JURNAL EMACS
[Engineering, MAthematics and Computer Science] Vol.7 No.2 May 2025: 241-248
e-ISSN: 2686-2573
DOI: 10.21512/emacsjournal.v7i2.12905

A Study of Machine Learning Approach to Predict the Market Performance of Japan's Stock Price

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Abstract – *This study employs machine learning algorithms to estimate the stock performance of Japanese companies in 2022, with a focus on examining the relationship between significant financial factors—Market Capitalization (Market Cap), Price-to-Earnings Ratio (PER), Price-to-Book Value (PBV), Return on Equity (ROE), and Debt-to-Equity Ratio (DER)—and stock performance, classified as either high-performing or low-performing. These factors are designated as independent variables. The dataset comprises 1,000 publicly listed companies in Japan and is analyzed using a logistic regression model. The dependent variable in this study is stock performance. The Akaike Information Criterion (AIC) guided model selection to optimize predictive accuracy and model complexity. The dataset was split into 70% for training and 30% for testing to ensure robust model validation. The best-performing model achieved a prediction accuracy of 62.67%, demonstrating strong sensitivity (88.83%) but weak specificity (18.75%). An AUC value of 0.6226 indicates moderate discriminatory power. The model shows good capability in detecting underperforming stocks, while its limitation lies in classifying well-performing stocks. The study suggests enhancing prediction accuracy by incorporating additional relevant variables such as macroeconomic indicators or market trends, as well as employing more complex machine learning algorithms like Random Forest or Gradient Boosting. These findings not only contribute to the literature on stock market prediction but also offer practical insights for investors in making investment decisions.*

Keywords: *Machine Learning; Stock Performance; Financial Ratios; Logistic Regression; Market Prediction*

I. INTRODUCTION

Predicting stock market performance has long been a central concern for investors and financial analysts, as it supports informed investment decisions and helps in maximizing returns while minimizing risks. This research applies machine learning techniques to analyze the performance of Japanese stocks in 2022. Beyond detecting complex patterns within the data, machine learning is also capable of handling large-scale datasets efficiently, thereby improving prediction accuracy and supporting more effective to get decision-making.

Numerous studies have demonstrated the importance of financial metrics in predicting stock performance. Key indicators of a company's financial health and market valuation include its stock price, market capitalization, earnings per share (EPS), price-to-earnings ratio (PER), price-to-book value ratio (PBV), return on equity (ROE), and debt-to-equity ratio (DER) (Muh et al., 2024). These indicators are crucial in evaluating financial profitability, leverage, and value, providing a solid foundation to determine the potential of stocks to outperform. (Pribadi et al, 2024; Lento et al, 2024.

Stock performance measures how well the company manages its shares to be able to generate funds from investors to fund the company and can measure the value of the company in front of potential investors (Abate et al., 2021). With a good stock performance, then potential investors will be interested to buy shares of the company. So, that funds coming from potential investors can be used by companies to fund the activities of the company. This influx of funds enables companies to support both expansion and operational activities, highlighting the significance of stock performance in both reflecting and forming a company's financial and market reputation.

Predictive analytics has been completely transformed using machine learning in the financial markets. Stocks has been categorized as either underperforming or outperforming using methods including logistic regression, and decision trees. Studies emphasize that incorporating financial metrics like PER, PBV, ROE, and DER significantly enhances the forecast accuracy when incorporated into machine learning models (Fischer & Krauss, 2018; Zhang et al., 2023). Furthermore, these models provide valuable insights in the impact of each metric, enhancing interpretability and decision making. In addition, research on stock price prediction using logistic regression models has been conducted by Dutta et al (2012), Zaidi et al (2016), and Hassa et al (2007).

The purpose of this study is to add to the financial literature, assess the efficacy of machine learning algorithms, and offer practical insights for investing strategies. This project aims to improve knowledge of stock market forecasts and assist real-world applications in investment decision-making by utilizing big data and advanced statistical techniques.

