# Comparison of Support Vector Machine (SVM) and Linear Regression (LR) for Stock Price Prediction


I Putu Candra Purnama
*Informatics Engineering*
Denpasar, Indonesia
candrapurnama368@gmail.com

Ni Luh Wiwik Sri Rahayu Ginantra
*Informatics Engineering*
Denpasar, Indonesia
wiwik@instiki.ac.id

I Wayan Agus Surya Darma
*Informatics Engineering*
Denpasar, Indonesia
surya@instiki.ac.id

I Putu Agus Eka Darma Udayana
*Informatics Engineering*
Denpasar, Indonesia
agus.ekadarma@gmail.com



2023 Eighth International Conference on Informatics and Computing (ICIC) | 979-8-3503-4260-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICIC60109.2023.10381982



**Abstract — Stocks are a type of investment with high risk and high returns because the data is dynamic. One of the capital market participating companies is PT. Vale Indonesia or commonly known by its issuer code INCO. Production PT. Vale Indonesia supplies 4% of the world's nickel needs. In the future, the need for nickel will continue to increase because it is used for electric vehicle batteries. As demand increases, selling prices will increase and share price movements will fluctuate. Therefore, we need a prediction that is able to describe stock prices based on stock price movements in the previous period. This research compares the Support Vector Machine (SVM) and Linear Regression (LR) algorithms in predicting stock prices. This research is expected to obtain an algorithm with the best level of accuracy as a consideration for investors in choosing an algorithm to make predictions. The results this research state that Linear Regression (LR) algorithm is better than the Support Vector Machine (SVM) in predicting stock prices at PT. Vale Indonesia. The best Linear Regression Model divides the data into 90% training data and 10% test data to obtain an RMSE of 42.82, which means it is quite good at making predictions because it is quite close to zero. Meanwhile, the best Support Vector Machine model divides the data into 90% training data and 10% testing data to obtain an RMSE of 64.32, which means the model is not good at making predictions because the accuracy results are not close to zero.**



***Keywords— Stock Price Prediction, Support Vector Machine, Linear Regression***


## I. INTRODUCTION

Human life will not be separated from the internet and technology because its use has many benefits. One of the benefits that can be obtained from the internet is investment knowledge. Investment is a form of investment in a company in order to get profits within a certain period of time [1]. One type of investment is stock market investment [2]. The stock market is characterized by high risk and high return [3].The stock market is a place where investors are connected with the sale and purchase transactions of IPO (Initial Public Offering) company shares [4]. Many business actors want to realize asset appreciation through investments made in the stock market [5]. Buyers will buy stock when the price is low, while sellers will sell them when the price is high [6]. Stock price fluctuations are very common in a capital market [7]. Factors that influence stock price fluctuations are inflation rates, political conditions, economic situation, performance of individual companies, and changes in the rupiah exchange rate against the US dollar [8][9].

Fluctuating stock price movements need to be predicted. Stock price predictions are very useful for investors or investors in knowing how investment moves, every investor has the hope of getting profits that depend on the price of each stock whose movements are always changing [10]. Stock price predictions can use machine learning, machine learning is a part of artificial intelligence that is used to perform analysis and manage investments efficiently [11] [12]. One of the companies participating in the capital market is PT. Vale Indonesia or commonly known as the issuer code INCO. Quoted from liputan6.com, this company was previously named PT. International Nickel Indonesia (PT. INCO) which was founded in 1968. PT INCO held an initial public offering (IPO) of 21.18% of its stock on May 16 1990. In 2011, the shareholders agreed to change the name of PT. INCO became PT. Vale Indonesia [13].

PT. Vale Indonesia is the largest nickel ore mining and processing company in Indonesia, located in South Sulawesi. The nickel production volume of PT. Vale Indonesia reaches 75,000 metric tons per year. Production PT. Vale supplies 4% of the world's nickel needs [14]. In the future, demand for nickel will continue to increase because it is used for electric vehicle batteries. With increasing demand, selling prices will increase and share price movements will fluctuate [15]. Therefore, technical analysis is needed to help determine stock price predictions at PT. Vale Indonesia as a consideration for investors in decision making. Technical analysis is information that provides investors with an overview of dynamic stock price movements [16]. Technical analysis uses past price levels information to determine trends and momentum [17].

