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Optimizing LQ45 Stock Portfolio to Maximize Sharpe Ratio Value using LSTM

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Abstract−Investment is an investment activity within a certain period with the hope of getting a profit. Things that need to be considered by investors when investing are not just yields (return), but investors need to consider the purpose of the investment and the investment period. This study optimizes the formation of portfolios by utilizing the predicted value of stock prices using LSTM. The test used five daily stock indices from LQ45, namely BBCA, BBRI, TLKM, UNVR, and BMIR, from April 2010 – April 2020. The portfolio was built using the Genetic Algorithm and Equal-Weight (EW) method. Portfolio of Genetic Algorithm and Equal-Weight (EW) without predictions used as a benchmark. The experimental results show that using the LSTM prediction and Genetic Algorithm can produce an optimal portfolio with the highest Sharpe ratio value at 1.3950.

Keywords: Optimization Portfolio; LSTM, LQ45; Sharpe Ratio; Genetic Algorithm

1. INTRODUCTION

Investment is an investment activity in the form of money or valuable assets within a certain period with the hope of getting a profit. To obtain maximum investment returns, investors are advised not to invest all of their capital in one company or instrument but to invest their money in several companies or agencies. When one of our investments suffers a loss, it is not sure that other investments will experience a loss. This is the basis of portfolio theory. Over the last decade, deep learning algorithms have been widely implemented in the financial sector [1], [2]. Deep learning helps investors make decisions; one example is using Deep learning. In research conducted by Van-Dai Ta, Chuan Ming Liu, and Direselign Addis Tadesse in 2020 [3] Using the LSTM algorithm to carry out Portfolio Optimization, LSTM aims to predict stock prices to assist investors in making decisions. LSTM showed good performance in his research compared to other algorithms such as LR and SVM.

The same year, Adhib Arfan and Lussiana ETP researched using the LSTM algorithm with stock price test data in Indonesia. The results obtained by LSTM can predict stock prices in 2017 – 2019 with accurate results [4].

In 2022, Tita Lattifia, Putu Wira Buana, and Ni Kadek Dwi Rusjayanthi researched Weather Prediction Model Using the LSTM Method using weather data in the form of rainfall and temperature. The parameters that affect the forecast results are batch size and epoch, with the results obtained for a batch size of 50 and epoch 100, and the best RMSE and MAPE values are obtained, namely 1.7444 and 1.9499% [5].

In 2018, research by Muhammad Wildan Putra Aldi, Jondri, and Annisa Aditsania carried out with the title "Analysis and Implementation of Long Short Term Memory Neural Networks for Bitcoin Price Prediction." time series patterns, the number of hidden neurons, max epoch, and the composition of the training and test data on the accuracy of the predictions obtained. The results are satisfactory, with an average accuracy rate of 93.5% [6].

LSTM can not only predict stock prices, as did Muhammad Kamal Wisyaldin, Gita Maya Luciana, and Henry Pariaman with the title Long Short-Term Memory Approach to Predict the Condition of 10 kV Motors in Coal Power Plants. The results are that the LSTM approach is more accurate than other conventional algorithm models. It can be seen from the impact that LSTM has the lowest MAE results, namely 3.8% [7].

In 2020, Prismahardi Aji, Tresna Maulana, Kartika Maulida, and Eristya Maya conducted a study entitled Analysis Of The Banking Sector Stock Price Prediction Using The Long Short Terms Memory (LSTM). The purpose of this study is to predict stock prices and analyze the accuracy of Machine Learning in predicting stock price data by analyzing the number of epochs in forming an optimal model. Adam's optimization shows that the higher the epoch value, the lower the loss value [8].

Research conducted by Muhamad Fadli Azim, Azizah, and Dian Anggraeni with the research title Stock Portfolio Optimization with Weighting Using Genetic Algorithms. The data used in this study is historical stock data every day from 6 stock indices, including ASII, TLKM, BBRI, BBCA, BMRI, and BNII. A portfolio of shares with a weighting percentage of 5% for ASII, 30% for TLKM, 20% for BBRI, 16% for BBCA, 12% for BMRI, and 17% for BBNI is obtained [9].

