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# Stock Investment Portfolio Optimization Using Mean-Variance Model Based on Stock Price Prediction with Long-Short Term Memory

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**Abstract**

Stock investment in the technology sector in Indonesia offers high potential returns. However, like any other investment instruments, the associated risks cannot be overlooked. Therefore, an appropriate portfolio optimization strategy is needed to enable investors to achieve optimal returns while managing risk. In this study, the author combines stock price prediction approaches with portfolio optimization methods to construct an efficient portfolio. The Long-Short Term Memory (LSTM) model is used to predict daily closing stock prices, with model performance evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics. An optimal LSTM model is obtained with a batch size hyperparameter of 16 for ISAT, MTDL, MLPT, and EDGE stocks, and a batch size of 32 for DCII stock. For all stocks, the average prediction error from the actual values falls within the range of $1.53\% \leq MAPE \leq 3.52\%$. The optimal portfolio is constructed using the Mean-Variance risk aversion model to maximize expected returns while considering risk. The resulting optimal portfolio composition consists of a weight allocation of 19.7% for ISAT stock, 36.8% for MTDL stock, 34.8% for MLPT stock, 3.6% for EDGE stock, and 15% for DCII stock. This portfolio yields an expected portfolio return of 0.001249 and a portfolio variance of 0.000311.

*Keywords:* portfolio optimization, stock investment, technology sector, Mean-Variance, stock price prediction, Long Short-Term Memory.

## 1. Introduction

Stock investment is one of the most popular investment instruments because it has high profit potential. Shares provide investors with the opportunity to own part of the company and benefit from rising share prices (capital gains) and profit sharing (dividends). Stock investment is known to have a higher risk than other investments such as bonds or deposits, this is because stock prices can fluctuate (Amal & Masdjodjo, 2021). Stock investments have the opportunity to earn greater profits if the invested company experiences significant growth. Despite the high risk, stocks have the potential to get a large return. This is the main attraction for investors who dare to take risks for the growth of investment value in the long term.

The technology sector in Indonesia in recent years has shown rapid growth, along with the need for digitization, connectivity, and information technology infrastructure. This sector has high growth potential in the capital market, especially after the pandemic as it drives the acceleration of digital transformation in various industry lines (Aminah & Saksono, 2021). This research is focused on stocks engaged in the technology sector, including according to IDN Financials PT Indosat Tbk (ISAT) is a telecommunications company that provides cellular, internet and data communication services; PT Metrodata Electronics Tbk (MTDL) a company engaged in the distribution of information technology (IT) hardware and software; PT Multipolar Technology Tbk (MLPT) a company that provides information technology services and solutions, including technology planning, design, and development; PT Indointernet Tbk (EDGE) a company that provides digital infrastructure services (connectivity solutions, data centers, and cloud computing); and PT DCI Indonesia Tbk (DCII) a company engaged in providing data center services.

One method that can be used to optimize a stock portfolio is the Markowitz model, known as the Mean-Variance Optimization model. The Mean-Variance model has the advantage of determining the optimal portfolio combination based on two main parameters, namely expected return and risk measured by the variance or standard deviation of the expected return.

expectations and risk measured by the variance or standard deviation of the portfolio return (Gubu et al., 2024). The successful application of the Mean-Variance model can depend on the accuracy of stock price predictions to determine the stock returns that are input into the Mean-Variance model. Therefore, accurate stock price prediction is very important in the portfolio optimization process. The development of computing technology and artificial intelligence has enabled the use of more complex and accurate prediction models. One such model for predicting stock prices is the Long-Short Term Memory (LSTM) model similar to Recurrent Neural Networks (RNNs). LSTM models are trained using various hyperparameters, including the number of hidden layers and neurons, to optimize prediction accuracy (Goodfellow et al., 2016).

Various studies in recent years have applied various methods to optimize investment portfolios. For example, Larasati et al. (2023) conducted research to determine the optimal portfolio using the Markowitz model on infrastructure companies listed on the Indonesia Stock Exchange. In Larasati et al. (2023) research, they produced recommendations as well as the proportion of fund allocation from stocks included in the optimal portfolio combination, thus providing the best expected return with measurable portfolio risk. Another study conducted by Ta et al (2020) conducted an analysis using historical stock price data in the Chinese stock market to train the Long-Short Term Memory (LSTM) model in predicting stock returns and implementing mean variance-based portfolio optimization. In Ta et al (2020), it shows that LSTM-based predictions can be used to improve asset allocation decisions in the Chinese stock market, and produce portfolios with lower risk and more stable returns. Furthermore, Nugraha et al (2024) conducted forecasting on stock prices at PT Astra International using the Long-Short Term Memory method. In the research of Nugraha et al (2024), the best LSTM model was obtained which had a hyperparameter batch size of 4 and epoch 50, with a MAPE of 2.3%.

