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Prediction-based Stock Portfolio Optimization Using Bidirectional Long Short-Term Memory (BiLSTM) and LSTM

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Abstract.
Purpose: Investment is the allocation of funds with the aim of obtaining profits in the future. An example of the investment instruments with high returns and high risks are stocks. The risks associated with the investment can be reduced by forming a portfolio of quality stocks optimized through mean-variance (MV). This is necessary because successful selection of high-quality stocks depends on the future performance which can be determined through accurate price prediction.
Methods: Stock price can be predicted through the adoption of different forms of deep learning methods. Therefore, BiLSTM and LSTM models were applied in this research using the stocks listed on the LQ45 index as case study.
Result: The utilization of LSTM and BiLSTM models for stock price prediction produced favorable outcomes. It was observed that BiLSTM outperformed LSTM by achieving an average MAPE value of 2.1765, MAE of 104.05, and RMSE of 139.04. The model was subsequently applied to predict a set of stocks with the most promising returns which were later incorporated into the portfolio and further optimized using the Mean-Variance (MV). The results from the optimization and evaluation of the portfolio showed that the BiLSTM+MV strategy proposed had the highest Sharpe Ratio value at k=4 compared to the other models. The stocks found in the optimal portfolio were BRPT with a weight of 19.7%, ACES had 16.9%, MAPI 11.8%, and BMRI at 51.6%.
Novelty: This research conducted a novel comparison of LSTM and BiLSTM models for the prediction of stock prices of companies listed in the LQ45 index which were further used to construct a portfolio. Past research showed that the development of portfolios based on predictions was not popular.

Keywords: Stock prediction, Portfolio optimization, Machine learning, BiLSTM, LSTM
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INTRODUCTION

Investors are typically interested in achieving maximum returns at minimal risk, leading to the need for the construction of an optimized stock portfolio. A particular model considered to be the best in solving portfolio optimization problems is the mean-variance (MV) developed by Markowitz [1]. This is due to the ability of the model to measure expected return and variation in risks in order to assist investors in making a trade-off between maximizing return and minimizing risk. However, the MV relies heavily on the expected return and risk of each stock in the portfolio to achieve optimization [2]. This shows that the selection of high-quality stocks from the outset is important for the model to produce optimal portfolios [3].

The expected return of each asset is important in the process of forming an optimal stock portfolio, indicating the significance of initial selection of stocks in portfolio management [4]. Moreover, popular knowledge shows that the total reliance on portfolio optimization without considering the input of quality stocks is unrealistic. The success of stock selection as an input in a portfolio is highly dependent on the potential performance in the future [1]. This shows that the accurate prediction of stock price movements or returns can increase the chances of maximizing investment returns while minimizing the risk of financial losses [5]. Previous research shows that the stock market is inherently a nonlinear, dynamic, noisy, and chaotic system [6]. The observation has led to the application of machine learning as the common method in the research related to stock price prediction [7]. However, the method has also been identified to have

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shortcomings such as the lack of necessary accuracy and reliability, indicating the need for more advanced predictive methods [8].

An aspect of machine learning which is observed to have succeeded in extracting information from stock time series data is deep learning [9]. The type most commonly used by investors to forecast stock prices is the recurrent neural network (RNN) [10] but the method is not capable of remembering past data . The shortcoming has led to the development of a special type of RNN which is known as the Long Short-Term Memory (LSTM) [11]. Moreover, some studies have shown that LSTM performed better than other methods in time series prediction [12]. The method has also been developed further to produce the Bidirectional Long Short-Term Memory (BiLSTM) which is a stack designed to use the "before and after" context of information [13]. Previous research by [11], [14], [15] proved that BiLSTM prediction performance was better than LSTM.

In this research, the background information provided was used to develop a stock portfolio based on price forecasts using LSTM and BiLSTM models. The portfolio developed was later optimized using the MV model and subsequently applied to a case study of 45 companies with stocks listed in the LQ45 index on the Indonesia Stock Exchange. Moreover, the companies were selected based on the significant market capitalization, strong liquidity, and other specific characteristics.

METHODS

The stages implemented in conducting this research are generally presented through the flow chart in Figure 1. The information on these stages is explained further in the following sub-sections.