In 2019, Eka Lestari, Evy Sulistianingsih, and Nurfitri Imro'ah conducted research entitled Determining Optimal Stock Portfolios Using Genetic Algorithms. This study uses weekly stock price closing data on the LQ45 stock index for January 2010 to June 2018. The determination of this portfolio does by comparing manual calculations using the Single Index Model. The results obtained by the genetic algorithm can build a stock portfolio with greater profits and minor risks. The yield obtained using the genetic algorithm method is 0.0081, and the risk is 0.0719. Meanwhile, using the Single Index Model, the profit is 0.0075, and the risk is 0.0746 [10].

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Previous research has proven that LSTM has good performance for data in the form of time series. According to Fischer, T., & Krauss, C. [11], when compared to Random Forest and logistic regression, LSTM performs well in extracting information from noise data in the form of time series. While the genetic algorithm can create an optimal portfolio, the use of this algorithm is only limited to optimizing the portfolio so that the weighting can be optimal. Thus, in this study, portfolio optimization was carried out by considering return predictions to maximize the value of the Sharpe ratio.

2. RESEARCH METODOLOGY

2.1 Research Stages

The portfolio consists of selected stocks—the selection of return predictions using the LSTM method. Five stock indices with the highest capitalization values will be chosen based on data for March 31, 2020. The selected stocks will be included in the portfolio and built using the Genetic Algorithm method by maximizing the value of the Sharpe ratio.

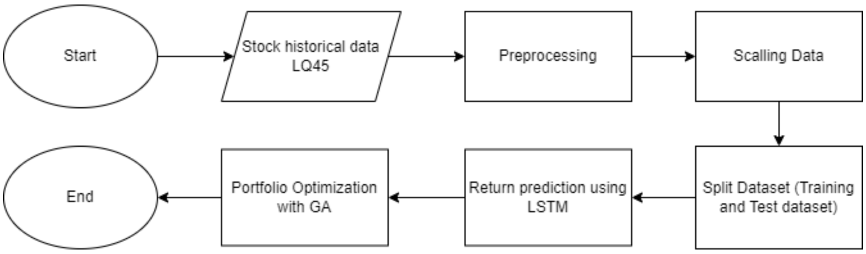

Figure 1. System Workflow

Figure 1 shows the workflow of the system. First, the historical LQ45 dataset is closed historical data, then preprocessing is carried out for data with a null value. The next step is scaling the data and splitting the dataset into two, then predicting returns using LSTM. The final step is portfolio optimization with a genetic algorithm.

2.2 Stock Historical Data LQ45

The stock data used in this study are the five LQ45 stock indices with the highest capitalization value on March 30, 2020, obtained by BBCA, BBNI, BMRI, UNVR, and TLKM top five stock indexes on LQ45 which have the highest capitalization value. This study uses the stock period from April 2012 – April 2022 using daily closing stock data, which can be accessed on Yahoo Finance.

2.3 Preprocessing

Until this stage, the data that we owned is still in the form of raw data, where this data can be has a null or empty value. This data preprocessing technique aims to prepare data so that easy to understand and free from missing values. The Last Observation Carried Forward Method (LOCF) fills the empty value with the previous day's worth. LOCF is used to handle missing values.

2.4 Scaling Data

At this stage, data scaling will be carried out to speed up the training process and avoid the risk of biased results.

2.5 Split Datasets

At this stage, the dataset will be divided into two parts: training data and testing data. Data training functions to train algorithms and model building, and data testing functions to test the model that has been taught. Data sharing is done by 70% for training data and 30% for testing data.

2.6 Return prediction using LSTM

At this stage, return prediction uses the LSTM method. The parameters used in the LSTM are described in Table 1.

Table 1. Parameter LSTM

Parameter	Value
Optimizer	Adam
Epoch	100
Loss Function	Mean-Square Error

Referring to table 1, there are three parameters used. The first optimizer parameter used is adam. Adam's optimizer is the algorithm that develops the Stochastic algorithm. The classic Gradient Descent (SGD) is where the network weights have been updated. Diederik Kingma first introduced this algorithm[12] . With an epoch of

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100, and the loss function uses the Mean Square Error (MSE). MSE is one method to evaluate forecasting. Each error or remainder is squared. This approach allows for significant forecasting errors because the errors are squared. The drawback of using MSE is that MSE tends to feature large deviations due to squaring [13], [14].

2.7 Portfolio Optimization with GA

2.7.1 GA System Design Flow

After predicting stock returns through LSTM, the next step is calculating the optimal weight for five stocks, namely BBCA, BBRI, BMRI, TLKM, and UNVR, so that the maximum Sharpe Ratio value can also be obtained.