Several good algorithms are used to carry out time series prediction analysis, including Support Vector Machine (SVM) and Linear Regression (LR) [18][19]. Therefore, this research compares the Support Vector Machine (SVM) and Linear Regression (LR) algorithms for stock prediction at PT. Vale Indonesia. The SVM algorithm is used because this algorithm is an algorithm that has a linear kernel which is suitable for regression cases. The SVM and LR algorithms are compared because they are equivalent in the case of regression. The purpose of comparing the SVM and LR algorithms is to find out which algorithm is superior in making stock predictions at PT. Vale Indonesia as a reference for investors in choosing the best algorithm. The research results can be in the form of a graph of the error accuracy level of the SVM and LR algorithms.

## II. LITERATURE REVIEW

Research using the SVM and LR algorithms has been carried out in previous studies. One of them was carried out by Fadilah who conducted an analysis of stock price predictions at PT. Telecommunications Indonesia using the Support Vector Machine algorithm. The research was conducted by comparing two algorithms, namely the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms. The RMSE accuracy results from the research using the SVM algorithm were 0.0932. Meanwhile, with the KNN algorithm, the accuracy obtained was 0.945. So after making a comparison it can be concluded that the SVM algorithm has a higher level of accuracy than the KNN algorithm, but it is not possible that there are other algorithms with higher accuracy [20].

Another research conducted by Winnos who compared the Multiple Linear Regression and Autoregressive Integrated Moving Average (ARIMA) algorithms for stock predictions for the company PT. BSI, Tbk.. This study obtained an accuracy of 98.9% and a MAPE value of 1.1% using the Linear Regression algorithm. Meanwhile, the ARIMA algorithm test results obtained an accuracy of 97.64% and a MAPE value of 2.36%. From the evaluation results it can be concluded that the Linear Regression algorithm is better than the ARIMA algorithm [21].

Further research concerns application of machine learning in algorithmic investment strategies on global stock markets. The research uses machine learning algorithms in the form of Neural Network, Regression Trees, Random Forest, Support Vector Machine. The results of the research show that the Support Vector Machine and Random Forest algorithms make the best predictions in bullish markets. Meanwhile, the Neural Network and Regression Trees algorithms make predictions in bearish markets [22].

## III. METHODOLOGY

### A. Support Vector Machine (SVM)

The SVM algorithm was first introduced by Vapnik, Noser and Guyon in 1992 at the Annual Workshop on Computational Learning Theory and since then the Support Vector Machine has begun to grow rapidly [23]. SVM is a data training algorithm used for data analysis for classification and regression needs [24]. SVM is one of the best algorithms for classifying based on the statistical learning framework with group separation using a boundary hyperplane developed by Vapnik and Chervonenkis [25] [26]. SVM resemble linear discriminants in general, classifying cases based on a linear function of their features [27]. SVM models aim to reduce overfitting and form the best line to differentiate n-dimensional spaces into groups so that new data can be easily divided into the correct category in the coming times [28] [29].

In mathematical form, the model aims to minimize the function represented in (1).

$$\begin{aligned} &minimize\ \frac{1}{2}||\beta||^2 + C\sum_{i=1}^{n}|x_i| \\ &subject\ to ||R_{train} - \hat{r}||_2^2 \le \varepsilon + |x_i| \end{aligned} \quad (1)$$

Where $\hat{r}$ is reconstructed reflectance calculated by:

$$\hat{r} = \chi\beta \quad (2)$$

the independent variable matrix is X, and $\beta$ is the vector of the regression model. $\varepsilon$ is a margin error, and $x_i$ is slack variables. All values that fall outside of $\varepsilon$, the margin deviation can be expressed as $x_i$. C is an advanced hyperparameter that determines the outside point of $\varepsilon$. Please note that there is also a gamma variable in the algorithm, namely the kernel coefficient [30].