In previous research, various approaches have been taken for investment portfolio optimization. LSTM-based stock price prediction and Mean-Variance portfolio optimization, can be one of the best tools to get the optimal portfolio on technology sector stocks in Indonesia.

## 2. Literature Review

### 2.1. Investment

Investment is an attempt to allocate assets in the hope of gaining profits in the future. In finance, investment refers to the purchase of assets with the expectation that the value of these assets will increase over time. The goal of investment is to optimize return with acceptable risk. Investors will look for ways to increase or maintain their wealth through profits from invested assets (Bodie et al., 2014).

Assets in investment vehicles are divided into two types, including; real assets which are investments in real or tangible assets such as gold, land, real estate, and artwork. Then there are financial assets which are instruments that represent claims on future income or profits, such as stocks and bonds. Financial assets are traded in capital markets, money markets, and derivatives markets. In financial assets, stocks generally have a higher potential return than other assets such as bonds.

### 2.2. Stock Return

Return is the result or profit obtained from investment in a certain period. Return reflects the rate of return earned by investors on the capital invested. The main factor that can encourage someone to invest is the return which is the reward for the risk that has been taken when investing (Utami et al., 2021).

Based on Miskolczi (2017), the return of stock $i$ at time period $t$ (where $t = 1, 2, 3, \dots, n$) can be calculated using equation (1),

$$r_{it} = ln\left(\frac{P_{it}}{P_{i(t-1)}}\right), \tag{1}$$

with,

$r_{it}$ : The return of stock $i$ at the $t$th time period,

$P_{it}$ : The price of stock $i$ at the $t$th time period,

$P_{i(t-1)}$ : The price of stock $i$ at the $(t-1)$th time period.

### 2.3. Expectation, Variance, and Covariance of Stock Return

Expected stock return is the average return or return that investors expect when investing. Return variance is how far the spread (dispersion) of actual returns is from return expectations.

According to Utami et al. (2021), the calculation of the expectation and variance return of stock $i$ can be shown in equations (2) and (3),

$$E(r_i) = \frac{1}{n}\sum_{t=1}^{n} r_{it}, \tag{2}$$

$$Var(r_i) = \sigma_i^2 = \frac{1}{n}\sum_{t=1}^{n}(r_{it} - E(r_i))^2, \tag{3}$$

when, $E(r_i)$ is expected return and $Var(r_i)$ or $\sigma_i^2$ is variance of stock return $i$.

Stock return covariance is a statistical measure that represents the extent to which two stocks move together. Covariance measures the relationship between the returns of two stocks by involving the correlation coefficient. If the covariance of returns is positive, the returns of both assets tend to move in the same direction. This means that when the return of one asset increases, the return of the other asset also increases. If the return covariance is negative, the returns of the two assets tend to move in the opposite direction (Kim, 2018). The covariation formula is shown in equation (4),

$$Cov(X,Y) = Cor \cdot \sigma_X \cdot \sigma_Y, \tag{4}$$

when, $Cor$ is correlation coefficient, $\sigma_X$ is standard deviation of variable X, and $\sigma_Y$ is standard deviation of variable Y.

## 2.4. Portfolio

Portfolio theory, first introduced by Harry Markowitz in 1952, is an important foundation in modern investment management. Markowitz showed that by combining various assets into a single portfolio, investors can achieve the optimal combination of expected return and risk (Gubu et al., 2024). This theory assumes that investors will choose a portfolio that offers the highest return for a given level of risk or a portfolio with the lowest risk for an expected level of return (Bodie et al., 2014). A portfolio is a collection of assets that can be owned by individuals or companies so as to obtain investment benefits.

### 2.4.1. Expected and Variance of Portfolio return

In portfolio theory, there are two main components to focus on: the expected return and the risk (variance return) of the portfolio. The expected return is the average of the possible returns of the portfolio, while risk is often measured by the standard deviation or variance of the portfolio return. The essence of portfolio theory is risk diversification, which is spreading investment across various assets to reduce risk.

Suppose an investment portfolio consists of $N$ risky stocks, the return of each stock is expressed as $r_{1t}, r_{2t}, r_{3t}, \ldots, r_{Nt}$where $t$ is the specific time period over which the return is calculated. Let $\mathbf{w}, \boldsymbol{\mu},$ and $\mathbf{e}$,denote the weight vector, mean vector, and unit vector, respectively. The vectors $\mathbf{w}$, $\boldsymbol{\mu}$, and $\mathbf{e}$,are expressed in equations (5), (6), and (7),

$$\mathbf{w} = \begin{bmatrix} \mathrm{w}_1 \\ \mathrm{w}_2 \\ \mathrm{w}_3 \\ \vdots \\ \mathrm{w}_\mathrm{N} \end{bmatrix}, \tag{5}$$

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \vdots \\ \mu_\mathrm{N} \end{bmatrix}, \tag{6}$$

$$\mathbf{e} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}, \tag{7}$$

where $\mu_i = E(r_{it}), (i = 1,2,3,\ldots,N)$ denotes the expected return. The weight allocated to stock $i$ is expressed as $w_i$, $(i = 1,2,3,\ldots,N)$ and the number 1 to $N$ is expressed as vector e.