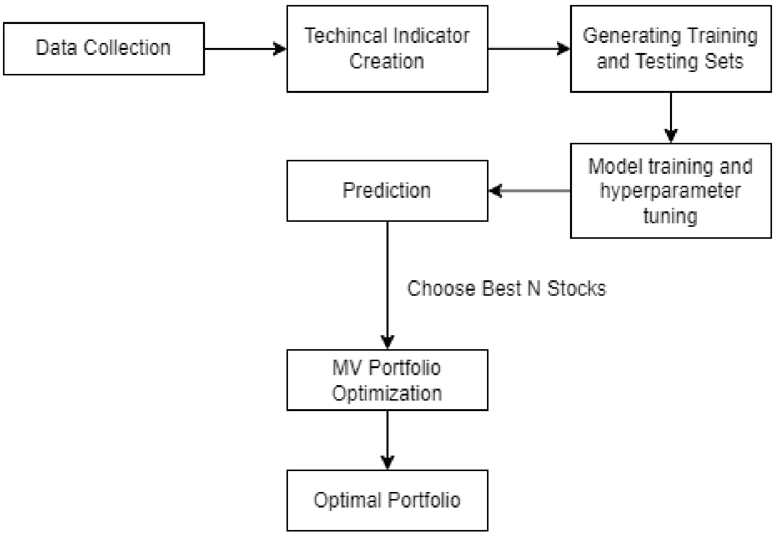

Figure 1. Research flow

Data collection

Secondary data collected through the Yahoo Finance website at https://finance.yahoo.com/ were used in this research. The site provides stock data consisting of open, high, low, close, adj close, and volume which are downloadable as a CSV file according to the time range of choice. The data used were close variable of 45 stocks covering the span from 2020 to 2023 listed in the LQ45 index (effective period February 01 to July 31, 2024). A total of 974 rows of data were retrieved on February 12, 2024.

Technical indicator creation

Previous research [16], [17] claim that there is information from the price movement of a financial asset. This information is believed to be useful to forecast the price of the financial asset, leading to the definition of technical indicators as a combination of past information on stock market behavior [18]. A total of 11 indicators used are adapted from several related research [16], [19], [20] and the formulas are described as follows.

The Simple Moving Average (SMA) is evaluated as the average of the closing prices over a specific number of periods which can be calculated using Equation (1). The Weighted Moving Average (WMA) also provides more weight to recent prices and is computed as Equation (2) and the Exponential Moving Average (EMA) gives more weight to recent prices as formulated in Equation (3).

$$\frac{C_{t-1}+C_{t-2}+\cdots+C_{t-n}}{n} \tag{1}$$

$$\frac{C_{t-1}\times n+C_{t-2}\times(n-1)+\cdots+C_{t-n}}{\frac{[n\times(n+1)]}{2}} \tag{2}$$

$$(C_t \times \alpha) + \left(EMA_{t-1} \times (1-\alpha)\right) \tag{3}$$

The Moving Average Convergence Divergence (MACD) is the difference between the 12-perion EMA and 26-period EMA calculated as Equation (4) and the Relative Strength Index (RSI) measures the magnitude of recent price changes to evaluate overbought or oversold conditions through Equation (5). Moreover, the Stochastic K% (StochK) indicator compares the closing price to the price range over a specific period and Stochastic D% (StochD) is the 3-period moving average of StochK, computed as Equations (6) and (7), respectively.

$$EMA_{12}(t) - EMA_{26}(t) \tag{4}$$

$$100 - \left(\frac{100}{1+\frac{n_{up}}{n_{down}}}\right) \tag{5}$$

$$\left(\frac{C_t-L_{t-14}}{H_{t-14}-L_{t-14}}\right) \times 100 \tag{6}$$

$$\frac{\sum_{i=0}^{2} K_{t-i}\%}{3} \tag{7}$$

The Price Rate of Change (ROC) is the percentage change in price over a given period which can be determined using Equation (8) while momentum is normally applied to determine the change in price over a specific period throughEquation (9). The True Range (TR) is the highest value from calculating current high minus the current low, the absolute value of the current high minus the previous close, or the absolute value of the current low minus the previous close as presented in Equation (10). Moreover, the Average True Range (ATR) is the moving average of the TR over a specified period, calculated as Equation (11).

$$\left(\frac{C_t}{C_{t-n}}\right) \times 100 \tag{8}$$

$$C_t - C_{t-n} \tag{9}$$

$$Max[(H_t - L_t), |H_t - C_{t-1}|, |L_t - C_{t-1}|] \tag{10}$$

$$\frac{ATR_{t-1}\times(n-1)+TR}{n} \tag{11}$$

Where, C_t is closed price, L_t is lowest price, H_t is highest price, α is *smoothing factor* = $\frac{2}{1+n}$, n_{up} is amount of profit, n_{down} is amount of lost, and n is number of periods.