1.1 Literature Review

A crucial field of research in financial analysis is stock performance prediction, with important financial measures acting as crucial instruments for determining whether a stock will perform better or worse. These measures help analysts and investors make well-informed judgments by providing insightful information about a company's market potential and financial health.

Key Financial Metrics

- Stock Price: Indicates the existing market value of one firm share. Investor sentiment and the market's assessment of the company's prospects for the future are reflected in this indicator (Bodie et al., 2014).
- Market Capitalization: Represents the overall worth of a company's equity and is calculated by multiplying the stock price by the total number of outstanding shares. It offers information about the size and position of the business in the market (Damodaran, 2012).
- Earnings Per Share (EPS): shows the profit divided among all outstanding shares (García et al., 2020).
- Price-to-Earnings Ratio (PER): Shows how much investors are ready to pay for every dollar of earnings by comparing the stock price to earnings per share. According to Penman (2013), it is a commonly used value metric.
- Price-to-Book Value Ratio (PBV): This ratio reflecting how the market values the company's assets in relation to their accounting value by comparing the stock price to the book value per share (Zhang et al., 2021).
- Return on Equity (ROE): quantifies how effectively a business makes money off the stock held by shareholders (Fischer & Krauss, 2018).
- Debt-to-Equity Ratio (DER): Evaluates financial leverage and offers information about a company's risk and financial structure (Damodaran, 2012).

These indicators, that provide a thorough understanding of value, profitability, and risk, serve as the cornerstone for assessing a stock's potential. Effective market performance forecasting is improved by their incorporation into predictive models.

Financial prediction has changed because of the use of machine learning techniques (Rouf et al., 2021). To categorize equities as outperforming or underperforming, techniques like logistic regression, decision trees, and neural networks are being used more and more. To find intricate patterns that conventional analytical techniques might overlook, machine learning models make use of historical data and important financial variables (Zhang et al., 2021).

Financial metrics such as P/E, P/B, ROE, and DER are essential input features. By strengthening the models' capacity to evaluate risk, profitability, and valuation, these indicators raise the predicted accuracy of the models. Zhang et al. (2021), for example, showed that adding these metrics to machine learning models greatly enhances their functionality.

To guaranteeing the accuracy of machine learning predictions. These analyses aid in determining the role that various financial indicators have in forecasting stock performance. Furthermore, evaluating the model's performance guarantees that the forecasts are not only precise but also understandable and useful (Fischer & Krauss, 2018).

Significant promise exists for improving investment strategies with machine learning models (Li et al., 2023). These models help portfolio managers make well-informed decisions, better manage risk, and maximize returns by precisely forecasting market outperformance. By offering practical insights gleaned from past and current data, Fischer and Krauss (2018) emphasized the function of machine learning in assisting with investment decisions.

This literature emphasizes how crucial it is to combine machine learning methods with financial variables to forecast stock performance. Researchers and practitioners can improve their comprehension of market dynamics and create more successful investment strategies by utilizing sophisticated analytical techniques.

II. METHODS

2.1 Variable's Definitions

The study aims to examine variables that influence the dependent variable such as Current Price, Last Year Price, Earning Price per Share, Market Capitalization, Price-to-Earnings Ratio, Price-to-Book Value Ratio, Return on Equity, and Debt-to-Equity Ratio.