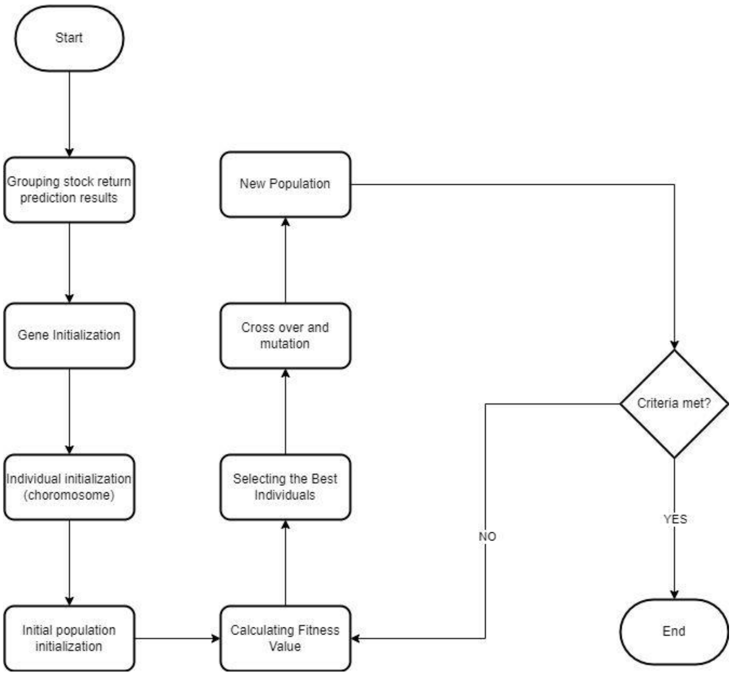

Figure 2. GA System Design Flow

Figure 2 shows the workflow of the genetic algorithm system. First, the predicted return results will be grouped into four groups, 3,6,12 and 36 months. Then the gene will be initialized; then, the chromosome will be initialized. The assumption of this chromosome is portfolio weighting. The next step is to initialize the population. Then do the fitness calculation because, in this study, it is intended to maximize the value of the Sharpe ratio, so the total of this fitness uses the Sharpe ratio formula. Next, the best individuals will be selected by crossing and mutation to get a new population. This process will continue to be carried out until you get the criteria or, in this case, until you get the maximum Sharpe ratio value.

2.7.1.1 Grouping the Prediction Results of Stock Returns

In this stage, the results of the return prediction will be grouped into four, namely, the predicted return of 3 months, six months, 12 months, and 36 months.

2.7.1.2 Gene Initialization

In simple terms, a gene is a place to fill in values called individuals or chromosomes. This value can be binary, float, integer, character, or combinatorial. In this case, the initialization of the gene is set with random numbers.

2.7.1.3 Individual Initialization (Chromosome)

Individual or chromosome initialization is carried out randomly with a note that the sum of all chromosomes results in a value of 1 with a range of 0.0 to 1.0. In this case, the chromosome is the portfolio weight.

2.7.1.4 Initial Population Initialization

Initial population initialization was carried out randomly with as many as 100, where this combination is a combination of chromosome values that builds portfolio weights.

2.7.1.5 Calculating Fitness Value

The fitness value is an evaluation value to measure individual performance. Because this research aims to maximize the Sharpe ratio value, equation (1) calculates the fitness value. The assumption is that the risk-free

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rate is 0.0450 or 4.50% based on the March 2020 BI Rate. The Sharpe ratio or measuring tool is obtained by calculating the return on income, then the return on income is divided by the standard deviation [14].

$$L = \frac{E_r - R_f}{\sigma_p} \quad (1)$$

Description :
E_r = Expected Return portfolio
R_f = Risk-free rate
σ_p = Standard deviation of a portfolio

The standard deviation is the total risk of a portfolio. The overall risk mentioned includes market risk and portfolio risk itself. To calculate the standard deviation value, you can use the following formula [15]:

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \quad (2)$$

Description :
σ = Population Standard Deviation
N = Number of data
X_i = The i-th value
μ = Average value of data

The expected return portfolio is the average expected return of each stock in a portfolio. Calculating the portfolio's expected return is relatively easy by adding up all the product predictions of each stock's price with the portfolio's weight, you can use the following formula :

$$E_r = WA \ x \ RA + WB \ x \ RB \quad (3)$$

Description :
WA = Portfolios weight of stock A
RA = Return stock A
WB = Portfolios weight of stock B
RB = Return stock B

2.7.1.6 Selecting the Best Individuals

At this stage, the selection is carried out to choose the best individual, who will later be carried out by crossover and mutation. This selection process uses the elite selection method.