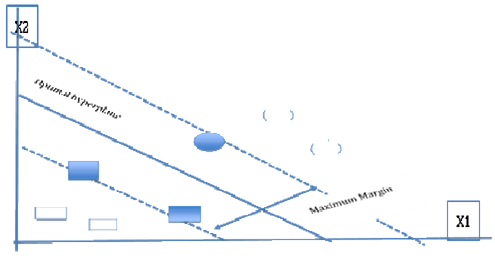


Fig. 1. Illustration of SVM [31]

Figure 1 shows an illustration of the Support Vector Machine algorithm that has found the best hyperplane, where the hyperplane functions as a separator of two classes in the middle. The distance between the hyperplane and the closest data from each class is called the margin. The closest data is called the support vector which is marked with a blue circle and square [31]. Similar to the regression case, SVM works to find the best hyperplane and find the closest support vector to get good regression results.

### B. Linear Regression (LR)

Linear Regression is a model used to predict the value of given input data. LR is a statistical measure used to see the ability of the relationship between the dependent variable and the independent variable. The main algorithm for prediction is to build a regression model by looking for the relationship between one or more independent variables or predictors (X) and the dependent or response variable (Y) [32]. LR is a representative regression algorithm that describes the linear relationship between a dependent variable and one or more independent variables [33]. Linear regression models are generally written like equations (3).

$$y = b_0 + b_1x_1 + _{...} + b_nx_n \quad (3)$$

From this equation $y$ is the dependent variable, which depends on the value of $x$ (independent variable). The value $b_0$ is a constant, b is the regression coefficient of variable $x$, and the value $n$ is an example [34].

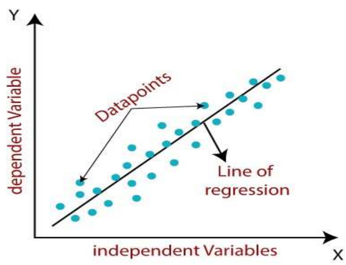


Fig. 2. Illustration of LR [35]

Figure 2 shows an illustration of the LR algorithm which shows the linear relationship between the dependent variable (y) and one or more independent variables (x). The blue circle shows the data used and the slash represents the boundary between the dependent variable and the independent variable [35].

To find out the best algorithm between the SVM algorithm and the LR algorithm, it is necessary to do research on this matter. There are several stages in conducting this research as explained in Figure 3.

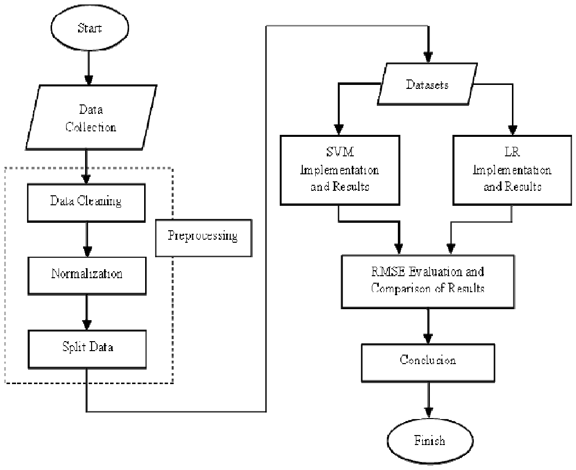


Fig. 3. Research Stages

*1) Data Collection:* The data used is the stock price at PT. Vale Indonesia with issuer code INCO. Data is collected by downloading on the finance.yahoo.com site. A total of 2.242 data from June 2014 to June 2023 were successfully collected.

*2) Preprocessing:* Preprocessing is done to prepare raw data into data that can be processed further. Preprocessing is done using the Python programming language on Google Colaboratory. The file extension used is Comma Separated Value (CSV). There are two stages in preprocessing, including data cleaning and split data.

