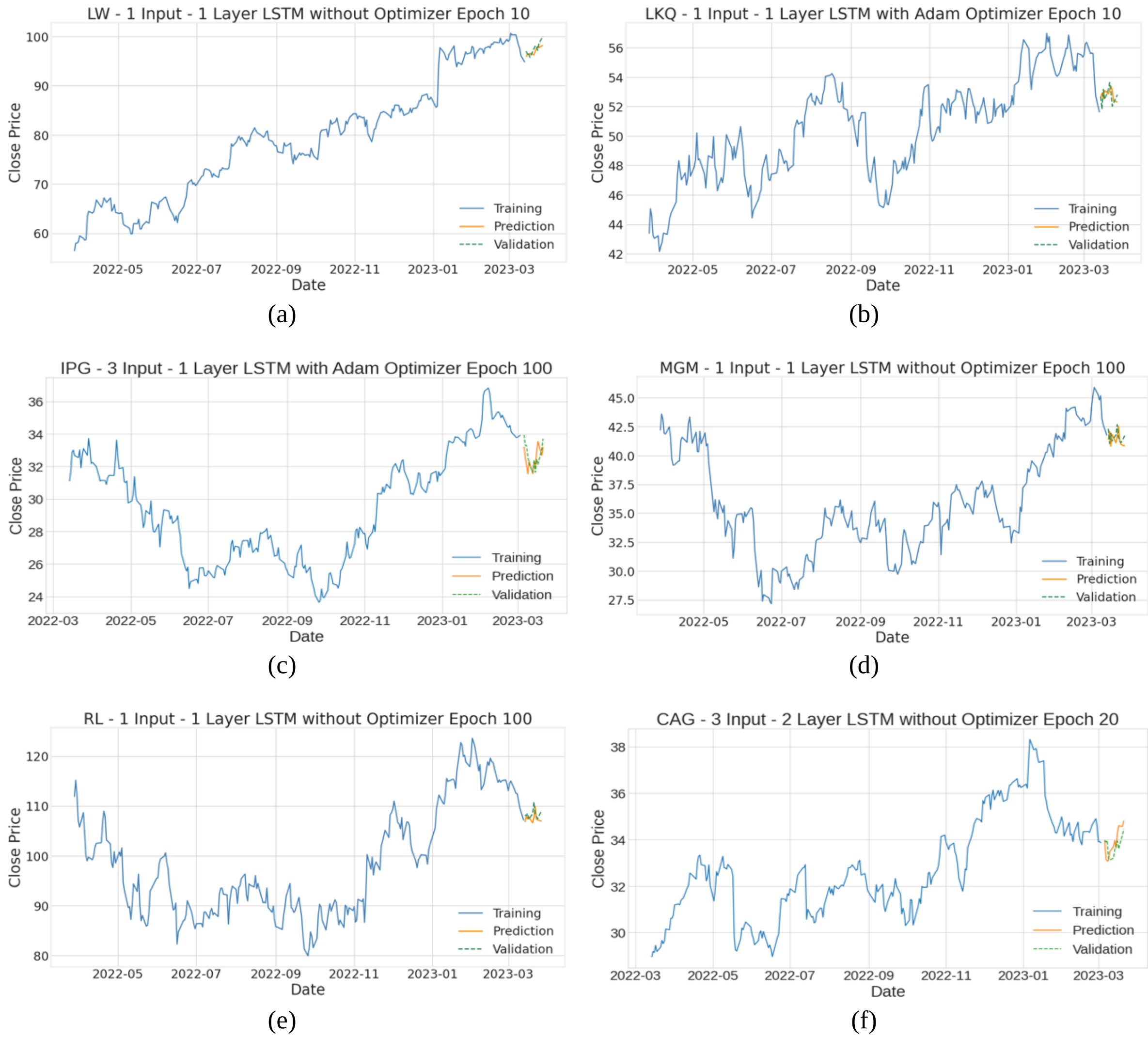


Figure 6. Training, prediction, and validation of stock prices (March 2023) of (a) LW (1 input, without Adam, 1 layer, 10 epoch), (b) LKQ (1 input, with Adam, 1 layer, 10 epoch), (c) IPG (3 inputs, with Adam, 1 layer, 100 epoch), (d) MGM (1 input, without Adam, 1 layer, 10 epoch), (e) RL (1 input, without Adam, 1 layer, 100 epoch), and (f) CAG (3 inputs, without Adam, 2 layers, 20 epoch)

Table 2. Profits March 2023

Selected stocks	Price day_1	Price day_{best}	Profit (%)
LW	95.72	100.04	4.5
LKQ	52.24	53.63	2.7
IPG	32.51	33.70	3.7
CAG	33.29	34.45	3.6
	Average		3.62