The expected return of portfolio $\mu_p$ can be expressed in equation (8),

$$\mu_p = E(r_p) = \mathbf{w}^T \boldsymbol{\mu}. \tag{8}$$

Let $\mathbf{\Sigma}$ and $\mathbf{I}$ denote the variance covariance matrix and identity matrix expressed in equations (9) and (10), respectively,

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_{22}^2 & \sigma_{23} & \cdots & \sigma_{2N} \\ \sigma_{31} & \sigma_{32} & \sigma_{33}^2 & \dots & \sigma_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \sigma_{N3} & \cdots & \sigma_{NN}^2 \end{bmatrix}, \tag{9}$$

$$\mathbf{I} = \begin{bmatrix} 1 & 0 & 1 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}. \tag{10}$$

The variance returns of portfolio $\mu_p$ can be expressed in equation (11),

$$\sigma_p^2 = \mathbf{w}^T \mathbf{\Sigma} \mathbf{w}. \tag{11}$$

### 2.4.2. Mean-Variance Model Portfolio Optimization

The Mean-Variance model in portfolio optimization only considers expected return and risk (Bodie et al., 2014). To obtain the optimal portfolio where $\rho$ denotes the risk aversion factor or the optimal weight value of a portfolio. For investors with risk aversion $\rho$ ($\rho \geq 0$) have a portfolio problem as in equation (12),

$$\text{Max} \left\{ \mathbf{w}^{\mathrm{T}} \boldsymbol{\mu} - \frac{\rho}{2} \mathbf{w}^T \mathbf{\Sigma} \mathbf{w} \right\} \tag{12}$$

with the condition $\mathbf{w}^{\mathrm{T}}\mathbf{e} = 1$, $w_i \geq 0$.
Solution of the Mean-Variance portfolio model in equation (13),

$$\mathbf{w} = \frac{1}{\rho} \mathbf{\Sigma}^{-\mathbf{1}} (\boldsymbol{\mu} + \lambda \mathbf{e}), \tag{13}$$

were, $\lambda = \frac{\rho - \boldsymbol{\mu}^{\mathrm{T}} \mathbf{\Sigma}^{-1} \mathbf{e}}{\mathbf{e}^{\mathrm{T}} \mathbf{\Sigma}^{-1} \mathbf{e}}$.

## 2.5. Preprocessing Data

Data preprocessing is the process of preparing data before use. The techniques performed have the aim of improving data quality before use (Fan et al., 2021). Scaling data using MinMaxScaler can be expressed in equation (14),

$$x_t' = \frac{x_t - x_{min}}{x_{max} - x_{min}}. \tag{14}$$

The equation to return the scaling result value after forecasting is completed is stated in equation (15),

$$x_t = x_t'(x_{max} - x_{min}) + x_{min}, \tag{15}$$

where $x_t$ is the actual data, $x_t'$ is the scaled data, $x_{max}$ is the maximum actual data of the overall data, and $x_{min}$ is the minimum actual data of the overall data (Scikit-learn Developers, 2022).

## 2.6. Long-Short Term Memory

Long-Short Term Memory (LSTM) has interconnected cells in the hidden layer that are designed to store information over a long period of time. Each LSTM cell maintains two types of states: cell state ($C_t$) and hidden state ($h_t$). Each LSTM cell has three sigmoid ($\sigma$) layers and one tanh layer which involves the calculation of weights and biases. The sigmoid and tanh activation functions are shown in equations (16) and (17) respectively where $z$ is the input data from the calculation results of each layer and $e$ is a mathematical constant value (Ma, 2015),

$$\sigma(z) = \frac{1}{1 + e^{-z}}, \tag{16}$$

$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}. \tag{17}$$

The weight matrices **W** and **U** modulate the contributions of the normalized input $x_t'$ and the previous hidden state $h_{t-1}$ of each gate ($i_t$, $f_t$, $o_t$) and candidate cell state $\tilde{C}_t$The vector b is the bias vector added to the value of each gate ($i_t$, $f_t$, $o_t$) and candidate cell state $\tilde{C}_t$ (Zhang et al., 2021). Forget gate, input gate, candidate cell state, cell state, output gate, hidden state, and dense layer, respectively in equation (18) to (24),

