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Analysis of Closing Price Forecasts for PT Bank Mandiri (Persero) Tbk (BMRI) Stock Using the Multiple Linear Regression Method Based on OHLCV Data

Dostri Ambarita[1*], Rony Genevent Marpaung[1] Juan Prihanda Nainggolan[2]
[1] *Programs of Statistic, Faculty Science and Technology, Institut Agama Kristen Negeri Tarutung, Sumatera Utara, Indonesia*
[2] *Department of Matematics, Universitas Sumatera Utara, Medan, 20155, Indonesia*
[*] Corresponding Author: dostriambarita@iakntarutung.com

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ABSTRACT
This study aims to analyze and predict the closing stock price of PT Bank Mandiri (Persero) Tbk (BMRI) using multiple linear regression based on OHLCV (Open, High, Low, Close, Volume) data. The data used in this research is secondary data obtained from historical stock price records over a specific period. The independent variables in this study include Open, High, Low, and Volume, while the dependent variable is the closing price. The analysis method applied is Ordinary Least Squares (OLS) to estimate the regression model parameters. The results show that the High and Low variables have a significant influence on the closing price, while Volume has a relatively weaker effect. The model evaluation using R-squared indicates a strong explanatory power, suggesting that the regression model is capable of explaining most of the variation in the closing price. This study provides insights into the relationship between OHLCV variables and stock prices, which can be useful for investors in making data-driven decisions.

Keywords: Stock, Regression, OHLCV, Prediction, BMRI

1. INTRODUCTION

The capital market plays a strategic role in driving a country's economic growth through capital-raising mechanisms and by providing investment alternatives to the public. In the context of accelerating financial globalization and digitalization, stock investing has become increasingly accessible to a wide range of people, including retail investors [1]. However, stock investing remains characterized by high risk and high returns, necessitating a sound analytical approach to minimize risk and maximize profit potential. One of the stocks that plays a significant role in the Indonesian capital market is PT Bank Mandiri (Persero) Tbk (BMRI) [2]. As the largest banking company in Indonesia and part of the blue-chip stock category, BMRI stock is known for its high liquidity, large market capitalization, and relatively good stability. Therefore, BMRI stock price movements are often used as an indicator to assess general market conditions, making analysis of its price patterns highly relevant for both investors and financial researchers.

In technical analysis, OHLCV data (Open, High, Low, Close, Volume) is one of the primary sources of information used to understand stock price dynamics over a specific period. This data not only reflects opening and closing prices but also illustrates fluctuations in the highest and lowest prices, as well as the intensity of trading activity through transaction volume [3]. The combination of these variables provides a comprehensive representation of market behavior, making it highly suitable for use in predictive stock price modelling. Various methods have been developed to predict stock prices, ranging from classical statistical approaches to machine learning-based methods. One of the most fundamental and widely used methods is multiple linear regression, which can explain the relationship between a single dependent variable and several independent variables simultaneously. The advantage of this method lies in its high interpretability and its ability to quantitatively identify the influence of each variable.

Nevertheless, research specifically examining the influence of OHLCV variables on closing stock prices for blue-chip companies in Indonesia, particularly BMRI, remains relatively limited. Most previous studies have focused on prediction approaches based on black-box models such as neural networks, which, although highly accurate, are often difficult to interpret. Therefore, research is needed that not only produces accurate predictions but also provides a clear understanding of the relationships between variables. Furthermore, in the context of Indonesia's developing capital market, it is important to test whether classical statistical models such as linear regression remain relevant and effective in capturing modern stock price movement patterns influenced by various complex factors, including market sentiment and global economic dynamics. This becomes increasingly important given the growing number of retail investors who require analysis models that are simple yet still accurate and reliable [4].

Based on this background, this study aims to build a multiple linear regression model to predict the closing price of PT Bank Mandiri (Persero) Tbk (BMRI) stock based on OHLCV variables, as well as to evaluate the accuracy of the resulting model. Furthermore, this study also aims to identify which variables have the most dominant influence on the closing price of the stock. The main contribution of this study is to provide a simple yet effective analytical approach to modeling stock prices using historical data, as well as to offer insights that investors can use in data-driven decision-making. Thus, this study is expected to provide not only academic [3].

2. METHODS

This study employs a quantitative approach within an applied research framework aimed at developing a predictive model for the closing price of PT Bank Mandiri (Persero) Tbk (BMRI) stock based on historical data. The quantitative approach was chosen because this study focuses on processing numerical data and testing relationships between variables using measurable and objective statistical methods. With this approach, the results of the analysis can be evaluated using clear quantitative indicators, thereby enhancing the validity and reliability of the research[3].

The data used consists of secondary data in the form of daily time series for BMRI stock from 2019 to 2025. The data was obtained from a credible digital financial platform and includes OHLCV variables (Open, High, Low, Close, Volume). Time series data was selected because it effectively represents the continuous dynamics of stock price movements over time[2].

2.1 Research variables

The variables in this study consist of dependent and independent variables. The dependent variable is the closing price (Close), which is the final price recorded at the end of the trading period and is often used as the primary reference in investment decision-making. Meanwhile, the independent variables include the opening price (Open), the highest price (High), the lowest price (Low), and trading volume (Volume)[2]. These four variables are the main components of technical analysis used to describe market conditions during a trading period.