*a) Data cleaning:* In this study, data cleaning was carried out manually by deleting missing values. This is done to ensure that the data used in analysis or decision making is valid, reliable and of good quality.

*b) Normalization:* After data cleaning is complete, then proceed to the normalization stage. Normalization aims to change actual data into values with an interval range of [0,1]. There are several normalization techniques, one of which is min-max normalization [36]. Min-max normalization is a normalization method that is carried out by changing the original data linearly so as to produce balanced values between the original data and normalized data [37].

*c) Split data:* After cleaning the data, then the next step is to split the data. The data is divided into two, namely training data and testing data. The training data is used by the algorithm to form a predictive model. While the testing data is used to measure the extent to which the algorithm predicts correctly. In this study, the data was divided into three scenarios, namely, 70:30, 80:20, 90:10.

*3) Implementing the SVM and LR models:* At this stage, the SVM and LR models are designed by initializing the two models in the Python program. Each model will be trained using training data according to the data split scenario to get prediction results from testing data. The SVM model initialization process for regression uses a linear kernel and the LR model uses linear regression initialization.

*4) RMSE evaluation and comparison of results:* RMSE evaluation was carried out as a reference for evaluating the performance of the two algorithms, namely the SVM and LR algorithms. RMSE evaluation is carried out from actual data and prediction results. After getting the RMSE evaluation results, a good comparison of the results between the two models is carried out. RMSE can be calculated using (4).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - Y'_t)^2}{n}} \quad (4)$$

Formula description:
$Y_t$ = Actual value
$Y'_t$ = Predicted value
n = The amount of data

*5) Conclusion:* Conclusion contains a summary of the results of the study. This is done to provide information to readers to find out quickly and easily about the final results of this study.

## IV. Results and Discussion

Stock data is obtained via the finance.yahoo.com site using the date, open, high, low and close attributes to make predictions. The data used to make predictions is 2.242 daily stock data. The data obtained will be tested using three scenarios split the data to obtain the best results, namely 70:30, 80:20, 90:10.

### A. Testing with data split 70%:30%

This testing split the data with 70% training data as model learning and 30% testing data as data to be predicted. The amount of training data is 1.569 data, while the testing data that will be predicted is 673 data.

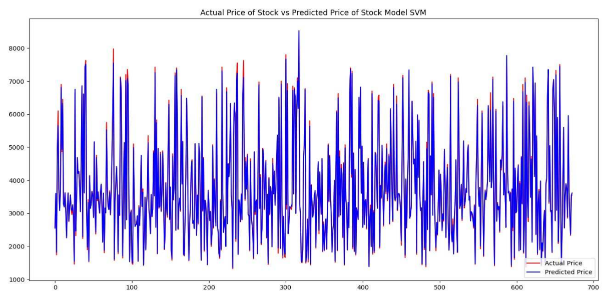


Fig. 4. Stock Price Prediction Results for the SVM Model

Figure 4 shows the stock price prediction results. In this graph, the prediction results obtained show a tight line because it uses 673 testing data. The blue line shows the predicted stock price, while the red line shows the actual price. The prediction results using the Support Vector Machine (SVM) algorithm obtained an RMSE of 76.28, which means that the prediction results were not good, as seen from the many prediction lines that were not close to the actual value.

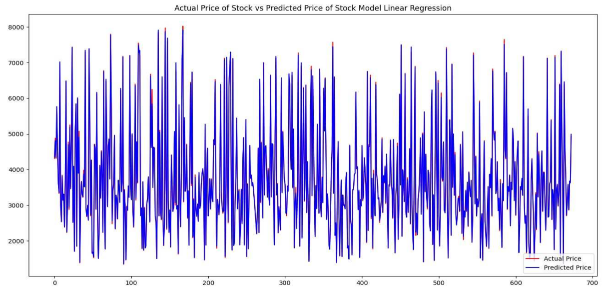


Fig. 5. Stock Price Prediction Results for the LR Model

Figure 5 shows the prediction results which show a very tight line because it uses 673 test data. The blue line shows the predicted stock price, while the red line shows the actual price. A rising line indicates the stock price is rising, while a falling line indicates the stock price is falling. Figure 5 makes predictions using the Linear Regression (LR) algorithm to obtain an RMSE result of 45.61, which means the prediction results are not good, it can be seen that many of the predicted lines are not close to the actual value.