$$f_t = \sigma(x_t' \cdot \mathrm{W_f} + \mathrm{h_{t-1}} \cdot \mathrm{U_f} + \mathrm{b_f}), \tag{18}$$

$$i_t = \sigma(x_t' \cdot \mathrm{W_i} + \mathrm{h_{t-1}} \cdot \mathrm{U_i} + \mathrm{b_i}), \tag{19}$$

$$\tilde{C}_t = tanh(x_t' \cdot \mathrm{W}_{\tilde{C}} + \mathrm{h_{t-1}} \cdot \mathrm{U}_{\tilde{C}} + \mathrm{b}_{\tilde{C}}), \tag{20}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \tag{21}$$

$$o_t = \sigma(x_t' \cdot \mathrm{W_o} + \mathrm{h_{t-1}} \cdot \mathrm{U_o} + \mathrm{b_o}), \tag{22}$$

$$h_t = o_t \odot tanh(C_t), \tag{23}$$

$$\hat{y}_c = \sigma(h_t \cdot W_{dense} + b_{dense}). \tag{24}$$

### 2.7. Adaptive Moment Estimation (ADAM)

Adaptive Moment Estimation (ADAM) is an optimization algorithm used in training deep learning models (Kingma and Ba, 2014). ADAM has the following steps:

1) The first moment ($m_t$) is the average gradient (momentum) which can be written in equation (25),

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t, \tag{25}$$

where, $g_t$is the loss gradient of the parameter at iteration $t$.

2) The second moment ($v_t$) is the variance of the gradient or RMSProp which can be expressed in equation (26),

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2. \tag{26}$$

3) The bias-corrected first moment $\widehat{m}_t$ and second moment $\hat{v}_t$ are expressed in equations (27) and (28),

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1}, \tag{27}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2}. \tag{28}$$

4) The parameter update $\theta$ is expressed in equation (29),

$$\theta_t = \theta_{t-1} - \frac{\eta \widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}. \tag{29}$$

In LSTM, the parameters $\theta_t$ are the weights $W_{dense,f,i,\tilde{C},o}$, $U_{dense,f,i,\tilde{C},o}$ and bias $b_{dense,f,i,\tilde{C},o}$ that have been updated at time $t$.

### 2.8. Evaluation Metrics for Prediction Accuracy

Root Mean Square Error (RMSE) measures the square root of the mean square error between the actual value and the predicted value (Hyndman and Koehler, 2006). The RMSE formula is written in equation (30),

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}, \tag{30}$$

Mean Absolute Percentage Error (MAPE) gives an idea of how much the prediction error is in percentage form. A lower MAPE value indicates that the model has better accuracy (Hyndman and Koehler, 2006). The MAPE formula is written in equation (31),

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100. \tag{31}$$

## 3. Materials and Methods

### 3.1. Materials

The data object in this study is stock data in the technology sector of the Indonesia Stock Exchange (IDX) including: Indosat Tbk (ISAT), Metrodata Electronics Tbk (MTDL), Multipolar Technology Tbk (MLPT), Indointernet Tbk (EDGE), and DCI Indonesia Tbk (DCII). The data taken is daily closing price data for stocks for the period February 09, 2021 - September 30, 2024. The data used is secondary data obtained from https://id.investing.com and taken on October 04, 2024.

### 3.2. Methods

1) Collected 881 historical daily closing price data for each stock.
2) Scaling using MinMaxScaler (14), then dividing the 881 daily closing price data into 70% training data (616 data) and 30% test data (265 data) for prediction purposes.
3) Determining the hyperparameters for the LSTM model can be seen in Table 1,

**Table 1:** Hyperparameter LSTM

| Hyperparameter | Value/Method |
|---|---|
| many neurons | 50 |
| Epoch | 200 |
| Batch size | 16, 32 |
| Time Step | 50 |
| Input Feature | 1 |
| Optimizer | ADAM |

4) Weight and bias initialization for LSTM calculation.
5) Perform a forward pass by calculating as in equations (18) through (24).
6) Calculate the gradient of each weight and bias.
7) Next, the backward pass calculates the gradient of each weight and bias, then performs the ADAM calculation with equation (25) until updating the weights and bias with (29).
8) Calculations 5) through 7) until the last batch then the last epoch.
9) Test the accuracy of model predictions using RMSE and MAPE in equations (30) and (31).
10) Denormalize the prediction results using equation (15).
11) Plot and display the overall prediction results.
12) Make predictions for the next 60 days.
13) Calculate the return of each stock with equation (1) with $x_t = P_{it}$.
14) Calculate the expectation, variance, and covariance of stock returns using equations (2), (3), and (4).
15) Form the vector $\boldsymbol{\mu}$, vector $\mathbf{e}$, and covariance matrix $\boldsymbol{\Sigma}$, in equations (6), (7), and (9).
16) Portfolio Optimization with the Mean-Variance model by determining the initial value of $\rho = 0$, then calculate the portfolio stock weight using equation (13).
17) Next, calculate the expectation and variance of the portfolio return using equations (8) and (11). Then with the same $\rho$ value, calculate the portfolio ratio by dividing the portfolio return by the portfolio variance.
18) Display the portfolio optimization results, then plot the efficient surface graph between the expected and variance of the portfolio return and plot the ratio graph against $\rho$.
19) The results of the selected stocks with the optimal portfolio stock weight composition are obtained.