2.7.1.7 Crossover and Mutation

After getting the best individual. Then, crossover and mutation were carried out. Cross over, or interbreeding, is a method to get parents to later get a new chromosome. The method used for crossover is the Arithmetic Crossover method. This method was chosen because the data is in the form of real numbers. After crossing over, the next step is to carry out mutations to cover chromosome values that may be lost due to the crossover process. Here is the calculation formula using the Arithmetic Crossover [16] :

$$offspring1 = a * parent1 + (1 - a) * parent2 \quad (4)$$

$$offspring2 = (1 - a) * parent1 + a * parent2 \quad (5)$$

Description :
$offspring\ 1$ = First Lineage
$offspring\ 2$ = Second Lineage
a = Crossover rate with a value of 0 to 1
$parent2$ = Second Parent

2.7.1.8 New Population

At this stage, a new population will be formed. This new population will be iterated to get the optimal Sharpe ratio value.

3. RESULT AND DISCUSSION

3.1 Stock Price Prediction Result

The following is a training model for predicting stock prices for BBCA, BBRI, TLKM, UNVR, and BMRI.

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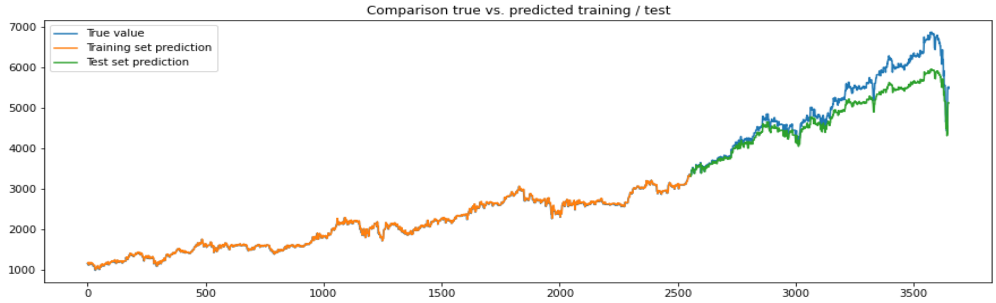