## *B. Testing with data split 80%:20%*

This testing split the data with 80% of the training data as the learning model and 20% of the testing data as the data to be predicted. The amount of training data is 1.793 data, while the testing data that will be predicted is 449 data.

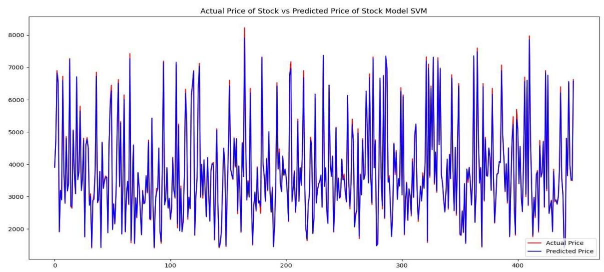


Fig. 6. Stock Price Prediction Results for the SVM Model

Figure 6 shows the results of share price predictions at PT. Vale Indonesia. In this graph the prediction results obtained show a fairly tight line because it uses 20% test data or 449 test data. Rising and falling lines also mean the stock price is very volatile. In Figure 6, the prediction using the Support Vector Machine (SVM) algorithm obtained an RMSE of 66.05, which means the prediction results are not good, it can be seen from the prediction results that they are not close to the actual value so the red line is still visible.

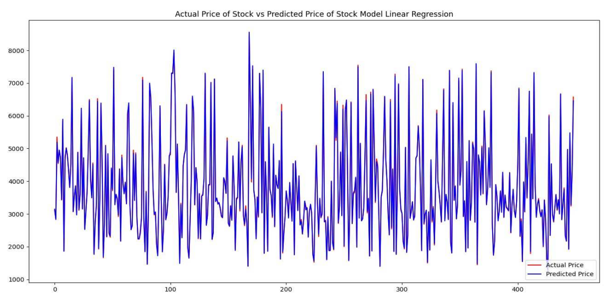


Fig. 7. Stock Price Prediction Results for the LR Model

Figure 7 shows the stock price prediction results. In this graph, the prediction results obtained show a fairly tight line because it uses 449 test data. In Figure 7, the prediction process using the Linear Regression (LR) algorithm obtained an RMSE result of 43.06, which means the prediction results are quite good, it can be seen from the line that the prediction results are quite close to the actual value.

## *C. Testing with data split 90%:10%*

This testing split the data with 90% of the training data as a learning model and 10% of the testing data as prediction data. The amount of training data is 2.017 data, while the testing data that will be predicted is 225 data.

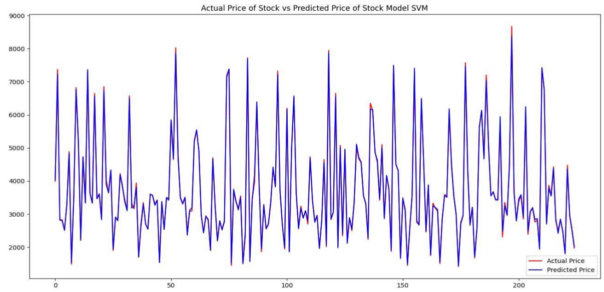


Fig. 8. Stock Price Prediction Results for the SVM Model

Figure 8 shows the prediction results for lines that are not too tight because they use 10% of test data or 225 stock data. In Figure 8, the prediction using the Support Vector Machine (SVM) algorithm obtained an RMSE result of 64.32, which means the prediction results were not good, as can be seen from the prediction results with the prediction result line not being close to the actual value so that the red line is still visible.