## 4. Results and Discussion

**Table 2:** Sample daily closing price data of five stocks

| Date | ISAT | MTDL | MLPT | EDGE | DCII |
|---|---|---|---|---|---|
| 09/02/2021 | 5,500 | 316 | 965 | 2,120 | 10,200 |
| 10/02/2021 | 5,800 | 315 | 975 | 2,540 | 12,225 |
| 11/02/2021 | 5,950 | 314 | 965 | 3,045 | 12,225 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 26/09/2024 | 2,825 | 640 | 5,225 | 4,500 | 52,500 |
| 27/09/2024 | 2,825 | 635 | 5,725 | 4,530 | 52,500 |
| 30/09/2024 | 2,738 | 635 | 6,275 | 4,450 | 52,000 |

In this study, the closing price data of technology sector companies on the Indonesia Stock Exchange (IDX) is used. The calculation process in this study uses the Python programming language and Microsoft Excel. Sample daily closing price data for each stock can be seen in Table 2 above.
Normalization using MinMax Scaler on data using equation (14). The following is a sample of closing price normalization results for each stock in Table 3,

**Table 3:** Sample normalized values on five stocks

| Date | ISAT | MTDL | MLPT | EDGE | DCII |
|---|---|---|---|---|---|
| 09/02/2021 | 0.611 | 0.004 | 0.005 | 0 | 0 |
| 10/02/2021 | 0.655 | 0.002 | 0.007 | 0.056 | 0.056 |
| 11/02/2021 | 0.677 | 0 | 0.005 | 0.123 | 0.123 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 26/09/2024 | 0.218 | 0.664 | 0.803 | 0.317 | 0.317 |
| 27/09/2024 | 0.218 | 0.654 | 0.897 | 0.321 | 0.321 |
| 30/09/2024 | 0.205 | 0.654 | 1 | 0.310 | 0.310 |

After doing the forward pass and backward pass until the end, the prediction accuracy of the LSTM model on each stock can be seen in Table 4,

**Table 4:** Prediction Accuracy

| Stock | Batch Size | Data | MAPE | RMSE |
|---|---|---|---|---|
| ISAT | 16 | Train | 2.70 | 254.05 |
| | | Test | **1.86** | **63.84** |
| | 32 | Train | 2.53 | 248.16 |
| | | Test | 1.88 | 65.08 |
| MTDL | 16 | Train | 1.81 | 15.82 |
| | | Test | **1.53** | **12.20** |
| | 32 | Train | 1.88 | 16.24 |
| | | Test | 1.57 | 12.29 |
| MLPT | 16 | Train | 1.73 | 92.91 |
| | | Test | **3.52** | **170.02** |
| | 32 | Train | 3.53 | 192.47 |
| | | Test | 10.77 | 492.69 |
| EDGE | 16 | Train | 3.56 | 281.49 |
| | | Test | **3.52** | **262.95** |
| | 32 | Train | 3.17 | 250.37 |
| | | Test | 3.78 | 268.70 |
| DCII | 16 | Train | 2.29 | 1,459.58 |
| | | Test | 2.10 | 1,613.02 |
| | 32 | Train | 2.19 | 1,449.73 |
| | | Test | **2.08** | **1,603.18** |

Overall, the evaluation results using MAPE show excellent prediction results. Judging from the prediction accuracy of MAPE < 4%, this shows that the LSTM model works very well on the data. Optimal LSTM parameters, namely weights and biases obtained during training using train data and tested using test data, then get the best evaluation results. Figure 1 to Figure 5 shows the comparison graph of actual data and predicted data for each stock,