Table 1. Variables in this Study

Variable	Notation	Description
Performance of Stock	Performance	Dependent Variable. Represent the stock's performance with the result of binary numbers. "1" indicates an Outperformed stock and "0" for underperformed stock.
Current Price	Current Price	Independent Variable. The recent market price at which stock being traded
Last Year Price	Last Year Price	Independent Variable. Indicating the price at the same time in the previous year. This variable is being used for performance comparison
Earning Price per Share	EPS	Independent Variable. Represent a number from company's net profit divided by the shares outstanding. Indicating the profitability of the company
Market Capitalization	Market Cap	Independent Variable. Represent the company's shares outstanding numbers. Result from the calculation of Current Price x Total Shares Outstanding
Price to Earning	PER	Independent Variable. Represent a ratio that reflecting on how on how much investors willing to pay each dollar of earnings
Price to Book Value	PBV	Independent Variable. Reflecting the market's valuation compared to their net assets.
Return on Equity	ROE	Independent Variable. Represent a result from calculating Net Income/Shareholder's Equity, showing how the equity effectively being used to generate the profits
Debt to Equity	DER	Independent Variable. Represent a financial leverage ratio that being calculated from Total Debt/Shareholder's Equity. Result shows the proportion on how the debt being used to finance their assets.

Table 1 shows the dataset that being collected from trusted sources commonly used for obtaining financial data, which is Refinitiv. Overall, the dataset consists of 1000 public companies that the stock being traded in Japan.

2.1 Research Method

The logistic regression method used in this study is to predict stock performance, where the target variable (performance) is a binary variable with the value 1 if the stock outperforms and 0 if the stock underperforms. Logistic regression is a statistical method frequently employed to examine the connection between one or more independent variables and a binary dependent variable. This model computes the probability of an outcome based on a combination of independent variable values.

The logistic regression model is formulated as follows:

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad (1)$$

In this context, p represents the probability of an outcome occurring (e.g., outperforming stock), X_k denotes the predictor variables, and β_k signifies the coefficients that reflect the influence of each variable on the logit probability.

In this study, the dataset was split into training data (70%) and test data (30%) to ensure adequate model validation. The model is trained using the training data, with variable selection based on the Akaike Information Criterion (AIC) to select the best model that optimizes the balance between model complexity and prediction accuracy. After training, the test data was used to evaluate the model's performance and ensure its generalization to new data.

The predictions generated by the model were probabilistic outcomes, which were converted into binary classifications using a threshold of 0.5. Stocks with a probability greater than 0.5 were classified as outperform, while those equal to or below 0.5 were classified as underperform. Model evaluation was conducted using metrics such as accuracy, sensitivity, specificity, and the Area Under the Curve (AUC) from the Receiver Operating Characteristic (ROC) curve. These metrics assessed the model's capability to predict stock performance and its overall effectiveness in distinguishing between outperforming and underperforming stocks.

III. RESULTS AND DISCUSSION

3.1 Results

3.1.1 Summary of Statistics

Table 2. Summary statistics

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Performance	0.0000	0.0000	0.0000	0.3930	1.0000	1.0000
Current Price	93.0000	898.0000	1542.0000	2662.0000	2503.0000	413000.0000
Last Year Price	69.0000	954.1000	1669.5000	2935.9000	2713.5000	416000.0000
EPS	2.3700	79.6200	141.6100	233.1800	243.3200	19106.7200
Market Cap	5.91E+08	2.26E+10	7.48E+10	4.48E+11	2.38E+11	2.96E+13
PER	1.3250	9.1530	13.0450	13.3940	17.5620	24.8080
PBV	0.2158	0.7102	0.9753	1.2645	1.4589	15.3217
ROE	0.0170	0.0730	0.1060	0.1280	0.1540	1.1650
DER	0.0000	0.0665	0.2833	0.6939	0.7718	16.2297

Note: this table contains all the variables that being used in the models, where Performance as the dependent variables

Table 2 is the summary statistics that provide an overview insight of the variables used in this study. It includes key indicators such as Min. as minimum value or the lowest number appears in each variable, the 1st Quartile, Median or middle Quartile, the average numbers (Mean) and the maximum value appeared (Max).