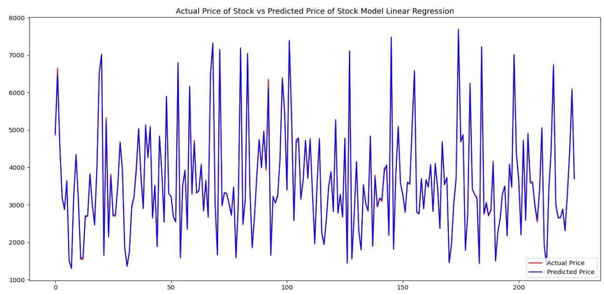


Fig. 9. Stock Price Prediction Results for the LR Model

Figure 9 shows the results of share price predictions at PT. Vale Indonesia. The graph shows the prediction results of the line which is a little loose because it uses 225 test data. The prediction results using the Linear Regression (LR) algorithm obtained an RMSE result of 42.82, which means the prediction results are quite good, it can be seen from the prediction results that they are quite close to the actual value.

## *D. Comparison of SVM and LR*

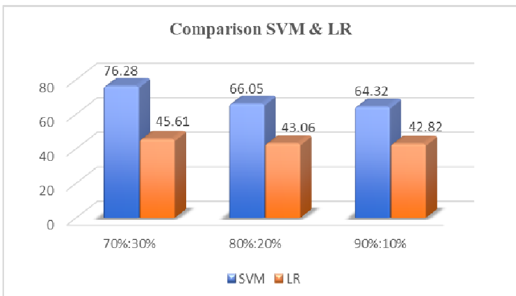


Fig. 10. Comparison of SVM and LR

Based on testing of three training and test data separation scenarios that have been carried out, namely 70:30, 80:20, and 90:10. The blue graph shows the Support Vector Machine (SVM) error rate, while the red graph shows the Linear Regression (LR) error rate. The graph shows that the Linear Regression (LR) algorithm is better than the Support Vector Machine (SVM) method in predicting stock at PT. Vale Indonesia. This is shown by the most optimal results of the LR algorithm obtaining an RMSE of 42.82, while the SVM algorithm obtained optimal results with an RMSE of 64.32. Where the Linear Regression (LR) algorithm is able to better understand trends and patterns in stock price data. From the graph results, it can be seen that the more training data used, the better the prediction results obtained. This happens because an algorithm can learn more variations in stock data.

## V. CONCLUSION

This research succeeded in applying and comparing the performance of the SVM algorithm with LR to predict stock prices at PT. Vale Indonesia. The stock price prediction process cannot be separated from the split data used. The results of this research state that the Linear Regression algorithm is better than the Support Vector Machine algorithm in predicting share prices at PT. Vale Indonesia. The best LR performance uses split data of 90% training data and 10% testing data with RMSE evaluation results of 42.82 which means it is quite good at making predictions because it is quite close to zero. Meanwhile, the SVM algorithm obtained the best results using split data of 90% training data and 10% test data with an RMSE evaluation result of 64.32 which means the prediction results are not good because the accuracy of the results is not close to zero. Next, the worst prediction uses the LR algorithm with a data division of 70% training data and 30% test data with an RMSE evaluation result of 45.61 which means it is quite good at making predictions because it is quite close to zero. Meanwhile, the worst prediction results in the SVM algorithm use split data of 70% training data and 30% test data with an RMSE evaluation result of 76.28 which means the prediction results are not good because the accuracy of the results is not close to zero. Based on the results obtained, split data affects the prediction value obtained by an algorithm. So, it is important to determine the best data split to make predictions. Suggestions that can be given for further research are to conduct research using deep learning algorithms or combining machine learning and deep learning as a comparison to obtain better prediction results.

## REFERENCES


[1] N. Cahyani, J. S. Informasi, U. Nasional, and K. Neighbors, "Pandemi Dengan Metode Support Vector Machine Dan K-Nearest Neighbors," vol. 7, no. 2, 2022.