Figure 3. BBCA Stock Price Prediction Results

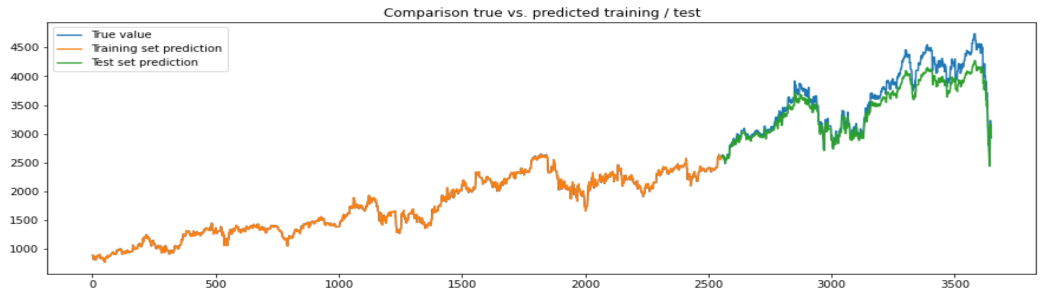

Figure 4. BBRI Stock Price Prediction Results

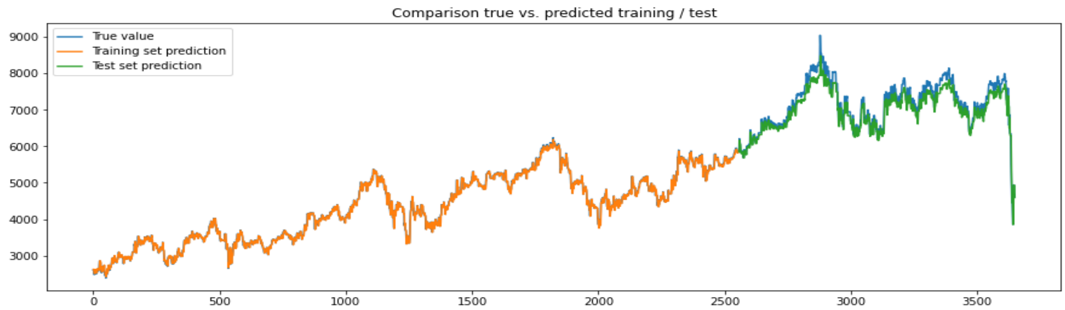

Figure 5. BBMRI Stock Price Prediction Results

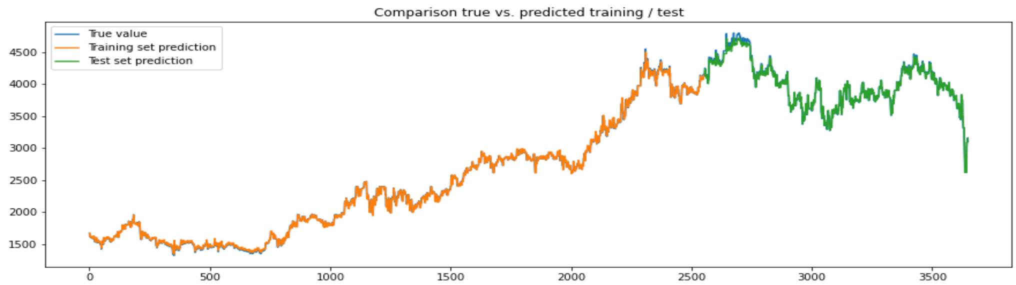

Figure 6. TLKM Stock Price Prediction Results

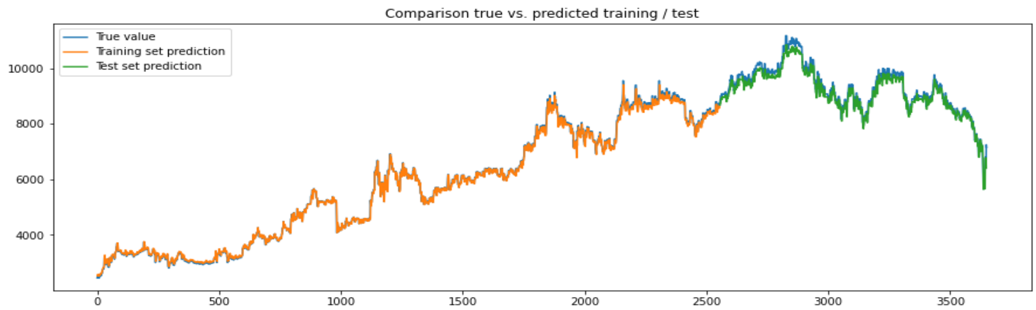

Figure 7. UNVR Stock Price Prediction Results

Figures 3,4,5,6 and 7 are the result of predicting stock prices for BBCA, BBRI, BMRI, TLKM, and UNVR using LSTM, where the blue line is stock prices, the orange line is the predicted result of training data, and the

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green line is the predicted result of test data. The results of predicting stock prices using LSTM using Root Mean Squared Error (RMSE) were evaluated, which can be seen in Table 2. RMSE (Root Mean Square Error) is a standard method used to measure model error from quantitative data predictions. RMSE determines the size of the deviation of data points from the linear regression line or the concentration of data around the linear regression line [17].

From the results of the RMSE, that of the five stocks used can be concluded that the LSTM model that the researcher created is very suitable for TLKM stocks, judging by the smallest RMSE value for the test data. Meanwhile, the LSTM model the researcher created is unsuitable for use in BBCA stock data. It can be seen that BBCA shares own the largest RMSE value for the test data.

Table 2. RMSE Evaluation Results

Stocks	RMSE Training	RMSE Test
BBCA	28.03	388.33
BBRI	29.82	199.73
BMRI	71.95	208.22
TLKM	36.17	60.39
UNVR	104.90	191.31

3.2 Portfolio Optimization Result

Portfolio optimization is carried out using two approaches, namely Genetic Algorithms and Equal-Weight, to see the differences between the two methods in maximizing the value of the Sharpe ratio. In genetic algorithms, several parameters are essential, including population size, cross-over probability, and mutation probability. These three parameters must be well-defined so that the genetic algorithm can produce optimal values. Therefore, in this study, the population size was 100, the mutation probability was 0.01, and the parameter cross-over probability was 0.99.