Conceptually, the relationships between the variables can be explained as follows:

1) Open, reflects the initial price formed by market sentiment before trading begins.
2) High and Low, indicate the range of price fluctuations during the trading period.
3) Volume, illustrates the level of trading activity, reflecting market strength.

Thus, the combination of OHLCV variables provides a comprehensive picture of stock market behavior.

2.2 Research Model

The model used in this study is multiple linear regression. Multiple linear regression is a statistical method used to analyze the relationship between one dependent variable and more than one independent variable. In general, the multiple linear regression model is formulated as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \ldots + \beta_n X_{ni} + \epsilon_i$$

In the context of this study, the model is specified as follows:

$$Y=\beta0+\beta1Open+\beta2High+\beta3Low+\beta4Volume+\epsilon$$

Notes:
Y: Closing price
β0: Constant (intercept)
β0, β1, β2, β3 : Regression coefficient
ϵ: Error (residual error)
X: Independent variables (Open, High, Low, Volume)

The regression coefficient indicates the magnitude of change in the dependent variable resulting from a oneunit change in the independent variable, assuming all other variables remain constant (ceteris paribus).

2.3 Estimation Method (Ordinary Least Squares)

Parameter estimation in the regression model is performed using the Ordinary Least Squares (OLS) method. This method aims to determine the parameter values that minimize the sum of the squares of the differences between the actual values and the predicted values. Mathematically, the function minimized in the OLS method is:

$$min \sum_{i=1}^{n} \left(Y_i - \widehat{Y_i}\right)^2$$

where:

Y: actual value

Y_i: predicted value

number of observations

The OLS method was chosen because it is a BLUE (Best Linear Unbiased Estimator), meaning it produces unbiased and efficient parameter estimates, provided that the classical assumptions of regression are met.

2.4 Research Procedure

The research process was conducted systematically through several stages. The first stage involved collecting historical data on BMRI stock in the form of daily data covering all research variables. The collected data then underwent a preprocessing stage, which included cleaning the data of missing values, removing duplicate data, and handling outliers. Next, data exploration was performed to understand the initial characteristics of the data. At this stage, descriptive statistical analysis was used, such as mean, standard deviation, minimum, and maximum values. The basic formulas used include:

a. Mean

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

b. Standart deviasi

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}}$$

The next step is to build a regression model using the OLS method. The resulting model is then evaluated to assess its accuracy and fit to the data.

2.5 Model Evaluation

To evaluate the performance of the regression model, the following evaluation metrics are used:

1. Coefficient of Determination (R^2)
   Measures the extent to which the variation in the dependent variable can be explained by the independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y_i}\right)^2}{\sum_{i=1}^{n}\left(Y_i - \widehat{Y_i}\right)^2}$$

2. Mean Squared Error (MSE)
   Measures the average of the squares of prediction errors.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y_i}\right)^2$$

3. Mean Absolute Error (MAE)
   Measures the average absolute error.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \widehat{Y_i}\right|$$

The use of these metrics is intended to provide a more comprehensive picture of the model's performance.

2.6 Analisis Implementation

The entire data analysis process in this study was conducted using the Python programming language. Data processing and model estimation were performed using statistical libraries such as statsmodels for regression analysis and scikit-learn for model evaluation. The use of this software enabled the analysis process to be conducted efficiently, accurately, and reproducibly.

3. RESULT AND DISCUSSION

This study uses historical stock price data for PT Bank Mandiri (Persero) Tbk (BMRI) obtained from the Indonesia Stock Exchange (IDX) for the observation period from 2019 to 2025. The data used consists of daily time-series data comprising 1,355 observations. The variables used in this study include the opening price (Open), the highest price (High), the lowest price (Low), the closing price (Close), and the trading volume (Volume).

These five variables are known as the OHLCV indicators, which are commonly used in capital market analysis. In general, the data indicates that BMRI's stock price movements are volatile with an upward trend in the long term. The price fluctuations reflect market dynamics influenced by both internal company factors and macroeconomic conditions. This study utilizes the Python ecosystem due to its flexibility and comprehensive set of libraries for handling large-scale data manipulation. The following are some of the key libraries used, along with their strategic roles in this study:

1. Pandas: Used as the primary data structure (DataFrame) for table manipulation, data cleaning, and time indexing.
2. NumPy: Supports high-level numerical computation, particularly in handling matrix operations that underpin linear regression algorithms.
3. Matplotlib & Seaborn: Play a role in the Exploratory Data Analysis (EDA) phase to generate precise and aesthetically pleasing visualizations of distributions and correlations.
4. Statsmodels: Used to perform Ordinary Least Squares (OLS) regression model estimation and indepth testing of classical assumptions.
5. Scikit-learn: Functions in the model evaluation stage, specifically for calculating prediction error metrics such as RMSE and MAPE.