Table 3. Profit August 2023

Selected stocks	Price day_1	Price day_{best}	Profit (%)
HUBB	303.79	325.07	7.0
AME	153.66	159.62	3.9
CTAS	485.23	502.61	3.6
GWW	694.06	720.62	3.8
	Average		4.57

Similar scenarios were also analyzed for December 2023, with the simulation results available in online supplement 2 *(https://zenodo.org/records/14615357)*. Following the application of filtering criteria using the MA and stochastic oscillator, 6 stocks were identified as candidates: Cadence Design Systems, Inc. (CDNS), Meta Platforms, Inc. (META), Broadcom Inc. (AVGO), Linde plc (LIN), Arch Capital Group Ltd. (ACGL), and Copart, Inc. (CPRT). LSTM models were then employed to predict stock price trends for the subsequent 10 days. Four of these stocks are experiencing trend reversals, while ACGL and CPRT are not. The profits of the four stocks are shown in Table 4.

Table 4. Profit December 2023

Selected stocks	Price day_1	Price day_{best}	Profit (%)
CDNS	260.04	275.82	6.1
META	335.46	353.36	5.3
AVGO	93.90	114.70	22.1
LIN	399.02	424.10	6.2
	Average		9.92

The overall performance of the proposed method for the three trading periods - March, August, and December 2023 is displayed in Table 5. It is observable that the method for filtering stock candidates by technical analysis, i.e., the 200-period MA and stochastic oscillator, selects 17 stocks, of which 12 stocks become uptrend. This results in a selection accuracy of 70.58%. Furthermore, these 12 uptrend stocks have average profits of 5.51%.

Table 5. Performance for three trading periods

Date	Initial stocks	Selected stocks	Uptrend stocks	Stock selection accuracy (%)	Average Profit (%)
14 March 2023	500	6	4	66.66	3.62
22 August 2023	500	5	4	80.00	4.57
9 December 2023	500	6	4	66.66	9.92
	Overall	17	12	70.58	5.51

Finally, the results of our proposed method will be compared with those of other methods, specifically Ni *et al.* [14] and Khodaee *et al.* [11], to assess profitability. To ensure consistency and comparability with previous studies, we will use the same dataset as those studies. Ni *et al.* [14] investigated whether investors can earn profits by using stochastic oscillator indicators for trading stocks. They used data from the DJ-30, FTSE-100, and SSE-50 indexes for the period 2004 to 2013, recommending that traders buy stocks when the stochastic oscillator generates oversold signals, where K <20. They reported that over a 10-day trading period, the average profits for the DJ-30, FTSE-100, and SSE-50 indexes were 0.37, 0.59, and 0.91%, respectively. Next, we applied our method to the same dataset, and the average profits for the DJ-30, FTSE-100, and SSE-50 indexes were 4.15, 3.71, and 8.89%, respectively. Detailed results of our simulation can be found in online supplement 3 *(https://zenodo.org/records/14615357)*. The profit comparison between Ni *et al*. [14] and the simulation of our method is summarized in Table 6.

Table 6. Our work and Ni *et al.* [14] profit comparison

Trading periods	Dataset	Number of trades		Average profits (%)	
		Ni *et al.* [14]	Our work	Ni *et al*. [14]	Our work
10 days	DJ-30 Index	2,038	34	0.37	4.15
	FTSE-100 Index	4,681	16	0.59	3.71
	SSE-50 Index	4,263	22	0.91	8.89

Then, we compare our method with that of Khodaee *et al.* [11], who forecasted stock price turning points using a CNN-LSTM-ResNet model to reduce the number of trades and achieve higher profits. They fed their model with 19 technical indicators, which were converted into 2D images. The dataset consisted of stocks from the DJ-30, with an initial investment of $10,000 to simulate the profits gained. Their study reported an average annual profit of 15.35%. Next, we applied our method to the same dataset and the same annual observation period as well as the same initial investment of $10,000. Our simulation, detailed in online supplement 4 *(https://zenodo.org/records/14615357)*, resulted in an end-of-year investment value of $13,463, representing an annual gain of 34.63%. A comparison of the profit between Khodaee *et al.* [11] and our simulation is summarized in Table 7.