The entire data were separated into training-testing sets with those in the 2020-2022 timeframe used as a training set while 2023 range was the testing set as previously applied in [21]. Moreover, all data were standardized using Min-Max Scaler with a range of 0 to 1 before subsequent application for the model training as used in [22].

LSTM modelling

LSTM was first introduced by Hochreiter and Schmidhuber in 1997 and observed to be very popular in the field of financial time series data prediction due to the ability to effectively handle the redundancy of historical data [23]. It is a type of RNN architecture with a memory function that allows the avoidance of long-term dependency problems [21]. The LSTM model also has the capacity to filter incoming information through a gates structure consisting of an input, forget, and output [24] as presented in the following Figure 2.

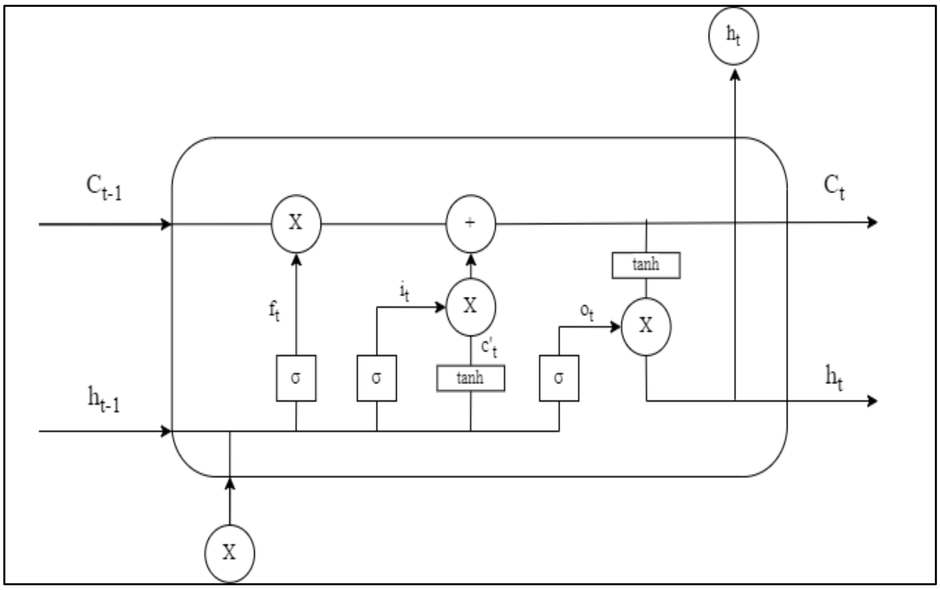

Figure 2. LSTM architecture [8]

BiLSTM modelling

BiLSTM is a variation of LSTM that utilizes "before and after" information to process data through 2 layers, including the forward and backward [13]. The forward layer functions to provide previous information while the backward is for the afterwards. The architecture of BiLSTM is presented in the following Figure 3 while the output formula is formulated as follows:

$$y_t = W_{\overrightarrow{hy}}\overrightarrow{h_t} + W_{hy^{\leftarrow}} h_t^{\leftarrow} + b_y \tag{12}$$

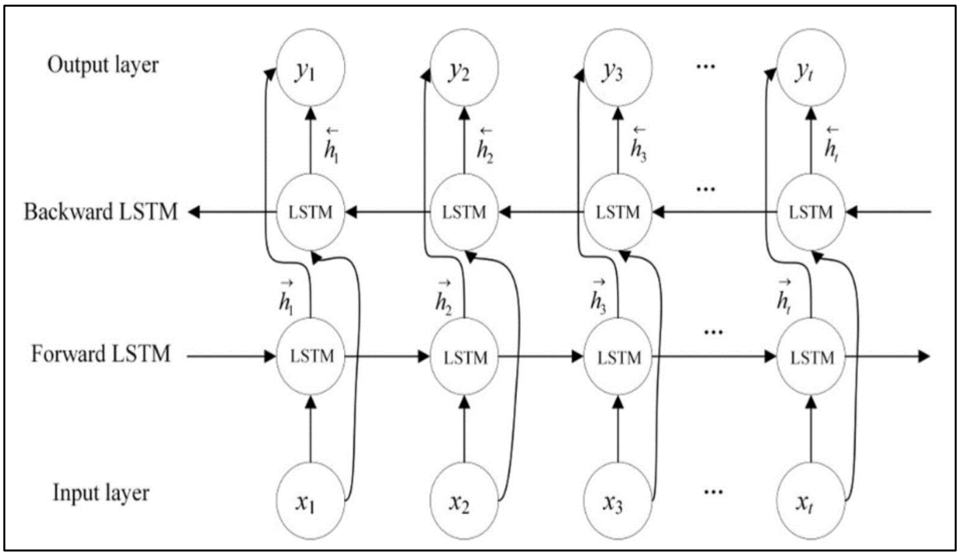

Figure 3. BiLSTM architecture [25]