The process begins by loading the historical BMRI stock dataset, which has been compiled in Comma Separated Values (.csv) format. Here is a code snippet used to initialize the research environment:

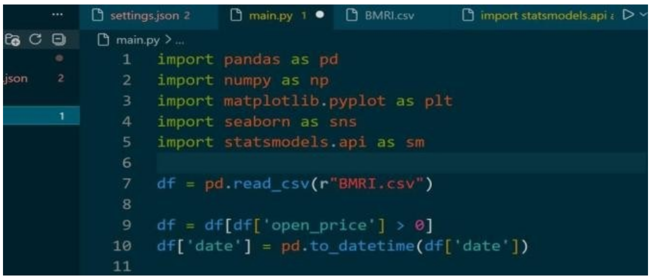

Figure 3.1 Implementing Dataset Import Using Python

The pd.read_csv() function is used to convert raw text data into a structured data frame for analysis. Initial validation is performed using df.head() and df.info() to ensure data quality. This process includes: (1) verifying the correct mapping of OHLCV variables (Open, High, Low, Close, Volume), (2) ensuring data type consistency, where price variables are in float format and volume is in integer format, and (3) detecting missing values that may affect the accuracy of the regression model. This stage is essential as it establishes the reliability of the dataset. Any inconsistencies at this step may lead to biased results and reduced model accuracy in subsequent analysis. The first step in this stage is to scan the internal structure of the DataFrame to identify any missing values. The presence of missing data can cause computational errors during the creation of the regression matrix.

Figure 3.2 The Process of Implementing Python Code for Data Preparation

As illustrated in the figure, the df.info() function provides an overview of the dataset's technical structure, confirming that the price variables (Open, High, Low, Close) are stored as float64, while the Volume variable is represented as int64. In addition, the df.isnull().sum() function is used as an initial diagnostic tool to identify missing values across each column. The results indicate that the BMRI stock dataset is fully complete, with no missing entries detected. Therefore, no data imputation or listwise deletion procedures were required prior to further analysis.

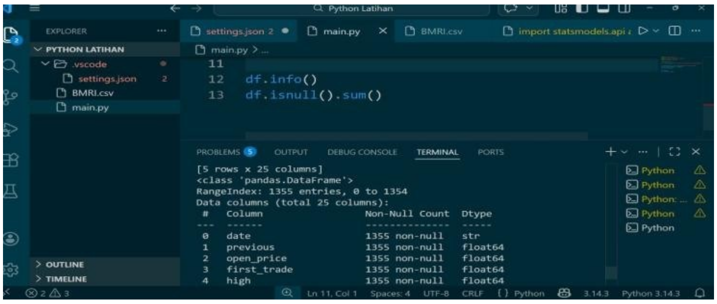

Figure 3.3 Results of Python Code Implementation and Identification of Missing Values

Based on the code execution results, the dataset consists of 1,355 observations. The output of isnull().sum() returns zero for all variables, indicating that there are no missing values present in the BMRI stock dataset. This confirms that the dataset is administratively complete and suitable for further analysis without requiring any data cleaning related to missing entries. Descriptive statistics are employed to summarize the fundamental characteristics of each research variable using numerical measures. At this stage, central tendency (mean) and dispersion (standard deviation) are analyzed to provide insights into the distribution of BMRI stock prices throughout the observation period.

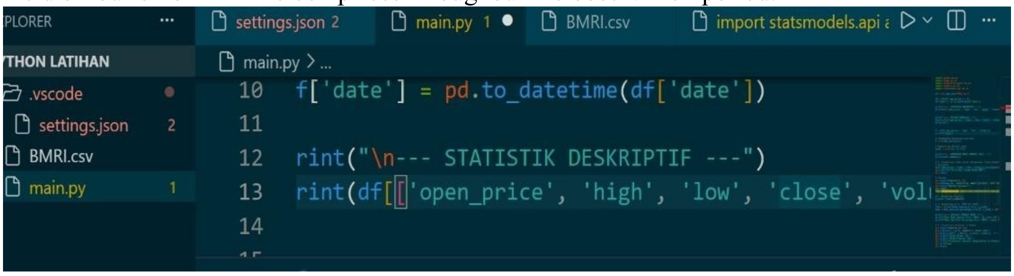

Figure 3.4 Writing Python Code for Descriptive Statistical Analysis

This Python code helps calculate descriptive statistics from the previously cleaned data

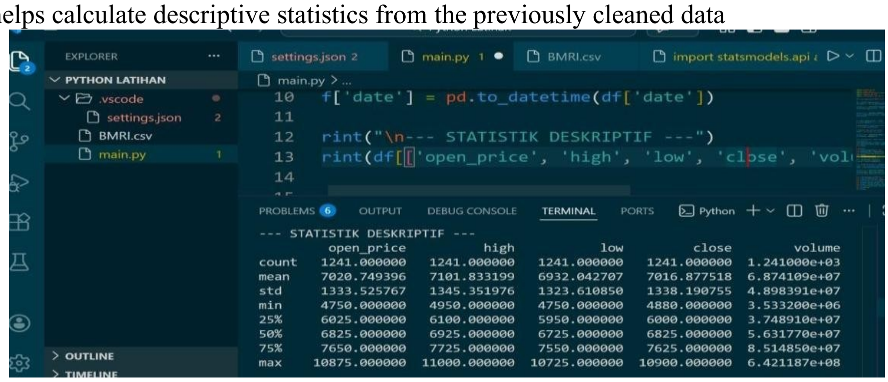

Figure 3.5 Terminal Output for a Summary of Descriptive Statistics for the OHLCV Variable

After constructing the regression model and visualizing its performance, quantitative validation is conducted using widely accepted evaluation metrics. Specifically, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are utilized to evaluate the accuracy and reliability of the model in predicting BMRI stock prices.