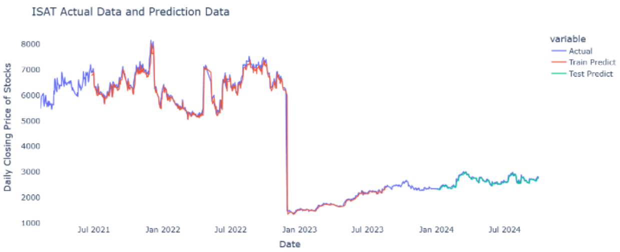


**Figure 1:** Comparison chart of actual data and prediction data on ISAT stock


**Figure 2:** Comparison chart of actual data and prediction data on MTDL stock


**Figure 3:** Comparison chart of actual data and prediction data on MLPT stock

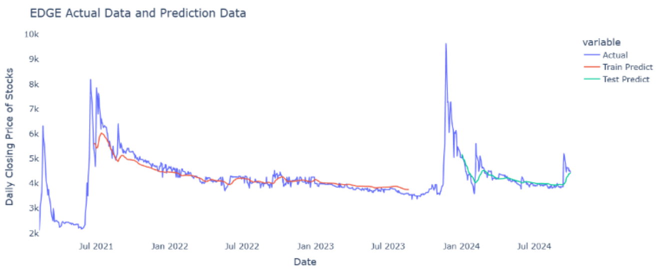


**Figure 4:** Comparison chart of actual data and prediction data on EDGE stock


**Figure 5:** Comparison chart of actual data and prediction data on DCII stock

The optimal weight and bias of each stock will then be used to predict the price of each stock for the next 60 days. The prediction includes the same forward pass calculation as the previous calculation.

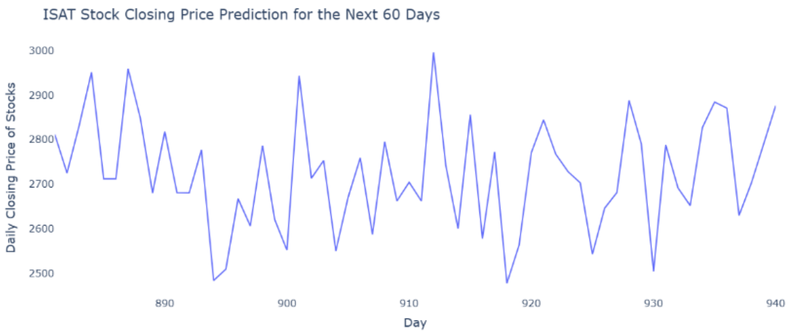


**Figure 6:** ISAT stock closing price prediction chart 60 days ahead

Figure 6 shows that ISAT's stock price fluctuated considerably during the prediction period. The closing price of the stock moves within the range of 25,000 to 3,000. The ISAT stock prediction chart shows significant volatility, where the stock price rises and falls sharply per day.

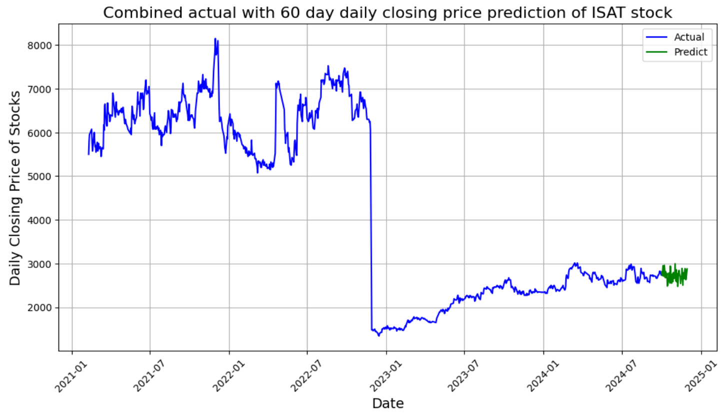


**Figure 7:** Combined Graph of Actual Data with 60 Predicted Data for ISAT stock

Next is to calculate the expected and variance returns on each stock using equations (2) and (3). The calculation results are shown in Table 5,

**Table 5:** Expected value and variance of returns of five stocks

| Stock | Expected Return | Variance Return |
|---|---|---|
| ISAT | 0.000773 | 0.000825 |
| MTDL | 0.000758 | 0.000588 |
| MLPT | 0.001966 | 0.001308 |
| EDGE | 0.000814 | 0.001921 |
| DCII | 0.002000 | 0.001990 |

In Table 5, the expected return shows the average expected profit of each stock, and the variance of the return shows the level of volatility or risk of each return.

The results of the calculation of the return covariance of each stock can be seen in Table 6,

**Table 6:** Covariance value of return of five stocks

| Stock $(i, j)$ | Covariance Return $(Cov(i, j))$ |
|---|---|
| (ISAT, MTDL) | 0.000102 |
| (ISAT, MLPT) | 0.000125 |
| (ISAT, EDGE) | 0.000120 |
| (ISAT, DCII) | 0.000103 |
| (MTDL, MLPT) | 0.000028 |
| (MTDL, EDGE) | 0.000078 |
| (MTDL, DCII) | 0.000021 |
| (MLPT, EDGE) | 0.000183 |
| (MLPT, DCII) | 0.000223 |
| (EDGE, DCII) | 0.000590 |

In Table 6, most stock pairs have positive covariance values, meaning that the returns of the two stocks tend to move together. In other words, if the price of stock $i$ rises, then the price of stock $j$ also tends to rise, as well as when the stock price falls.