Development and optimization of portfolio

The prediction of all stocks was expected to be followed by the selection of high-quality stocks through sorting depending on the highest predicted return. Moreover, the formula (13) used in determining the predicted returns are presented as follows.

$$\hat{R}_t = \frac{\hat{p}_t - \hat{p}_{t-1}}{\hat{p}_{t-1}} \tag{13}$$

Where, $\hat{R}_t$ is the stock return at time t, $\hat{p}_t$ is the predicted stock price at time t, and $\hat{p}_{t-1}$ is the predicted stock price at time (t-1).

The top (k) number of stocks was included in the portfolio and optimized. Moreover, Markowitz introduced the mean-variance model to achieve a trade-off between maximizing return and minimizing risk. This research focused on the optimization process to minimize the variance of the portfolio. Therefore, the MV model formula applied is presented as follows [24].

$$\sum_{i=0}^{K} \sum_{j=0}^{K} s_i s_j \sigma_{ij} \tag{14}$$

$$subject\ to\ \sum_{i=0}^{K} s_i \mu_i = \gamma \tag{15}$$

$$\sum_{i=1}^{K} s_i = 1 \tag{16}$$

$$s_i \geq 0 \tag{17}$$

Where, k represents the total number of stocks, s_i is the weight of stock i in the optimal portfolio, σ_{ij} represents the covariance of returns between stocks i and j, μ_i is the expected return of stock i, and γ symbolizes the target return of the portfolio.

Evaluation

The accuracy of the model prediction results was assessed through the application of the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root-Mean-Square Error (RMSE) [26]. The formula of each criterion is presented as follows:

$$MAPE = \frac{1}{p} \sum_{i=1}^{p} \frac{|\hat{y}_i - y_i|}{y_i} \tag{18}$$

$$MAE = \frac{1}{p} \sum_{i=1}^{p} |y_i - \hat{y}_i| \tag{19}$$

$$RMSE = \sqrt{\frac{1}{p} \sum_{i=1}^{p} (y_i - \hat{y}_i)^2} \tag{20}$$

Where, y_i is the original value, $\hat{y}_i$ represents the predicted value, and p is the total samples.

The optimal portfolio performance was subsequently assessed using the Sharpe Ratio, mean return, and standard deviation. The preference for these criteria is based on their common application in the process of evaluating and comparing the performance of different forms of stock portfolios [24], [27], [28]. The formula of Sharpe Ratio is presented as follows:

$$Sharpe\ ratio = \frac{\mu_p - r_f}{\sigma_p} \tag{21}$$

Where, μ_p is the return of the portfolio, r_f is the risk-free rate, and σ_p represents the standard deviation or risk. This research was conducted by setting the risk-free rate value at 0.067, in accordance with the last 10 years of Indonesian bond yields.

RESULTS AND DISCUSSIONS

Stock price prediction

A total of 45 stocks contained in the LQ45 index for the effective period of February 01 to July 31, 2024 were collected. Meanwhile, only the 39 stocks with historical data starting from 2020 to 2023 were selected in this research. The data covering 2020 to 2022 consisting of 735 rows were used as a training set while those for 2023 with 239 rows were applied as a testing set. The next stage was the determination of input variables in the form of technical indicators using the "pandas_ta" library in Python. The data retrieved were later transformed using the Min-Max Scaler with a range of 0 to 1.

Prior to the modelling process, a single stock was selected at random for the purpose of hyperparameter tuning simulation conducted using a grid search method and assessed through 5-fold cross validation. The grid search focuses on systematically testing different combinations of parameters and assessing the performance of each to identify the optimal set. In this research, GridSearchCV function from "Scikit-learn" library of Python was applied with the parameter combinations presented in the following Table 1.