Table 7. Our work and Khodaee *et al*. [11] profit comparison

Trading periods	Dataset	Number of trades		Average profits (%)	
		Khodaee *et al.* [11]	Our work	Khodaee *et al.* [11]	Our work
annually	DJ-30 Stocks	568	78	15.35	34.63

4.2. Discussion

Our study employs a two-stage approach: first, we apply conventional technical analysis to filter which stocks to buy, followed by an LSTM-based method to predict future stock prices and then calculate potential profits. Previous studies typically either use only technical analysis [14] to estimate potential profits or integrate technical analysis with AI to predict future prices [11], before calculating the profits. We found that by applying our first step, we can narrow Fortune 500 stocks down to 5 or 6 with the potential to become uptrends during each trading period. Then, using our second step, we predicted future prices and trends, with only 4 of those stocks showing an uptrend. The average profit we achieved was 5.51% within a 10-day trading period. The method proposed in our study tends to provide a simple yet effective approach for selecting which stocks are worth trading.

We also applied our method to the same datasets and trading periods that were used by Ni *et al.* [14] and Khodaee *et al*. [11]. The results in Table 6 show that compared to [14] our average profits were significantly higher. This is likely because our method can selectively choose only the stocks whose prices will rise, which we then buy and sell at a higher price. This explanation is further supported by the number of trades made. For example, as shown in Table 6, in the case of the DJ-30 index, Ni *et al.* [14] conducted 2,038 trades, while our method executed only 34 carefully selected trades. A similar pattern was observed when we compared our method with [11], as shown in Table 7. Our average profit was approximately double that of [11], and we only made 78 trades compared to their 568.

Our study demonstrates that initial filtering using two technical indicators can help identify potential stocks, which are then further refined with AI-based (LSTM) price predictions. However, further research is needed to ensure that the initial filtering is optimal meaning it does not exclude potential stocks or allow non-potential stocks to pass through. Additionally, it is important to evaluate whether the LSTM-based price predictions are yielding optimal results. Future research could explore more optimal technical indicators and compare LSTM with other deep learning models in the second stage to achieve more accurate price predictions.

5. CONCLUSION

In this work, a scheme for selecting stocks and predicting their future prices has been developed to achieve optimal profits in swing trading. The model combines technical analysis (200-day MA, stochastic oscillator) with LSTM deep learning using data splitting. Technical analysis is used to filter downtrend stocks that have the potential to reverse their trend. LSTM price prediction is then employed to ensure that the selected stocks enter an uptrend and increase in price. Experimental results show that the lowest RMSE for the LSTM model is 0.45. Moreover, the proposed scheme can select 4 winning stocks out of 500 in each 10-day trading period, with an average profit of 5.51%. The profit performance of our proposed method surpasses the profits obtained from other methods. However, as the current experiment is limited to two technical indicators along with LSTM, further exploration of additional technical analysis techniques and deep learning models could increase the number of selected winning stocks and enhance profitability. Furthermore, in order to make it more reliable for stock trading practitioners, the model can be generalized and tested using cross-validation methods.

ACKNOWLEDGEMENTS

The authors acknowledge funding support from the Research and Community Service Program, Fiscal Year 2024, of the Directorate General of Higher Education, Research, and Technology, Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia.

REFERENCES

[1] S. Sun, R. Wang, and B. An, "Reinforcement learning for quantitative trading," *ACM Trans. Intell. Syst. Technol.*, vol. 14, no. 3, 2023, doi: 10.1145/3582560.

[2] D. R. Gallagher, P. A. Gardner, and P. L. Swan, "Governance through trading: Institutional swing trades and subsequent firm performance," *J. Financ. Quant. Anal.*, vol. 48, no. 2, pp. 427–458, 2013, doi: 10.1017/S0022109013000203.

[3] S. Zaheer *et al.*, "A multi parameter forecasting for stock time series data using LSTM and deep learning model," *Mathematics*, vol. 11, no. 3, 2023, doi: 10.3390/math11030590.

[4] A. Syukur and D. Istiawan, "Prediction of LQ45 index in indonesia stock exchange: a comparative study of machine learning techniques," *Int. J. Intell. Eng. Syst.*, vol. 14, no. 1, pp. 453–463, 2020, doi: 10.22266/IJIES2021.0228.42.

[5] L. Li, Y. Wu, Y. Ou, Q. Li, Y. Zhou, and D. Chen, "Research on machine learning algorithms and feature extraction for time series," *IEEE Int. Symp. Pers. Indoor Mob. Radio Commun. PIMRC*, vol. 2017-Octob, pp. 1–5, 2017, doi: 10.1109/PIMRC.2017.8292668.