Next, the vectors $\boldsymbol{\mu}$ and $\mathbf{e}$ and the matrix $\boldsymbol{\Sigma}$ are formed. Vector $\boldsymbol{\mu}$ is a vector whose entries are the expected return value of each stock. The vector $\mathbf{e}$ is the vector used to form the constraint that the total portfolio weight must be equal to one. The $\boldsymbol{\Sigma}$ matrix with its entries is the variance value of each stock and the covariance value of stock $i$ with other $j$ stocks.

$$\boldsymbol{\mu} = \begin{bmatrix} 0.000773 \\ 0.000758 \\ 0.001966 \\ 0.000814 \\ 0.002000 \end{bmatrix}, \mathbf{e} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \boldsymbol{\Sigma} = \begin{bmatrix} 0.000825 & 0.000102 & 0.000125 & 0.000120 & 0.000103 \\ 0.000102 & 0.000588 & 0.000028 & 0.000078 & 0.000021 \\ 0.000125 & 0.000028 & 0.001308 & 0.000183 & 0.000223 \\ 0.000120 & 0.000078 & 0.000183 & 0.001921 & 0.000590 \\ 0.000103 & 0.000021 & 0.000223 & 0.000590 & 0.001990 \end{bmatrix}.$$

**Table 7:** Composition of capital allocation weights, expected return variances, and portfolio ratios

| $\rho$ | $\mathbf{w}^{\mathbf{T}}$ | | | | | $\mathbf{w}^{\mathbf{T}}\boldsymbol{e}$ | $\mu_p$ | $\sigma_p^2$ | Rasio |
|---|---|---|---|---|---|---|---|---|---|
| | ISAT | MTDL | MLPT | EDGE | DCII | | | | |
| 8.27 | 0.147401 | 0.313324 | 0.329282 | −0.00009 | 0.210082 | 1 | 0.001419 | 0.000373 | 3.807622 |
| 8.28 | 0.147526 | 0.313460 | 0.329080 | 0.000001 | 0.209933 | 1 | 0.001418 | 0.000372 | 3.808574 |
| 8.38 | 0.148750 | 0.314804 | 0.327084 | 0.000894 | 0.208468 | 1 | 0.001414 | 0.000370 | 3.817882 |
| 8.48 | 0.149946 | 0.316115 | 0.325136 | 0.001765 | 0.207038 | 1 | 0.001410 | 0.000369 | 3.826828 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 15.58 | 0.195603 | 0.366212 | 0.250735 | 0.035037 | 0.152412 | 1 | 0.001255 | 0.000312 | 4.022606 |
| 15.68 | 0.195951 | 0.366594 | 0.250168 | 0.035291 | 0.151996 | 1 | 0.001254 | 0.000312 | 4.022718 |
| 15.78 | 0.196294 | 0.366971 | 0.249609 | 0.035541 | 0.151585 | 1 | 0.001253 | 0.000311 | 4.022804 |
| 15.88 | 0.196633 | 0.367343 | 0.249056 | 0.035788 | 0.151180 | 1 | 0.001252 | 0.000311 | 4.022865 |
| 15.98 | 0.196968 | 0.367710 | 0.248511 | 0.036032 | 0.150779 | 1 | 0.001251 | 0.000311 | 4.022902 |
| **16.08** | **0.197299** | **0.368073** | **0.247972** | **0.036273** | **0.150383** | **1** | **0.001249** | **0.000311** | **4.022916** |
| 16.18 | 0.197625 | 0.368431 | 0.247440 | 0.036511 | 0.149993 | 1 | 0.001248 | 0.000310 | 4.022908 |
| 16.28 | 0.197948 | 0.368785 | 0.246914 | 0.036746 | 0.149607 | 1 | 0.001247 | 0.000310 | 4.022877 |
| 16.38 | 0.198266 | 0.369135 | 0.246395 | 0.036978 | 0.149226 | 1 | 0.001246 | 0.000310 | 4.022826 |
| 16.48 | 0.198581 | 0.369480 | 0.245882 | 0.037208 | 0.148849 | 1 | 0.001245 | 0.000309 | 4.022755 |
| 16.58 | 0.198892 | 0.369821 | 0.245375 | 0.037434 | 0.148477 | 1 | 0.001244 | 0.000309 | 4.022665 |

Based on Table 7, an efficient portfolio collection is obtained when the value of $\rho = [8.28;\ \infty)$. The composition of the portfolio capital location weights with $\rho < 8.28$ results in negative entries, so the portfolio is not included in the efficient portfolio collection even though the sum of the composition weights is worth 1. The efficient surface graph and risk comparison with risk aversion can be seen in Figure 8 and Figure 9.