Table 1. LSTM and BiLSTM hyperparameter combination

Parameter	Value
Units	32, 64, 128, 256
Dropout Rate	0.1, 0.2
Learning Rate	0.0001, 0.001, 0.01
Epochs	100, 250, 500
Batch Size	32, 64, 128

The next step was to train the model using the training set and the total number of LSTM and BiLSTM models developed was 1080. The value was determined by multiplying the number of parameter combinations attempted by 5 used as the value of k in the cross-validation process. The optimal combination produced through the hyperparameter simulation is presented in the following Table 2.

Table 2. Optimal hyperparameter of LSTM and BiLSTM

Parameter	LSTM	BiLSTM
Units	256	128
Dropout Rate	0.2	0.2
Learning Rate	0.001	0.0001
Epochs	250	500
Batch Size	128	32

The LSTM model was redeveloped using the hyperparameter consisting of 256 number of units, 0.2 dropout rate, 0.001 learning rate, 250 epochs, and 128 batch size. Similarly, the BiLSTM model used 128, 0.2, 0.0001, 500, and 32 respectively. Both models used timesteps of 10 in accordance with the results of research [29] that the value produced optimal evaluation. Moreover, "keras" library in Python was used for the development and both models were later applied to predict stock prices during the test set period or the year 2023.

Figure 4 is a plot of ICBP and TLKM stocks predicted by the BiLSTM model and Figure 5 is the result of the prediction through the LSTM. The blue line represents the real stock price data while the red line is the predicted stock price data. The observation from the figures shows that both models have the capacity to accurately predict stock prices.

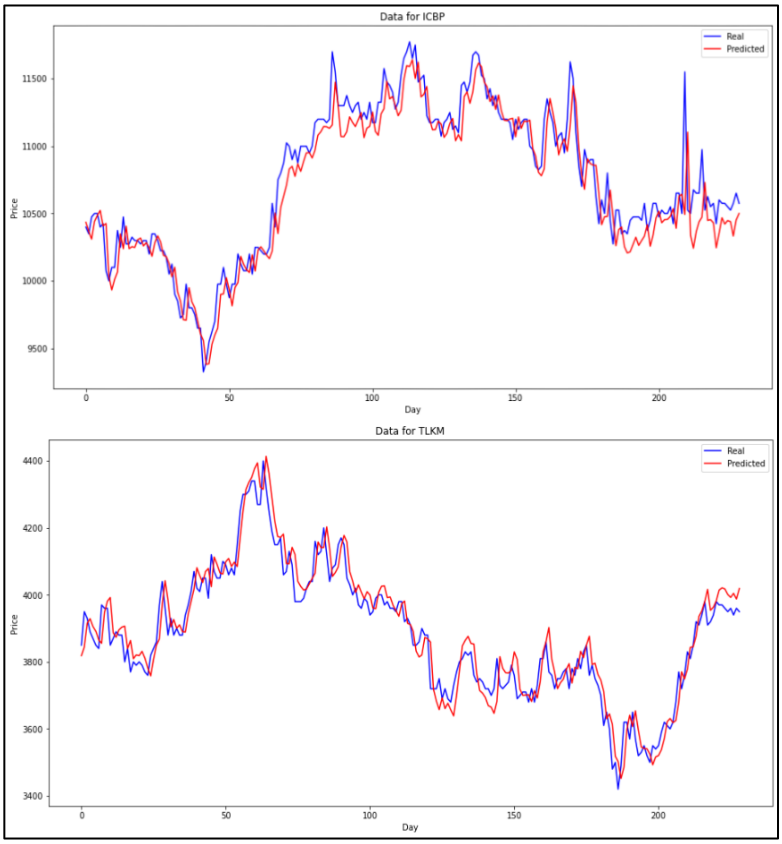

Figure 4. Example of BiLSTM predicted plot and actual value (ICBP and TLKM)