[6] M. M. Billah, A. Sultana, F. Bhuiyan, and M. G. Kaosar, "Stock price prediction: comparison of different moving average techniques using deep learning model," *Neural Comput. Appl.*, vol. 36, no. 11, pp. 5861–5871, 2024, doi: 10.1007/s00521-023-09369-0.
[7] N. Ayyildiz and O. Iskenderoglu, "How effective is machine learning in stock market predictions?," *Heliyon*, vol. 10, no. 2, 2024, doi: 10.1016/j.heliyon.2024.e24123.
[8] S. Goutte, H. V. Le, F. Liu, and H. J. von Mettenheim, "Deep learning and technical analysis in cryptocurrency market," *Financ. Res. Lett.*, vol. 54, 2023, doi: 10.1016/j.frl.2023.103809.
[9] M. M. Navarro, M. N. Young, Y. T. Prasetyo, and J. V. Taylar, "Stock market optimization amidst the COVID-19 pandemic: Technical analysis, K-means algorithm, and mean-variance model (TAKMV) approach," *Heliyon*, vol. 9, no. 7, 2023, doi: 10.1016/j.heliyon.2023.e17577.
[10] L. Yin, B. Li, P. Li, and R. Zhang, "Research on stock trend prediction method based on optimized random forest," *CAAI Trans. Intell. Technol.*, vol. 8, no. 1, pp. 274–284, 2023, doi: 10.1049/cit2.12067.
[11] P. Khodaee, A. Esfahanipour, and H. Mehtari Taheri, "Forecasting turning points in stock price by applying a novel hybrid CNN-LSTM-ResNet model fed by 2D segmented images," *Eng. Appl. Artif. Intell.*, vol. 116, 2022, doi: 10.1016/j.engappai.2022.105464.
[12] S. B. Achelis, *Technical analysis from A to Z*, vol. 77. McGraw-Hill, 2000.
[13] C. Pistolese, *Select winning stocks using technical analysis*. McGraw Hill, 2007.
[14] Y. Ni, Y. C. Liao, and P. Huang, "Momentum in the Chinese stock market: evidence from stochastic oscillator indicators," *Emerg. Mark. Financ. Trade*, vol. 51, pp. S99–S110, 2015, doi: 10.1080/1540496X.2014.998916.
[15] J. Ma, Y. Ding, V. J. L. Gan, C. Lin, and Z. Wan, "Spatiotemporal prediction of PM2.5 concentrations at different time granularities using IDW-BLSTM," *IEEE Access*, vol. 7, pp. 107897–107907, 2019, doi: 10.1109/ACCESS.2019.2932445.
[16] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.
[17] G. Sonkavde, D. S. Dharrao, A. M. Bongale, S. T. Deokate, D. Doreswamy, and S. K. Bhat, "Forecasting stock market prices using machine learning and deep learning models: a systematic review, performance analysis and discussion of implications," *Int. J. Financ. Stud.*, vol. 11, no. 3, 2023, doi: 10.3390/ijfs11030094.
[18] D. Sheth and M. Shah, "Predicting stock market using machine learning: best and accurate way to know future stock prices," *Int. J. Syst. Assur. Eng. Manag.*, vol. 14, no. 1, pp. 1–18, 2023, doi: 10.1007/s13198-022-01811-1.
[19] Y. Guo, "Stock price prediction based on LSTM neural network: the effectiveness of news sentiment analysis," *Proc. - 2020 2nd Int. Conf. Econ. Manag. Model Eng. ICEMME 2020*, pp. 1018–1024, 2020, doi: 10.1109/ICEMME51517.2020.00206.
[20] N. Sakinah, M. Tahir, T. Badriyah, and I. Syarif, "LSTM with adam optimization-powered high accuracy preeclampsia classification," *IES 2019 - Int. Electron. Symp. Role Techno-Intelligence Creat. an Open Energy Syst. Towar. Energy Democr. Proc.*, pp. 314–319, 2019, doi: 10.1109/ELECSYM.2019.8901536.
[21] 50Pros, "List of Fortune 500," 50Pros™. Accessed: Oct. 29, 2024. [Online]. Available: https://www.50pros.com/fortune500
[22] A. Persakis, A. Fassas, and A. Koutoupis, "How does world economic policy uncertainty influence the carbon dioxide emission reporting and performance? Study of Fortune Global 500 firms," *Environ. Sci. Pollut. Res.*, vol. 31, no. 16, pp. 24014–24041, 2024, doi: 10.1007/s11356-024-32643-0.
[23] Yahoo! Finance, "Yahoo! Finance," Yahoo. Accessed: Oct. 29, 2024. [Online]. Available: https://finance.yahoo.com/
[24] X. Li, P. Wu, and W. Wang, "Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong," *Inf. Process. Manag.*, vol. 57, no. 5, 2020, doi: 10.1016/j.ipm.2020.102212.
[25] D. A. Anggoro and D. Novitaningrum, "Comparison of accuracy level of support vector machine (SVM) and artificial neural network (ANN) algorithms in predicting diabetes mellitus disease," *ICIC Express Lett.*, vol. 15, no. 1, pp. 9–18, 2021, doi: 10.24507/icicel.15.01.9.
[26] H. Baek, "A CNN-LSTM stock prediction model based on genetic algorithm optimization," *Asia-Pacific Financ. Mark.*, vol. 31, no. 2, pp. 205–220, 2024, doi: 10.1007/s10690-023-09412-z.
[27] S. Wang, "A stock price prediction method based on BiLSTM and improved transformer," *IEEE Access*, vol. 11, pp. 104211–104223, 2023, doi: 10.1109/ACCESS.2023.3296308.
[28] K. Chaudhari and A. Thakkar, "Neural network systems with an integrated coefficient of variation-based feature selection for stock price and trend prediction," *Expert Syst. Appl.*, vol. 219, 2023, doi: 10.1016/j.eswa.2023.119527.
[29] X. D. Zeng, S. Chao, and F. Wong, "Optimization of bagging classifiers based on SBCB algorithm," *2010 Int. Conf. Mach. Learn. Cybern. ICMLC 2010*, vol. 1, pp. 262–267, 2010, doi: 10.1109/ICMLC.2010.5581054.
[30] P. Sharma, C. Sharma, and P. Mathur, "Machine learning-based stock market forecasting using recurrent neural network," *9th Int. Conf. Smart Comput. Commun. Intell. Technol. Appl. ICSCC 2023*, pp. 600–605, 2023, doi: 10.1109/ICSCC59169.2023.10335083.