For the dependent variable, the notation "Performance" has a mean of 0.393, indicating that there approximate 39.3% from the data set tends to reflect the overperformed result. The current price and the last price being obtained from 2022 and 2021 respectively, shows mean of 2,662 and 2,935.9 this means that there was a substantial variability. Furthermore, the Market Cap and EPS range has a significant variation. For EPS ranges from 2.37 to 19,106.72 and for Market Capitalization displays 590,600,000 to 29,570,000,000,000. With these findings it suggests that there is a significant variation across the firms in terms of size. PER and PBV show average of 13.39 and 1.26, respectively. And lastly ROE and DER, with means values of 0.128 and 0.0694, exhibit profitability and leverage levels. With some outliers that are included in the observation (DER maximum value at 16.23).

3.1.2 Correlation Matrix

Table 3. Correlation Matrix

	Performance	Current Price	Last Year Price	EPS	Market Cap	PER	PBV	ROE	DER
Performance	**1**	-0.0341	-0.0614	-0.0356	0.0646	0.1341	0.0125	0.0056	0.1292
Current Price	-0.0341	**1**	0.9946	0.9640	0.0127	0.0537	0.0088	-0.0263	-0.0078
Last Year Price	-0.0614	0.9946	**1**	0.9623	0.0158	0.0542	0.0176	-0.0191	-0.0137
EPS	-0.0356	0.9640	0.9623	**1**	0.0185	-0.0589	-0.0404	-0.0726	-0.0038
Market Cap	0.0646	0.0127	0.0158	0.0185	**1**	0.0921	0.0471	0.0226	0.0712
PER	0.1341	0.0537	0.0542	-0.0589	0.0921	**1**	0.3997	-0.2132	-0.0505
PBV	0.0125	0.0088	0.0176	-0.0404	0.0471	0.3997	**1**	0.4693	-0.0178
ROE	0.0056	-0.0263	-0.0191	-0.0726	0.0226	-0.2132	0.4693	**1**	-0.0037
DER	0.1292	-0.0078	-0.0137	-0.0038	0.0712	-0.0505	-0.0178	-0.0037	**1**

Note: Colour scales are used to determine the strength of the relationships between variables. Variables with strong correlations are indicated by darker colours, while weaker correlations are represented by lighter colours.

Table 3 exhibits the correlation matrix for all the variables included in this study. The correlation coefficient ranges from -1 to 1. Value of 1 indicates a positive correlation meanwhile -1 a perfect negative correlation. Values that are close to 0 mean it has a weak or no correlation. Using the Color-Scales, darker shades denote stronger correlations.

The result between Performance and Variables such as Current Price for 0.996, Last Year Price for 0.966 and EPS 0.905, indicate these financial metrics have the strongest relationship with the performance outcome. Furthermore, Current Price and Last Year Price show almost perfect correlation 0.996 or 99%, reflecting that there is a positive movement which resulted in similar direct for both variables.

Moderate correlations are observed between the EPS and Market Cap variables, with a correlation coefficient of 0.592. Suggesting that it has a positive relationship between the earnings and firm size. On the other hand. Weaker correlations show evidence in metrics PER and PBV, as shown by lighter shades in the matrix. It indicates it may have a less direct or weaker relationship.

3.1.3 Model Building and Selection

We used the logistic regression method to predict stock performance based on key financial variables. Several models were built with different combinations of variables such as Market Cap, PER, PBV, EPS, ROE, and DER.

Table 4. Comparison of 10 Logistic Regression Models

Model	Variables Used	AIC	Significant Variables
1	Market Cap, PER, PBV, EPS, ROE, DER	917.76	All variables except EPS
2	PER, PBV, EPS, ROE, DER	924.47	All variables except EPS
3	Market Cap, PBV, EPS, ROE, DER	932.05	Market Cap, DER
4	Market Cap, PER, EPS, ROE, DER	922.36	Market Cap, PER, DER
5	Market Cap, PER, PBV, ROE, DER	**916.98**	All variables
6	Market Cap, PER, PBV, EPS, DER	921.68	Market Cap, PER, DER
7	Market Cap, PER, PBV, EPS, ROE,	926.94	All variables except EPS
8	Market Cap, PER, PBV, DER	920.30	All variables except PBV
9	Market Cap, PER, DER	920.10	All variables
10	PER, DER	926.87	All variables

Among the ten models developed, Model 5 was selected as the best due to its optimal balance between simplicity and predictive accuracy, achieving the lowest AIC value of 916.98. This model includes five variables: Market Cap, PER, PBV, ROE, and DER, all of which are statistically significant ($p < 0.05$).