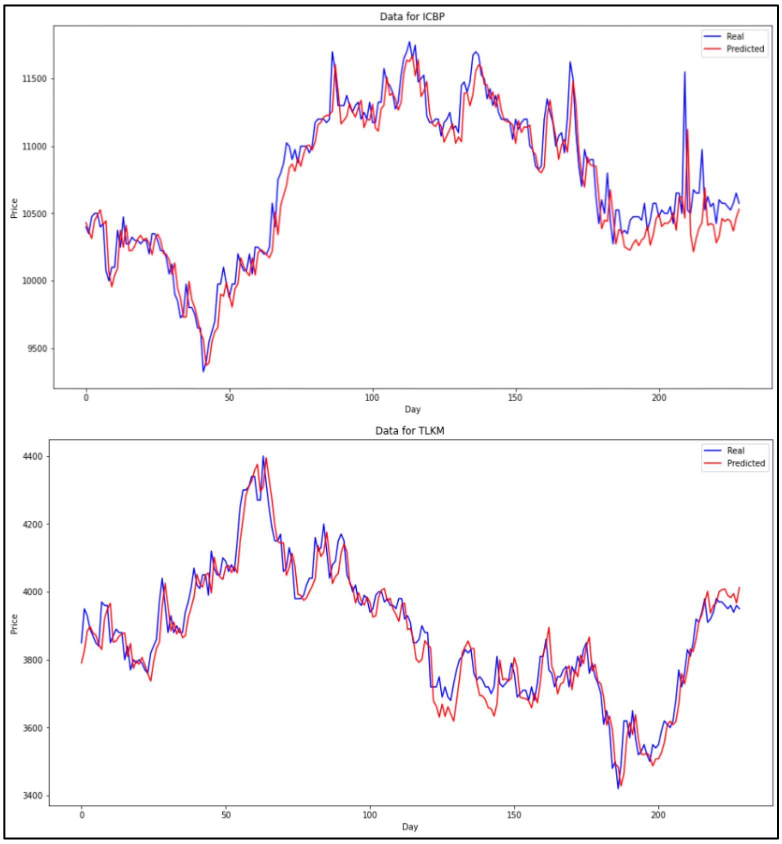

Figure 5. Example of LSTM predicted plot and actual value (ICBP and TLKM)

The hyperparameters with the best prediction performance for LSTM and BiLSTM models were compared and the results presented in Table 3 showed that both had good performance. For the MAPE criteria, the average value for the BiLSTM model was 2.1765 which was higher than the 2.2736 recorded for the LSTM. The same trend was observed in the RMSE and MAE with the average value for the BiLSTM model found to be 139.04 and 104.05 while the LSTM had 140.854 and 104.164 respectively. In conclusion, the BiLSTM was considered superior based on the three criteria and the stocks predicted were included in a portfolio.

Table 3. Comparison of LSTM and BiLSTM prediction performance

Stock Tickers	LSTM			BiLSTM		
	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE
ACES	2.874	24.123	17.9	2.677	23.422	17.0
ADRO	2.199	76.179	57.7	2.364	82.382	62.1
AKRA	2.047	37.061	29.3	2.073	37.904	29.8
AMRT	1.475	56.264	42,0	1.560	58.250	44.3
ANTM	1.906	45.680	36.5	1.663	41.212	31.8
ARTO	5.198	163.293	128.3	4.957	157.653	122.6
ASII	1.254	101.045	77.3	1.176	98.228	72.4
BBCA	0.961	109.525	85.6	0.897	101.668	79.8
BBNI	1.274	75.925	60.7	1.198	71.525	56.5
BBRI	1.149	76.111	60	1.619	104.503	85.2
BBTN	1.462	24.084	18.6	2.827	41.064	35.9
BMRI	2.535	159.193	139.6	1.229	87.484	67.3
BRIS	2.674	56.680	43,0	1.968	44.532	31.9
BRPT	3.177	61.891	35.4	3.273	59.767	35.8
CPIN	2.365	152.073	122.4	1.641	114.316	85.2
EMTK	3.231	27.959	22.2	3.122	27.244	21.5
ESSA	8.105	61.115	53.6	4.170	34.970	28.0
EXCL	1.897	54.057	40.4	2.197	61.318	46.8
GGRM	2.371	857.589	594.6	2.108	776.554	529.7
HRUM	2.186	43.933	33.8	2.174	43.666	33.4
ICBP	1.179	176.387	126.9	1.228	179.554	132.5
INCO	2.310	172.018	139.1	2.048	152.948	122.6
INDF	0.989	85.367	66.7	0.976	84.257	66.2
INKP	1.963	240.683	169.6	1.951	236.173	168.4
INTP	1.566	224.514	160.6	1.584	224.742	162.5
ITMG	2.224	901.011	659	2.661	962.064	779.2
KLBF	1.795	44.033	34.8	1.688	42.253	32.6
MAPI	4.166	86.846	72.9	3.725	77.768	64.8
MDKA	2.727	113.655	86.2	2.880	120.722	90.4
MEDC	3.677	58.677	43.1	3.824	62.756	44.9
PGAS	1.660	29.199	22.8	2.019	35.378	27.7
PTBA	2.341	104.782	74.2	2.181	98.493	68.7
SIDO	1.589	14.695	10.7	1.782	16.274	12.2
SMGR	1.536	132.440	100.5	1.673	141.74	108.9
SRTG	2.707	59.110	47.6	3.586	75.616	63.5
TLKM	1.115	54.469	43.2	1.136	55.443	44.0
TOWR	1.538	20.053	15.2	1.585	20.429	15.7
UNTR	1.673	624.622	427.1	1.836	679.038	471.0
UNVR	1.579	86.966	63.4	1.629	89.172	65.5