Table 3. Result Genetic Algorithm with forecasting LSTM

Stocks	Stock Portfolio		
	Results of the 1st run	Result of the 2nd run	Result of the 3rd run
BBCA	0.1044	0.05278	0.09839
BBRI	0.4463	0.45959	0.53325
BMRI	0.06431	0.09890	0.06470
TLKM	0.3680	0.3827	0.28768
UNVR	0.01673	0.005937	0.01596

Based on Table 3, portfolio optimization using the genetic algorithm was carried out with three trials, with each 15 iterations very satisfactory. Even though in 3 times the trials, UNVR shares always get the most negligible share weight. This could be because the share price increase for UNVR is not that good compared to the other four stocks. After getting the weight for each stock, the next step is to calculate the expected return and standard deviation to get the maximum Sharpe ratio.

Table 4. Genetic Algorithm Sharpe Ratio Results with forecasting LSTM

Running	Expected Return	Standard Deviation	Sharpe Ratio
1st	0.05927	0.01032	1.12476
2nd	0.06021	0.01037	1.39500
3rd	0.06104	0.01153	1.23149

Table 4 shows that from the weighted value of each stock, portfolio values are obtained for expected return, standard deviation, and Sharpe ratio. Where to calculate the expected return can be seen in formula (3), the standard deviation can be seen in formula (2), and the Sharpe ratio value can be seen in formula (1). To calculate the return value of a stock in formula (3), use the formula below, where the stock price is obtained from the LSTM forecasting results :

$$R_i = \frac{S_i - S_{i-1}}{S_{i-1}} \tag{6}$$

Description :
$R_i =$ Return in period i
$S_i =$ Stock price in period i
Meanwhile, to calculate the predicted return value, you can use the formula below:

$$\hat{R}_i = \frac{\hat{S}_i - \hat{T}_{i-1}}{\hat{T}_{i-1}} \tag{7}$$

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Description :
$\hat{R}_{\text{i}}$ = Return prediction in period i
$\hat{S}_i$ = Stock prediction price in period i
$\hat{T}_i$ = Stock price in period i

Calculating the predicted return value is the same as calculating the actual return value, namely by taking the previous day's predicted stock price minus today's predicted stock price and then dividing it by today's expected stock price.

To calculate the Sharpe ratio, it is assumed that the risk-free value is 0.0450 or 4.5% based on the March 2020 BI Rate. The smallest standard deviation value is the first running trial; although it has a small standard deviation value, the Sharpe ratio value in this first experiment is also relatively small. This is because the expected return value of 0.0592 is not comparable to the standard deviation value—the highest Sharpe ratio value from the second experiment with a Sharpe ratio value of 1.3950.

3.3. Evaluation Portfolio

Portfolio optimization testing using Equal-Weight and Genetic Algorithms carried out through the LSTM forecasting stages and without LSTM forecasting as a portfolio benchmark. Based on a journal conducted by B.H. Taljaard and E. Mare in 2021 showed that since 2016, equal-weight portfolios in the S&P 500 have significantly outperformed market cap weight portfolios. And equal-weighted portfolios indeed appear to outperform market-cap-weighted portfolios in the long term but with periods of significant short-term underperformance [18]. Equal weight is a type of weighting that gives equal weight to each portfolio stock. Portfolio weighting using equal weight produces 2.0 for each stock. The expected return, standard deviation, and Sharpe ratio results can be seen in Table 5.

Table 5. Sharpe Ratio Result with Equal Weight

Dataset	Expected Return	Standard Deviation	Sharpe Ratio
With forecasting LSTM	0.02917	1.1867	-0.01452
Without forecasting LSTM	0.02744	1.1912	-0.01608

Although in research conducted by B.H. Taljaard and E. Mare's equal weight managed to outperform their cap-weighted portfolio. But in this test, equal weight cannot be a method capable of producing the maximum Sharpe ratio value. It can be seen in Table 5 that with LSTM forecasting and without forecasting LSTM as the benchmark, the equal weight method gets a minus value. This means the performance of this portfolio is not good.