Table 5. Variance Inflation Factor (VIF) for Model 5

Variable	VIF
Market Cap	1. 016708
PER	1.955655
PBV	2.480760
ROE	2.052264
DER	1.014527

In this study, a Variance Inflation Factor (VIF) analysis was conducted to examine the possibility of multicollinearity between independent variables in Model 5. The VIF values for all variables in the model were determined to be comparatively low, ranging from 1.01 to 2.48, as shown in Table 5. According to standard guidelines, a VIF value below 5 indicates that there is no significant multicollinearity between variables.

This suggests that the independent variables in Model 5 exhibit weak dependency, thus ensuring the validity of the logistic regression coefficient. Consequently, the findings of this VIF analysis support the conclusion that Model 5 is a stable and appropriate choice for predicting stock performance.

3.1.4 Model Evaluation

Model performance is evaluated using various metrics, including Confusion Matrix, Accuracy, and Receiver Operating Characteristic (ROC) Curve analysis.

Table 6. Confusion Matrix Result

Observed	Predicted		
	Underperform	Outperform	Percentage Correct
Underperform	167	91	88.83%
Outperform	21	21	18.75%
Overall Percentage			62.67%

Table 6 displays the Confusion Matrix illustrating the model's predictive outcomes for each stock category. The model accurately identified 167 stocks as "underperform" (True Negatives) and 21 stocks as "outperform" (True Positives). Nevertheless, there were 91 prediction mistakes in which outperforming stocks were misclassified as underperforming stocks (False Negatives) and 21 underperforming stocks were misclassified as above-average performance equities (False Positives).

The model sensitivity attained 88.83%, signifying effective performance in identifying underperforming stocks. Nonetheless, the specificity was at 18.75%, signifying the model's challenge in forecasting outperforming stocks.

The overall model accuracy of 62.67% signifies that the model properly predicts stock performance for 62.67% of the total test dataset. Nevertheless, this value still shows mediocre and less than optimal performance. The Balanced Accuracy score of 53.79% also signifies an imbalance in the model's predictive capability regarding the two stock categories.

Table 7. Evaluation Metrics

Metric	Value
Accuracy	62.67%
Balanced Accuracy	53.79%
Kappa	0.0868
Area Under the Curve (AUC)	0.6226
Sensitivity	88.83%
Specificity	18.75%
Positive Predictive Value (PPV)	64.73%
Negative Predictive Value (NPV)	50.00%

A Kappa value of 0.0868 indicates that the match between predictions and actual outcomes is only slightly better than random estimates, highlighting limitations in the reliability of the model.

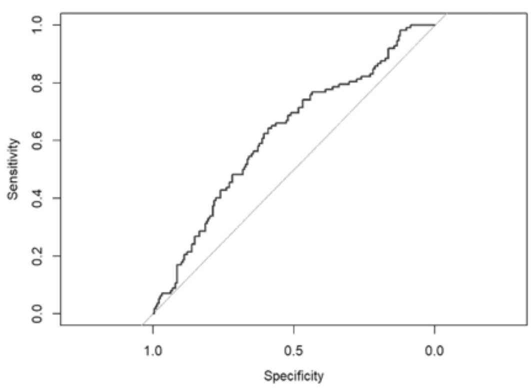

Figure 1. ROC Curve

The ROC Curve analysis offers further insight into the model's capacity to differentiate between underperforming and outperforming stocks. An AUC value of 0.6226 indicates moderate discriminative capability. While this value is better than random guessing (AUC = 0.5), it remains significantly inefficient for forecasting stock performance. These results underscore the necessity for improvement in variable selection, threshold calibration, or the employed method for enhancing model performance.