Portfolio formation and optimization

A portfolio was formed using several predicted stocks with the highest predicted return. It is important to state that the existence of several different stocks in a portfolio can lead to difficulty in controlling and managing, especially for individual investors. Previous research [30] already showed that a portfolio consisting of seven stocks had the most optimal performance while [31] suggested three or four for individual investors. Another research [16] reported that portfolios containing ten stocks performed the best when compared to other numbers. Therefore, the analysis conducted used $k \in \{4,5,6,7,8,9,10\}$ which was the number of stocks in the portfolio. The stocks for each k obtained through the BiLSTM highest predicted return are presented in the following Table 4.

Table 4. Stocks in each *k* portfolio based on BiLSTM highest predicted return

k	Stocks
4	BRPT, ACES, MAPI, BMRI
5	BRPT, ACES, MAPI, BMRI, BRIS
6	BRPT, ACES, MAPI, BMRI, BRIS, BBRI
7	BRPT, ACES, MAPI, BMRI, BRIS, BBRI, GGRM
8	BRPT, ACES, MAPI, BMRI, BRIS, BBRI, GGRM, BBNI
9	BRPT, ACES, MAPI, BMRI, BRIS, BBRI, GGRM, BBNI, ARTO
10	BRPT, ACES, MAPI, BMRI, BRIS, BBRI, GGRM, BBNI, ARTO, BBCA

The mean-variance model was implemented to optimize the stock portfolio in order to ensure more optimal allocation of investor funds. The output was in the form of the weight for each stock in the portfolio and values from the mean-variance (MV) were compared with those from the equal weight (EW). Moreover, the portfolios were formed through random stock selection and optimized using the MV and EW for the purpose of comparison.

Figure 6 is the graph of each portfolio performance with the X-axis used to represent the number of stocks in the portfolio while the Y-axis provides values for the Sharpe Ratio, mean annual return, and annual standard deviation. The results showed that both BiLSTM+MV and BiLSTM+1/N had the best performance on Sharpe Ratio and annualized mean return when k=4. This was observed from the fact that the Sharpe Ratio for BiLSTM+MV was 0.7 and BiLSTM+1/N had 0.52 while the mean return was 21.3 and 19.92 respectively. When compared to Random+MV and Random+1/N, the prediction-based portfolio was far superior except when k was higher than 7 where almost all portfolios had a negative Sharpe Ratio. Moreover, the standard deviation graph showed that an increase in the number of stocks in the portfolio led to a reduction in the standard deviation. In general, the portfolio with k=4 provided the best evaluation for all proposed strategies and the BiLSTM+MV strategy was the most superior.

All portfolios formed through different strategies were later simulated for growth in the testing set period of 2023 which was the year of prediction results. In Figure 7, each model was provided an initial value of 1.0 and the cumulative return was plotted over the period. The strategy proposed was presented with a red line and BiLSTM+1/N produced the highest cumulative return at the end of the period but the volatility was also found to be the largest. Moreover, the Random+MV and Random+1/N strategies seemed to be in the pattern of the cumulative return movement produced by the BiLSTM but at the end of the period there was a significant decline. The comparison conducted showed that LQ45 had the lowest level of cumulative return even though it was not volatile. The trend was observed to have led to the conclusion that the BiLSTM strategy produced the highest return prediction when compared to the others and this was in agreement with the results obtained in the previous research [24].