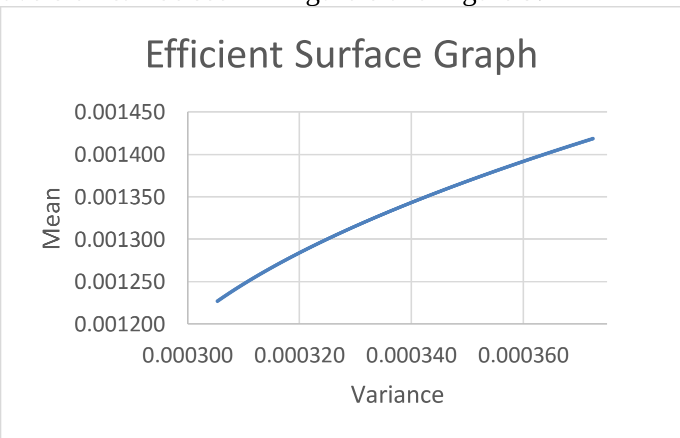


**Figure 8:** Portfolio Efficient Surface Graph

Figure 8, the graph shows the relationship between variance (portfolio risk) and mean (expected portfolio return). The greater the risk taken, the higher the expected return. The points on this curve show the efficient portfolio that has the best combination of assets based on expected return and risk.

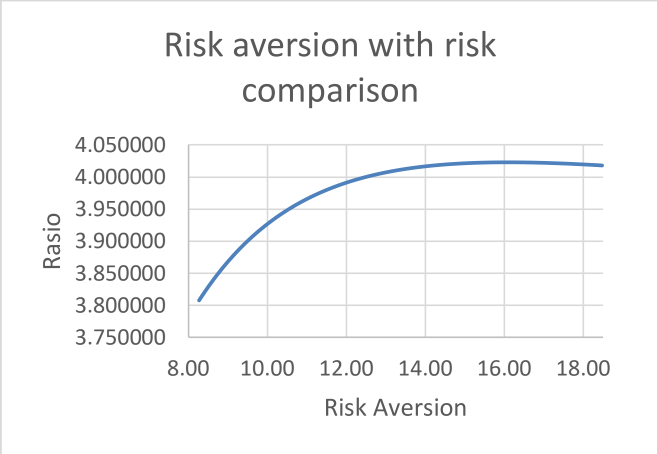


**Figure 9:** Comparison of risk with risk aversion

Figure 9 shows that the higher the level of risk aversion, the ratio also increases until it reaches the optimal point and then decreases. After obtaining the efficient portfolio, the optimal portfolio is then determined by selecting the efficient portfolio with the highest ratio. The ratio value continues to increase when $8.28 \leq \rho < 16.08$ and decreases when
$\rho > 16.08$. The highest ratio is obtained when $\rho = 16.08$, which is 4.02219.

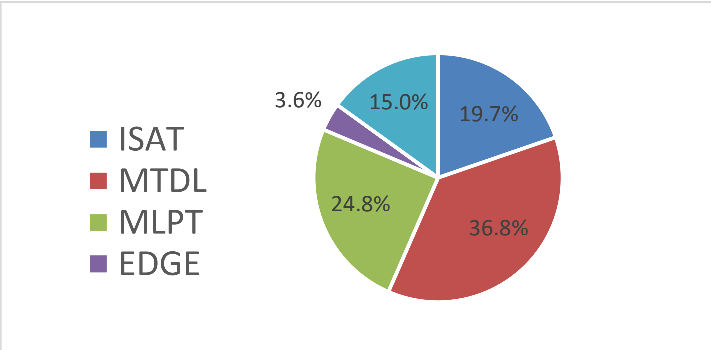


**Figure 10:** Optimal portfolio weight composition

The percentage of optimal portfolio weight composition for each stock is 19.7% for ISAT; 36.8% for MTDL; 34.8% for MLPT; 3.6% for EDGE; and 15% for DCII. The portfolio has an expected portfolio return value of 0.001249 and a portfolio variance of 0.000311.

## 5. Conclussion

The results of predicting stock prices in the technology sector in Indonesia using the LSTM model show excellent performance with MAPE < 4% for all stocks. The optimal LSTM model is generated using 50 neuron units, 200 epochs, and batch size 32 for DCII and batch size 16 for ISAT, MTDL, MLPT, and EDGE. The RMSE values on the test data are 63.84 (ISAT), 12.20 (MTDL), 170.02 (MLPT), 262.95 (EDGE), and 1603.18 (DCII). Based on the prediction results, the optimal portfolio composition with the Mean-Variance risk aversion model gives a weight of 19.7% (ISAT), 36.8% (MTDL), 34.8% (MLPT), 3.6% (EDGE), and 15% (DCII), with an expected portfolio return of 0.001249 and a portfolio variance of 0.000311.

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