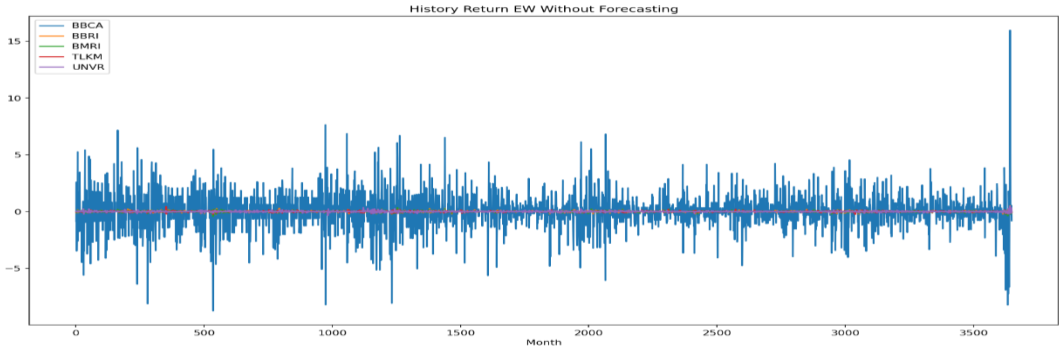

Figure 8. Development of stock returns with Equal-Weight without forecasting LSTM

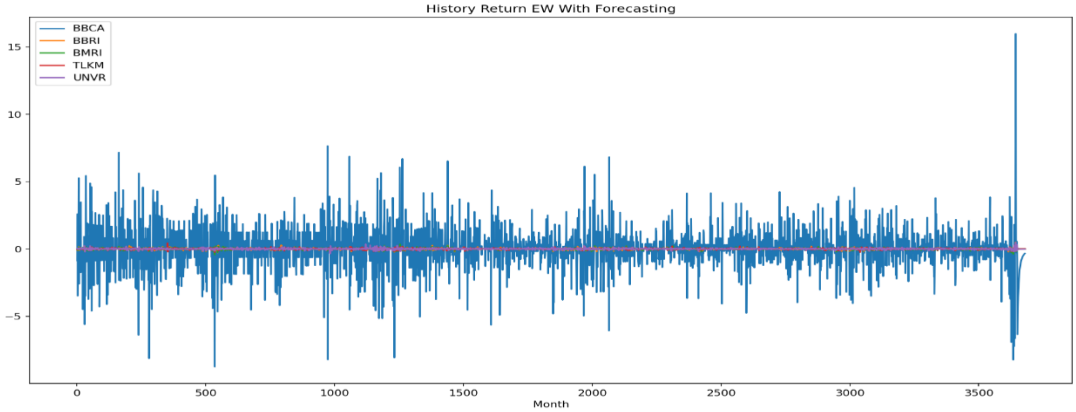

Figure 9. Development of stock returns with Equal-Weight with forecasting LSTM

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It is based on figures 8 and 9. You can see the development of stock charts with Equal Weight with and without forecasting. The difference between stock development using Equal Weight was relatively minor in the first quarter. It is because the testing data used in forecasting is only 30% of the total data. The final quarter looks more striking; the difference can be seen in Equal Weight with forecasting; the last line can reduce returns from almost -5 to close to 0.

Table 6. Result Genetic Algorithm without forecasting LSTM

Stocks	Stock Portfolio		
	Results of the 1st run	**Result of the 2nd run**	**Result of the 3rd run**
BBCA	0.17559	0.19318	0.20111
BBRI	0.41376	0.38461	0.41484
BMRI	0.09526	0.08841	0.09221
TLKM	0.25957	0.31664	0.25328
UNVR	0.05579	0.01713	0.03853

Table 6 shows the results of the genetic algorithm without using forecasting. LSTM was carried out with three trials, with every 15 iterations. Like optimization with LSTM forecasting, UNVR shares always get the most negligible portfolio weight out of 3 tests. This is because the increase in UNVR shares is insignificant. Because of that, the weighting UNVR is the smallest because the return from this stock is also not necessarily good and stable.