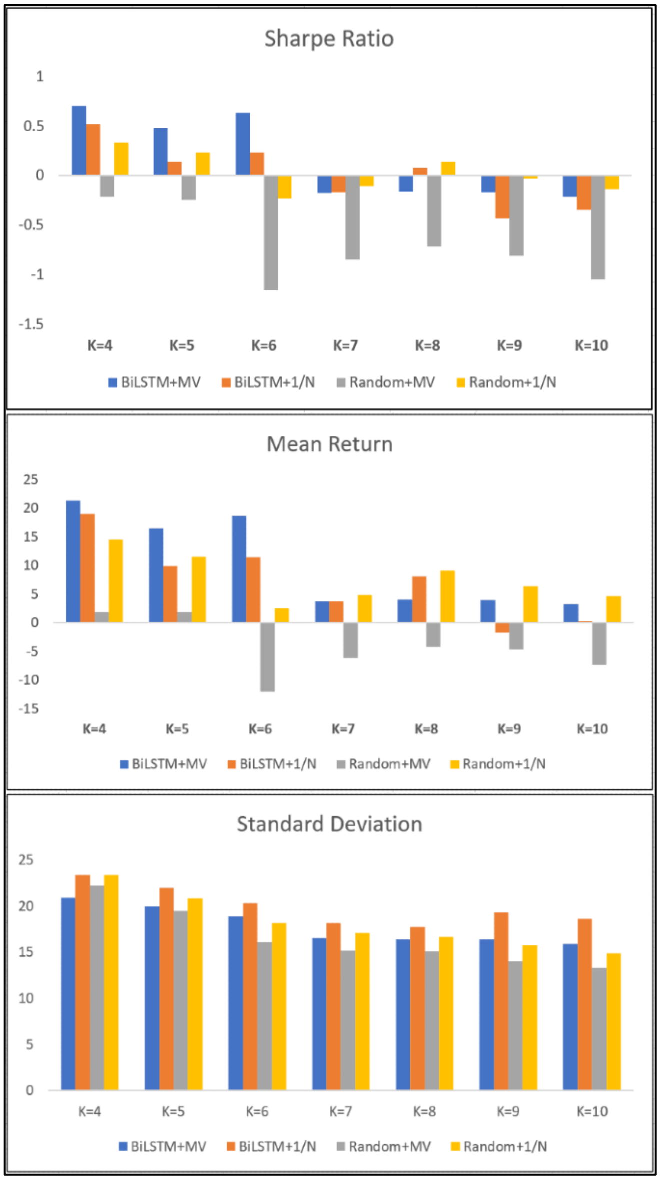

Figure 6. Portfolio evaluation

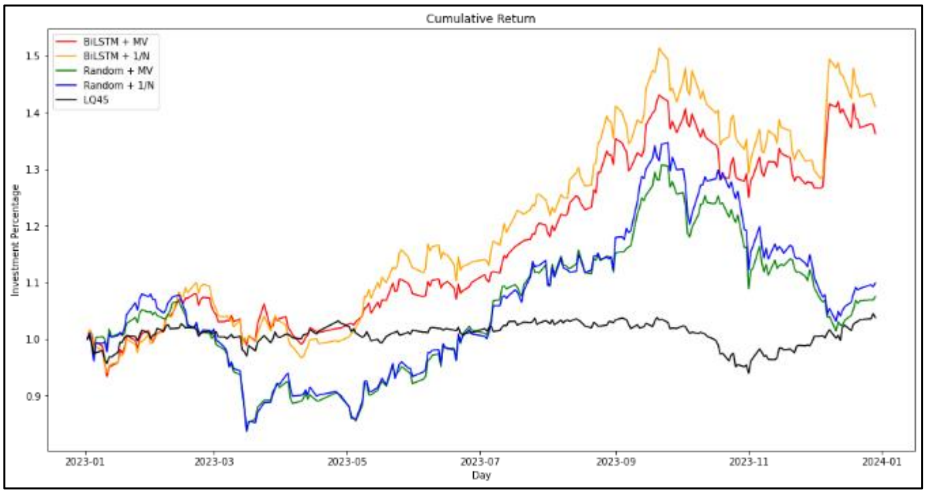

Figure 7. Cumulative return of portfolio on testing period

CONCLUSION

In conclusion, the prediction of stock prices using LSTM and BiLSTM models was observed to have produced good results with the BiLSTM identified to have performed better with an average MAPE of 2.1765%, MAE of 104.05, and RMSE of 139.04. Moreover, the proposed BiLSTM+MV strategy led to the production of the highest Sharpe Ratio value of 0.7 at k=4, a mean return of 21.3, and a standard deviation of 20.9. This showed the importance of integrating stock price predictions in portfolio optimization as well as the ability of deep learning models such as BiLSTM to provide more accurate forecasts and lead to better investment. Moreover, the MV model applied ensured a balanced trade-off between risk and return which was considered important to achieving successful portfolio management.

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