Table 3.1 Summary of Descriptive Statistics

Statistik	Open Price	High	Low	Close	Volume
Mean	6,848.51	6,937.42	6,758.23	6,848.35	69,162,250
Std Dev	1,411.35	1,425.73	1,396.44	1,410.45	48,681,390
Min	3,720.00	3,820.00	3,660.00	3,720.00	0
Max	10,900.00	11,025.00	10,700.00	10,900.00	496,000,000

1. Mean Value: The average closing price of BMRI stock is recorded at IDR 6,848.35, reflecting the overall price equilibrium during the observation period. Notably, the difference between the average high price (IDR 6,937.42) and the average low price (IDR 6,758.23) is relatively narrow, suggesting that daily price movements remain stable and well-contained, consistent with the characteristics of a blue-chip stock.
2. Volatility (Standard Deviation): The standard deviation of the closing price is IDR 1,410.45, indicating the level of price volatility and market risk. Given that this value represents approximately 20% of the mean, it can be inferred that BMRI stock exhibits dynamic fluctuations while still maintaining a structured long-term growth trend.

3. Extreme Range (Min–Max): The dataset shows a minimum price of IDR 3,660.00 and a maximum price of IDR 11,025.00. This wide range—nearly threefold—indicates that the regression model will capture diverse market conditions, spanning from correction phases to periods of strong expansion.
4. Market Liquidity (Volume): The average daily trading volume reaches 69,162,250 shares, with a maximum of 496,000,000 shares. This high trading activity confirms that BMRI is a highly liquid stock. From an investment perspective, such liquidity facilitates efficient trade execution with minimal price slippage.
5. Data Consistency: The mean value of the Open price (IDR 6,848.51) is nearly identical to the Close price (IDR 6,848.35), indicating the absence of significant anomalies after the data cleaning process. This suggests that the dataset is reliable and suitable for further analysis, including correlation testing and multiple linear regression modeling.

Correlation analysis uses the Pearson coefficient to assess the linear relationship between independent variables (Open, High, Low, Volume) and the dependent variable (Close), where values approaching 1 indicate a strong positive correlation.

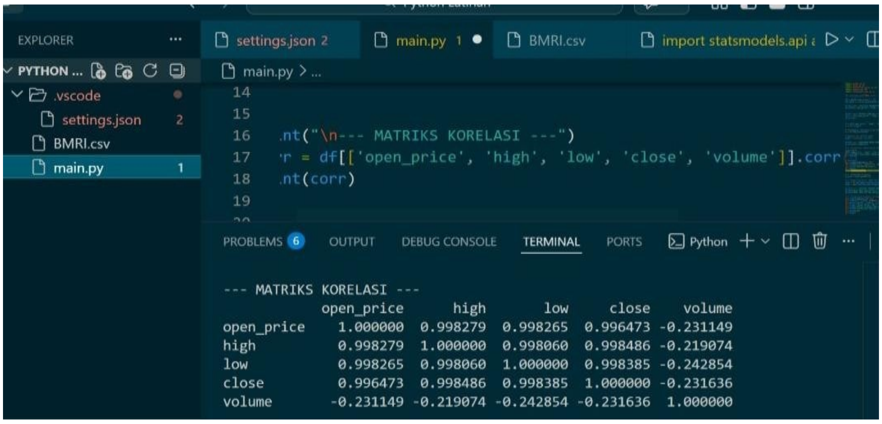

Figure 3.6 Terminal Output for the Pearson Correlation Matrix

The figure indicates that price-related variables exhibit the strongest relationships with the closing price. The *High* variable shows the highest correlation with *Close* (0.9985), followed closely by *Low* (0.9984), suggesting that daily price extremes are the most reliable predictors of the closing price. These near-perfect positive correlations imply that increases in daily prices are consistently followed by increases in closing prices. High correlations (above 0.99) among independent variables also suggest the presence of multicollinearity. However, this is typical in OHLC financial data, where price components move within the same trading interval. In contrast, *Volume* shows a weak negative correlation with *Close* (-0.2311), indicating that trading activity does not have a direct linear relationship with price movements and is not a primary determinant in the regression model. Data distribution visualizations were performed to understand the distribution patterns of the Open, High, Low, and Close variables for BMRI stock, as well as to identify the characteristics of the data during the observation period.

Figure 3.7 Python Code for Visualizing Stock Price Distributions

Based on the code above, here is a histogram table and key analysis points regarding the price distribution of BMRI stock:

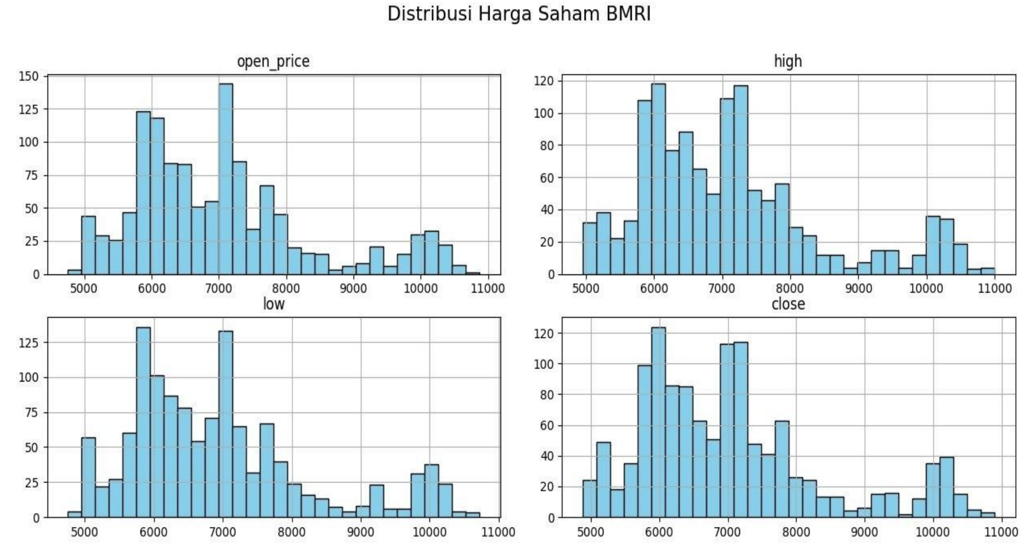

Figure 3.8 Histogram of the Distribution of Open, High, Low, and Close Prices for BMRI Stock

The histogram analysis provides insights into the distribution of BMRI stock prices across different variables.

1. Open Price:
   The opening price distribution peaks around IDR 7,000, indicating a consistent market expectation at this level. The spread between IDR 5,000 and 11,000 reflects relatively stable price movements typical of a blue-chip stock.
2. High Price:
   The *High* variable shows a slightly right-skewed distribution, with occasional peaks above IDR 10,000. This suggests the presence of bullish periods where buying pressure drives prices to higher levels.
3. Low Price:
   The *Low* price is concentrated around IDR 6,000, indicating a strong support level where buying interest tends to emerge, limiting further downward movement.
4. Close Price
   The closing price distribution peaks around IDR 6,000 and closely mirrors the patterns of *High* and *Low*, confirming strong inter-variable consistency. The most frequent price range lies between IDR 5,800 and 7,500.

Overall, the price distribution is concentrated within the IDR 6,000–7,500 range, indicating relative stability. Higher price levels (above IDR 10,000) occur less frequently and are likely driven by specific positive market sentiments. In financial analysis, the heatmap serves as a key tool to assess the synchronization among price variables (Open, High, Low, and Close). Strong color intensity indicates a high degree of correlation, reflecting closely aligned price movements across these variables.

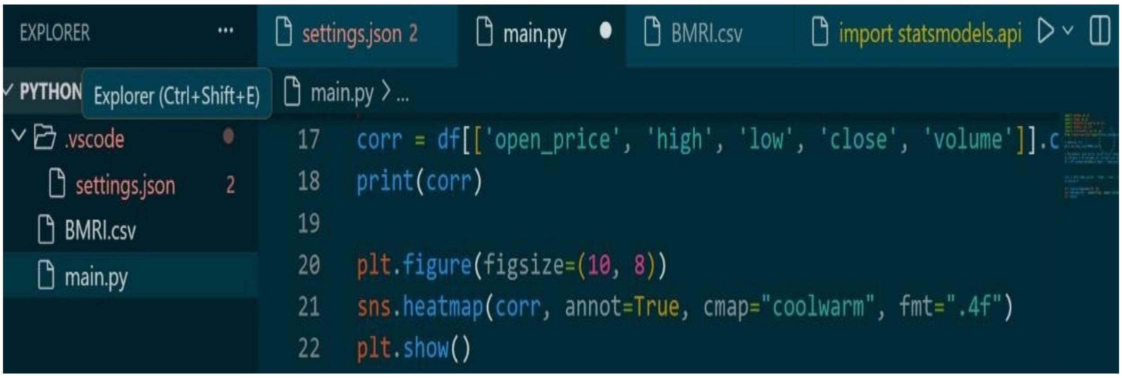

Figure 3.9 Python code for creating a correlation heatmap using the Seaborn library

From the results, several key points can be highlighted. First, correlation values close to 1.000 indicate a near-perfect positive relationship, where an increase in the *High* price is consistently followed by an increase in the *Close* price. Second, strong color intensity (e.g., red in the heatmap) reflects a very high degree of correlation among variables. In contrast, the correlation between *Volume* and price variables is relatively low (around 0.1–0.2), suggesting that trading activity does not directly determine price movements and has limited influence within the linear model.