3.2 Discussion

This study's findings demonstrate that logistic regression is applicable for predicting stock performance using key financial variables. However, model evaluation reveals limitations in predictive performance that require further analysis.

In the model building phase, Model 5 was selected as the best model due to its lowest AIC value of 916.98. This model contains five statistically significant independent variables: Market Cap, PER, PBV, ROE, and DER. The VIF analysis shows an absence of significant multicollinearity between the independent variables, as all VIF values remain below the threshold of 5. This ensures the validity and stability of the logistic regression coefficients in Model 5.

However, the evaluation of the model's performance on the test data indicates an accuracy of 62.67%, which is classified as moderate and suboptimal. The high sensitivity of 88.83% demonstrates the model is good at detecting underperforming stocks. Nonetheless, the low specificity (18.75%) suggests that the model struggles to accurately predicting outperforming stocks, as evidenced by the high number of False Negatives (91). This reflects an imbalance in the model's capacity to differentiate between the two categories of stock performance.

The ROC Curve analysis reveals an AUC value of 0.6226, signifying moderate discriminatory capability of the model. Although this value is better than random guessing, it remains inadequate for more dependable predictive applications. In addition, the low Kappa value (0.0868) indicates that the model's predictions align with the actual outcomes marginally better than random guessing, highlighting the model's reliability limitations.

Based on the findings, several improvements are suggested to improve the model's performance. Selecting additional more relevant independent variables, such as macroeconomic indicators or market trend data, might enhance predictive capability. Furthermore, other machine learning methods, such as Random Forest or Gradient Boosting, may be employed to improve the model's accuracy and discrimination ability. Adjusting the classification threshold may also be considered to mitigate the imbalance between sensitivity and specificity.

Overall, this study's results demonstrate that although logistic regression is a valid method for predicting stock performance, the resultant model requires further optimization to achieve better prediction performance. Based on the above explanation, the limitations of this study are that the data is limited to a single country, namely Japan, and only for the year 2022. The method employed is logistic regression. Future research is recommended to use stock data from multiple countries and across different years. Additionally, incorporating alternative models to predict stock performance is encouraged.

IV. CONCLUSION

This study demonstrates that the logistic regression algorithm can predict stock performance by incorporating various financial variables, including Market Capitalization (Market Cap), Price-to-Earnings Ratio (PER), Price-to-Book Value Ratio (PBV), Return on Equity (ROE), and Debt-to-Equity Ratio (DER). The optimal model is selected based on the Akaike Information Criterion (AIC), ensuring an appropriate trade-off between prediction accuracy and model complexity. In this analysis, Model 5, which consists of five independent variables, provides the lowest AIC value, which certainly indicates its effectiveness as a predictive tool.

The assessment of the model highlights aspects that need enhancement in its performance. With an accuracy of 62.67%, the model exhibits great sensitivity (88.83%) while showing low specificity (18.75%). This suggests that although the model is effective at pinpointing underperforming stocks, its capacity to recognize outperforming stocks is restricted. The low Kappa value (0.0868) indicates the dependence of predictions on random processes, while the Area Under the Curve (AUC) value of 0.6226 indicates the moderate discriminative ability of the model.

These results indicate that there is still room for improvement in the model. The addition of other important variables, such as macroeconomic indicators, market trends, or other external factors, may improve the predictive ability of the model. To get better accuracy, it can also use more complex machines teaching algorithms such as Random Forest or Gradient Boosting. This research contributes to financial literature, especially on the use of machine learning algorithms for capital market prediction. This study emphasizes the advantages and drawbacks of logistic regression models, while offering useful advice for investors looking for data-driven investment approaches. Future studies should aim to create models that are more precise, flexible, and applicable to assist investors in making wiser and more effective investment choices.

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