Table 7. Genetic Algorithm Sharpe Ratio Result without forecasting LSTM

Running	Expected Return	Standard Deviation	Sharpe Ratio
1st	0.05214	0.01132	0.63091
2nd	0.05625	0.01218	0.92412
3rd	0.05404	0.01184	0.76413

Table 7 shows the weight value of each stock. The portfolio value is obtained for expected return, standard deviation, and Sharpe ratio. Where to calculate the standard deviation can be seen in formula (2), and the Sharpe ratio value can be seen in formula (1). Assuming that the risk-free value is 0.0450 or 4.5% based on the March 2020 BI Rate. The smallest standard deviation value is the first running trial; even though it has a small standard deviation value, the Sharpe ratio value in this first experiment is also the smallest. This is because the expected return value at 0.05214 is not proportional to the standard deviation value. The highest Sharpe ratio value from the second experiment with a Sharpe ratio value of 0.92412. Portfolio optimization testing without forecasting LSTM gets quite good performance; it can be seen with a reasonably good Sharpe ratio value. Even so, portfolio optimization with LSTM forecasting is still much better, with an average Sharpe ratio value of 3 trials of 1.2504.

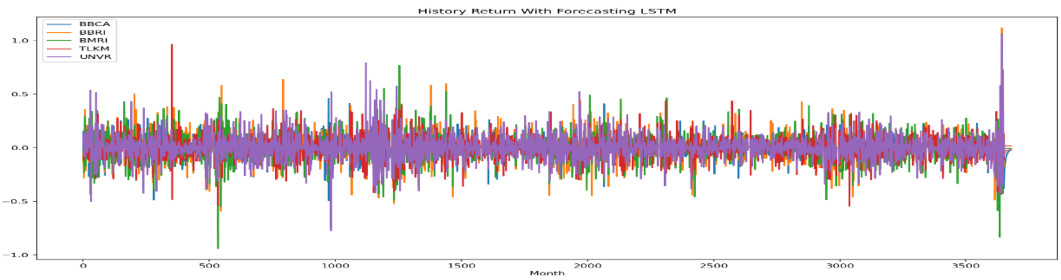

Figure 10. Development of stock returns with GA with forecasting LSTM

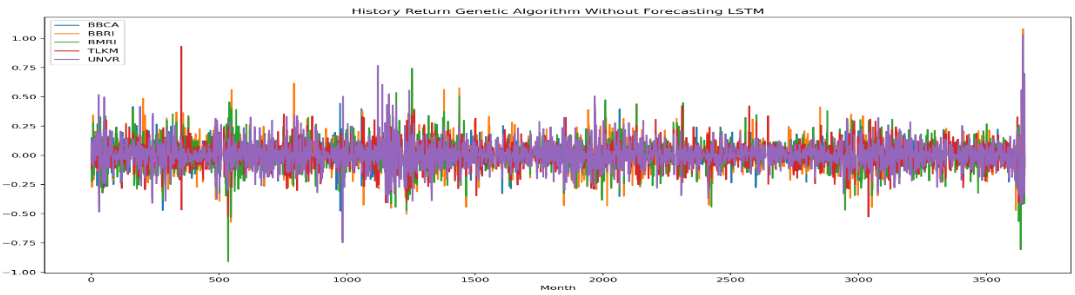

Figure 11. Development of stock returns with GA without forecasting LSTM

With and without going through LSTM forecasting, genetic algorithms can produce good weights for the best returns shown in Figures 10 and 11. The movement of stock returns using the Genetic Algorithms method

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with and without LSTM forecasting looks no different. The only striking difference is that in the final quarter, based on figure 10, the red TLKM shares are close to point 0.

4. CONCLUSION

Based on the research that has been done, researchers have built a system for optimizing the LQ45 stock portfolio by maximizing the value of the Sharpe ratio. Portfolios are made using the Genetic Algorithm and Equal Weight (EW) method by considering the predictive value of stock prices using LSTM. Without going through LSTM forecasting, GA and EW portfolios are used as benchmarks to present portfolio advantages with forecasting. The experimental results show that portfolio optimization with Genetic Algorithm using LSTM forecasting for five stocks is the best portfolio, with the highest Sharpe ratio value of 1.3950. Meanwhile, portfolio optimization using Equal Weight produces a minus Sharpe ratio value, even using LSTM forecasting. Sharpe ratio value Equal weight with LSTM forecasting produces a Sharpe ratio value of -0.01452. This means that portfolio optimization using Equal Weight is less optimal when compared to the Genetic Algorithm. Thus, portfolio optimization using a genetic algorithm can build an optimal portfolio even without going through the forecasting stage.

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