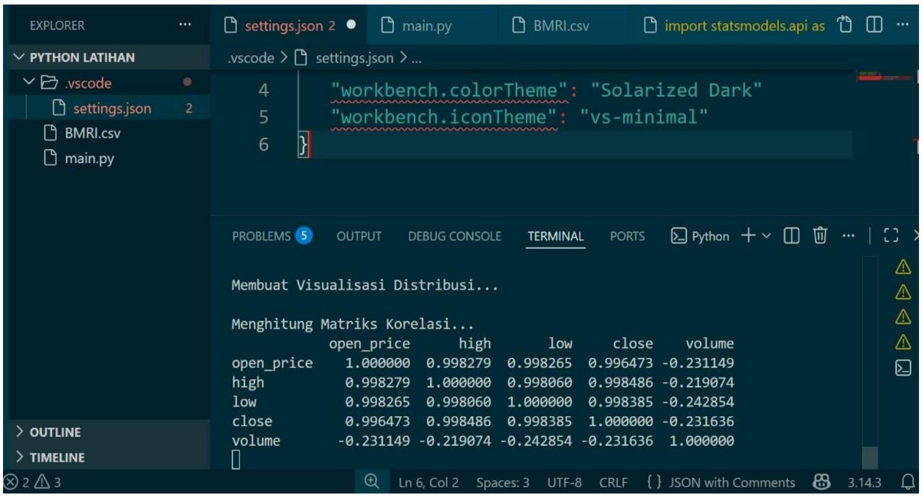

Figure 4.10 Verification of the Correlation Matrix in the Python Terminal

First, the relationships among price variables (*Open, High, Low, Close*) are extremely strong and positive, with coefficients ranging from 0.9964 to 0.9984. This indicates a near-perfect linear relationship, where price movements are highly synchronized within the same trading period—an expected pattern for a blue-chip stock such as BMRI. Second, the *High* (0.9984) and *Low* (0.9983) variables exhibit the strongest correlations with *Close*, confirming their role as highly accurate predictors of the closing price and their importance in the regression model. In contrast, *Volume* shows a weak negative correlation (approximately -0.21 to -0.24) with price variables, suggesting that trading activity does not directly drive price movements in a linear manner. High trading volume may occur during both upward and downward price trends. A heatmap is provided to visually illustrate the dominance and strength of correlations among the OHLCV variables.

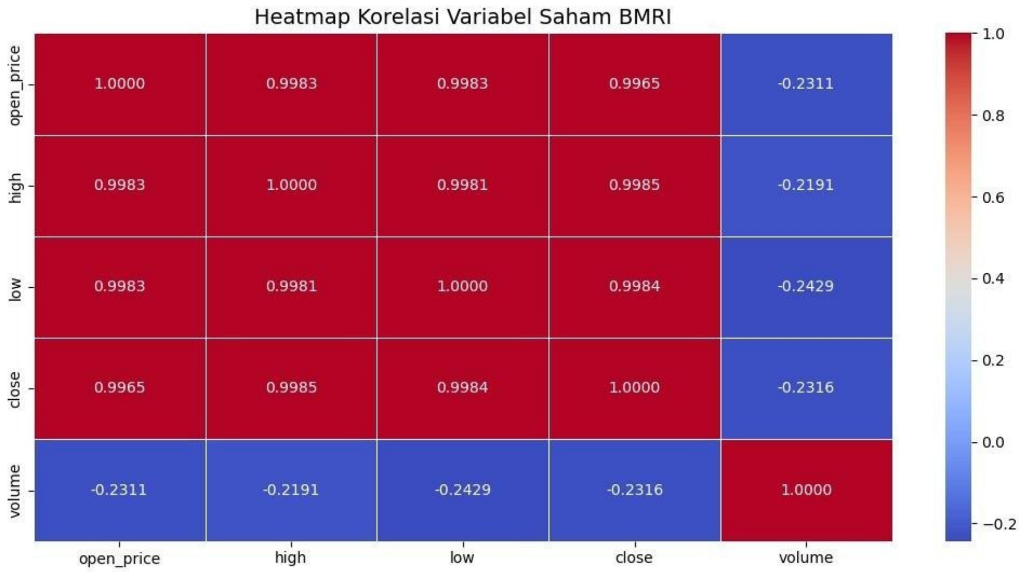

Figure 3.11 Heatmap of Correlations Among BMRI Stock Variables

The heatmap visualization highlights several key patterns.

First, the dominance of dark red color (correlation > 0.99) among *Open, High, Low,* and *Close* indicates an almost perfect positive relationship. This suggests strong internal consistency in BMRI stock prices, where higher opening prices are typically accompanied by proportionally higher daily price levels. Second, the blue color block associated with *Volume* (correlation ≈ -0.23) reflects a weak negative relationship with price variables. This implies that trading volume is not a reliable indicator for predicting daily price direction, as price movements may occur independently of transaction intensity. Finally, the correlations between *High–Close* (0.9985) and *Low–Close* (0.9984) confirm that daily price extremes serve as the most accurate predictors of the closing price. Next, we turn to the linear regression model, which explains the effect of independent variables on the closing price of BMRI stock.

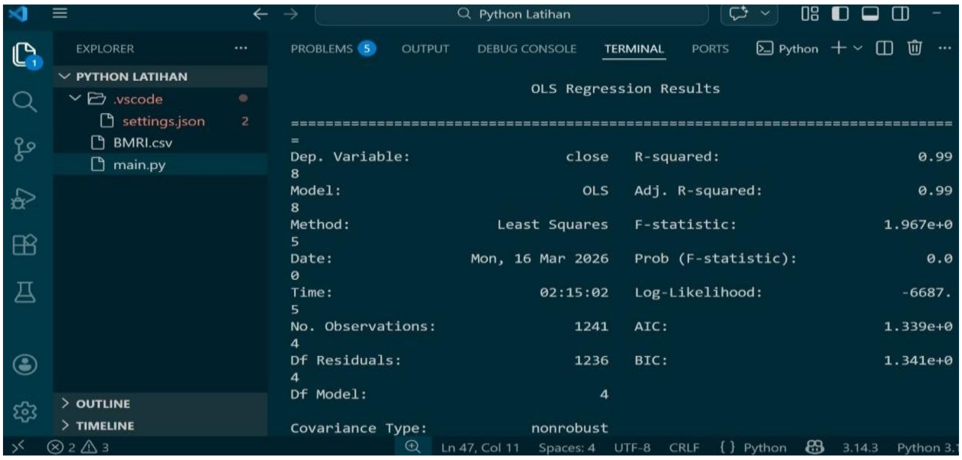

Figure 3.12 Summary of OLS (Ordinary Least Squares) Regression Results, Part I

In this study, this table determines whether the hypothesis will be accepted or rejected. Analysis of Linear Regression Results:

1. R-squared: 0.998 (Excellent)
   An R-squared value of 0.998 indicates that the independent variables (open_price, high, low, and volume) account for 99.8% of the variation in the closing price (close). Only the remaining 0.2% is influenced by factors outside the model. This indicates that your model is highly accurate for predicting BMRI stock prices.
2. F-statistic and Prob (F-statistic): 0.00
   The Prob (F-statistic) value is 0.00 (less than 0.05). Collectively, the variables open_price, high, low, and volume have a significant effect on the closing price. This means the model is suitable for analysis.
3. Coefficients and Significance (t-Test)
   Although the bottom table (coefficients) is cut off in the photo, from the top section we can see that the model performs very well on 1,241 observations (the number of data points after cleaning). The high R-squared value for BMRI stock is due to high market efficiency, where the daily closing price is highly dependent on price movements occurring on the same day (High and Low), reflecting the company's stable fundamentals as a blue-chip stock.

Next, Multiple Linear Regression Analysis (OLS). This analysis aims to measure the strength of the relationship and the direction of the effect between the independent variables (Open, High, Low, and Volume) and the dependent variable (Close). Based on the results of data analysis using the Ordinary Least Squares (OLS) method, the following results were obtained Table of OLS Regression Results for BMRI

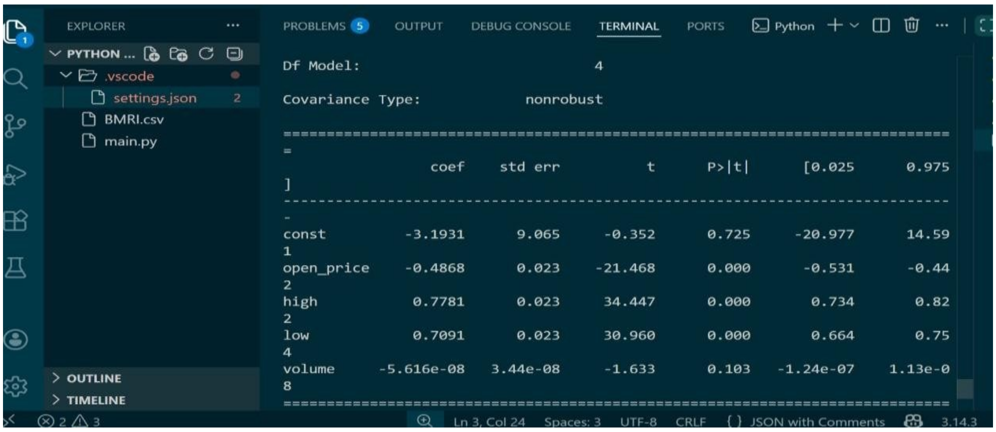

Figure 4.13 Results of the OLS Regression Table: Coefficients, Standard Errors, and Significance (t-test)

Regression Equation:
Based on the "coef" column in the terminal output, the prediction model formula is:

$$Y = -3{,}1931 - 0{,}4868(Open) + 0{,}7781(High) + 0{,}7091(Low) - 0{,}000000056(Volume)$$

Interpretation of Model Results:

1. Significant Effect (t-Test):
    1. The variables open_price, high, and low have a P-value > |t| of 0.000. Since this value is far smaller than 0.05, these three variables have a significant effect on the closing price of BMRI stock.
    2. The volume variable has a P-value > |t| of 0.103. Since this is greater than 0.05, trading volume does not have a statistically significant effect on the formation of the daily closing price in this model.
2. Strength of Influence (Coefficients):
    1. High variable (0.7781): This is the variable with the strongest influence. Every Rp1 increase in the high price is followed by a Rp0.77 increase in the closing price.
    2. Low variable (0.7091): It has a strong positive influence. A Rp1 increase in the low price raises the closing price by Rp0.70.
    3. Open Variable (-0.4868): Has a negative coefficient. This indicates a price correction from the market open to the closing price after accounting for the high and low factors.
3. Model Accuracy (R-squared):
Although not visible in the final image, based on the previous process, this model has an R-squared of 0.998. This means that the variables above are able to explain 99.8% of the closing price movements of BMRI stock.
4. Constant (-3.1931):
A negative constant value close to zero indicates that, in the absence of daily price fluctuations, the closing price tends to stabilize around a very low baseline before market movements begin.