BIOGRAPHIES OF AUTHORS

Ignatius Wiseto Prasetyo Agung After retiring from PT. Telkom Indonesia, he has now dedicated his time to the ARS University, Bandung, Indonesia, as a lecturer and Vice-Rector for Collaboration and Innovation, since October 2019. In Telkom Indonesia, he worked since 1988 in various divisions e.g., satellite development, network operation, R&D, and Digital Business. He received the Sarjana (Bachelor's Degree) in Telecommunication from Institut Teknologi Bandung, Indonesia in 1987. He also graduated from the University of Surrey, UK, and received an MSc in Telematics (1994) and a PhD in Multimedia Communication (2002). He was also in charge of several professional forums, for instance, the Asia Pacific Telecommunity Wireless Forum (AWF) as Convergence Working Group Chairman (2008- 2011); in ITU-D as Vice Rapporteur (2007-2009); as Chairman (2020, 2021) and Vice Chair (2018-2019) of IEEE Communications Society Indonesia Chapter; and as Senior Member of IEEE. He can be contacted at email: wiseto.agung@ars.ac.id.

Toni Arifin is a member of the Informatics Study Program, Faculty of Engineering, Adhirajasa Reswara Sanjaya (ARS) University, and researcher ARS Digital Research & Innovation (ADRI). He received his Bachelor's Degree in Informatics Engineering from Bina Sarana Informatika University in 2013 and graduated from the computer science master's program at Nusa Mandiri University Jakarta in 2015. He has authored or co-authored more than 68 publications: 4 proceedings and 66 journals, with 12 H-index and more than 528 citations. Research interests include machine learning, image processing, and deep learning. He can be contacted at email: toni.arifin@ars.ac.id.

Erfian Junianto is a member of the Informatics Study Program, Faculty of Engineering at Adhirajasa Reswara Sanjaya (ARS) University, and a researcher at ARS Digital Research & Innovation (ADRI). He graduated from the computer science master's program at Nusa Mandiri University Jakarta in 2014. He has authored or co-authored more than 38 publications, including 2 proceedings and 36 journals, with an H-index of 10 and more than 450 citations. His research interests include text mining, artificial intelligence, and classification. He can be contacted at email: erfian.ejn@ars.ac.id.

Muhammad Ihsan Rabbani is a bachelor's student in the Information System Study Program, Faculty of Engineering at Adhirajasa Reswara Sanjaya (ARS) University, and works as a research assistant at ARS Digital Research & Innovation (ADRI). He has participated in research focused on stock prediction using AI, utilizing the Python programming language. He can be contacted via email: ihsanm7782@gmail.com.

Ariefa Diah Mayangsari is a bachelor's student in the Informatics Study Program, Faculty of Engineering at Adhirajasa Reswara Sanjaya (ARS) University, and works as a research assistant at ARS Digital Research and Innovation (ADRI). Previously, she participated in research focused on A Systematic Literature Review: Performance Comparison of Edge Detection Operators in Medical Images. She can be contacted via email: ariefadiah06@gmail.com.