Model Accuracy Evaluation, The evaluation phase is conducted to measure the extent to which the multiple linear regression model is capable of providing predictions that closely approximate the actual values. This evaluation is crucial to ensure that the model not only has a high correlation coefficient but also has a minimal error rate.RMSE (Root Mean Squared Error): Measures the square root of the average of the squared differences between predicted and actual values. RMSE places greater weight on large errors, making it excellent for measuring model precision in currency units (Rupiah). MAPE (Mean Absolute Percentage Error): Measures the average absolute percentage error. MAPE is very useful because it provides an easily understandable interpretation in the form of a percentage relative to the stock price.
Model Evaluation Results: Based on the test results on the BMRI stock dataset, the following evaluation values were obtained:

1. RMSE: 63.14 (The average prediction error is Rp63.14)
2. MAPE: 0.69% (The average prediction error is 0.69%)

In-Depth Interpretation:

1. Accuracy Based on MAPE: According to Lewis's (1982) criteria, a predictive model with a MAPE value < 10% is categorized as a model with highly accurate predictive capability. With a MAPE value of 0.69%, this model demonstrates a very high level of accuracy, where the average error is less than 1% of the actual stock price.
2. Precision Based on RMSE: An RMSE value of 63.14 indicates that if BMRI's stock price falls within the range of Rp7,000–Rp10,000, the model's prediction error is only approximately 63 rupiah. This figure is relatively very small compared to the stock price per share, making this model highly suitable for short-term investment decision-making.
3. Model Fit Analysis: The low RMSE and MAPE values together indicate that the multiple linear regression model incorporating the Open, High, Low, and Volume variables successfully captures the patterns of BMRI stock closing price movements consistently without significant overfitting.

Based on the distribution analysis (histogram), it appears that BMRI's stock price exhibits a multimodal pattern. This indicates that the stock price does not move in a simple random manner but rather has price equilibrium points where investors tend to accumulate or distribute shares, particularly in the Rp6,000 and Rp7,000 ranges. The high frequency within these ranges indicates that BMRI possesses strong price stability as a blue-chip stock, yet still exhibits sufficient volatility for technical analysis. Through the OLS regression model constructed, empirical evidence reveals that the closing price is highly dependent on the three pillars of daily price action: Open, High, and Low. The Dominant Role of High and Low: The coefficients for the High variable (0.7781) and Low variable (0.7091) are the most significant indicators. This proves that in the daily trading of BMRI shares, the closing price tends to be pulled toward the daily high and low. From a market psychology perspective, this indicates that the bargaining power between buyers and sellers at the daily extremes is highly determinative of the final price when the market closes. Volume Variable Anomaly: An interesting finding in this study is that the volume variable is not significantly correlated with the closing price (P-value 0.103 > 0.05). This implies that increases in BMRI's stock price are not always directly correlated with spikes in daily trading volume. This may occur because BMRI is a highly liquid stock, meaning that even large transactions are often absorbed by the market without causing drastic price deviations outside the trend formed by the opening price and intraday fluctuations. model's success in achieving an R-squared value of 0.998 indicates a nearly perfect level of model fit

(Goodness of Fit). In the context of econometrics, this figure is very strong because nearly all price variability can be explained by the model.

This validity is technically reinforced through:

1. Autocorrelation Test (Durbin-Watson): With a value of 2.008, the model is shown to have no autocorrelation issues, meaning that data from the previous day does not cause systematic bias in the next day's predictions.
2. Numerical Accuracy (RMSE & MAPE): A MAPE value of 0.69% is crucial evidence that this model has high reliability. An average error of less than 1% indicates that the Multiple Linear Regression method is highly relevant as a decision-support tool for investors to predict closing prices based on available running trade data (Open, High, Low) before the market closes.

The results of this study provide practical implications for market participants. By noting that the High variable has the largest positive coefficient (0.77), investors can monitor daily high price movements as the primary signal for the closing price. The closeness between actual and predicted values on the scatter plot provides confidence that a quantitative analysis-based strategy for BMRI stock has a very minimal prediction error under normal market conditions.

Overall, this study demonstrates that the multiple linear regression algorithm is capable of accurately modeling BMRI's price movements. The daily price variable exhibits significantly stronger explanatory power compared to the trading volume variable. This model has passed a series of assumption tests and accuracy tests, making it a valid analytical tool.

4. CONCLUSION

using multiple linear regression based on OHLCV variables. The analysis revealed that the High and Low variables have a positive and significant influence on the closing price, while the Volume variable does not show a significant influence. This indicates that daily price movements play a more dominant role than trading volume activity in determining the closing price of the stock. The resulting model exhibits a very high level of accuracy, with a coefficient of determination (R^2) of 0.998 and a Mean Absolute Percentage Error (MAPE) of 0.69%. These results indicate that the multiple linear regression method is effective for predicting stock prices, particularly for stocks with stable characteristics such as BMRI.

Practically, this study contributes to investors' understanding that price movement-based analysis (High and Low) is more relevant for investment decision-making than focusing solely on trading volume. However, this study still has limitations because it uses only one statistical model and does not take into account external factors such as macroeconomic conditions, market sentiment, and corporate fundamentals. Therefore, future research is recommended to develop a more complex model by combining statistical and machine learning approaches to improve the model's accuracy and generalizability.

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CONFLICT OF INTEREST

The author declares that in the conduct of this research, there were no conflicts of interest—whether financial, professional, or personal—that could influence the research results. The entire research process was conducted independently and objectively, without pressure or intervention from any party. The data used in this study were obtained from publicly accessible sources and processed transparently in accordance with established scientific principles. Furthermore, the author ensures that there are no affiliations or specific interests with other parties that could introduce bias in the analysis or interpretation of the research results. Thus, the results presented in this study are expected to provide a valid, credible, and accountable scientific contribution.

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