[2] B. Siregar, F. A. Pangruruk, and P. A. Widjaja, "Comparison Of Various Forecasting Models For The Jakarta Stock Exchange Composite ( JKSE ) During The Covid-19 Pandemic Perbandingan Berbagai Model Peramalan Indeks Harga Saham Gabungan ( IHSG ) Di Masa Pandemi Covid-19," *J. Multidisiplin Madani*, vol. 2, no. 2, pp. 1035–1046, 2022.

[3] Y. W. Chuanjun Zhao, Meiling Wu, Jingfeng Liu, Zening Duan, Jie li, Lihua Shen, Xuekui Shangguan, Donghang Liu, "Progress and prospects of data-driven stock price forecasting research." International Journal of Cognitive Computing in Engineering.

[4] J. Maqbool, P. Aggarwal, R. Kaur, A. Mittal, and I. A. Ganaie, "Stock Prediction by Integrating Sentiment Scores of Financial News and MLP-Regressor: A Machine Learning Approach," *Procedia Comput. Sci.*, vol. 218, no. 2022, pp. 1067–1078, 2023, doi: 10.1016/j.procs.2023.01.086.

[5] J. Liu, H. Li, M. Hai, and Y. Zhang, "ScienceDirect Tenth International Conference on Information Technology and Quantitative Management A study of factors influencing financial stock prices based on causal inference," *Procedia Comput. Sci.*, vol. 221, pp. 861–869, 2023, doi: 10.1016/j.procs.2023.08.062.

[6] D. O. Oyewola, A. Ibrahim, J. A. Kwanamu, and E. G. Dada, "A new auditory algorithm in stock market prediction on oil and gas sector in Nigerian stock exchange," *Soft Comput. Lett.*, vol. 3, p. 100013, 2021, doi: 10.1016/j.socl.2021.100013.

[7] Juliansyah dkk., "Pengaruh Return on Assets (Roa), Earning Per Share (Eps) Dan Price Earning Ratio (Per) Terhadap Harga Saham Perusahaan Sub Sektor Farmasi yang Terdaftar Di Bursa Efek Indonesia," *Fak. Ekon. Dan Bisnis Islam Inst. Agama Islam Negeri Bengkulu*, p. 77, 2021.

[8] M. Arnani, "penyebab fluktuasi saham kompas.com." p. 25/02/2023, 2023. [Online]. Available: https://money.kompas.com/read/2023/02/25/170039626/apa-yang-menyebabkan-harga-saham-naik-dan-turun?page=all#page2

[9] B. Gülmez, "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm," *Expert Syst. Appl.*, vol. 227, no. April, p. 120346, 2023, doi: 10.1016/j.eswa.2023.120346.

[10] R. F. T. Wulandari and D. Anubhakti, "Implementasi Algoritma Support Vector Machine (Svm) Dalam Memprediksi Harga Saham Pt. Garuda Indonesia Tbk," *IDEALIS Indones. J. Inf. Syst.*, vol. 4, no. 2, pp. 250–256, 2021, doi: 10.36080/idealis.v4i2.2847.

[11] C. Alzaman, "Forecasting and optimization stock predictions: Varying asset profile, time window, and hyperparameter factors," *Syst. Soft Comput.*, vol. 5, p. 200052, 2023, doi: 10.1016/j.sasc.2023.200052.

[12] M. Obthong, N. Tantisantiwong, W. Jeamwatthanachai, and G. Wills, "A survey on machine learning for stock price prediction: Algorithms and techniques," *FEMIB 2020 - Proc. 2nd Int. Conf. Financ. Econ. Manag. IT Bus.*, pp. 63–71, 2020, doi: 10.5220/0009340700630071.

[13] F. P. Samodra, "profil-pt-vale-indonesia-perusahaan-tambang-nikel-di-indonesia @ www.liputan6.com." p. 3, 2022. [Online]. Available: https://www.liputan6.com/hot/read/5152548/profil-pt-vale-indonesia-perusahaan-tambang-nikel-di-indonesia

[14] M. A. Faiz, S. Sufriadin, and S. Widodo, "Analisis Perbandingan Kadar Bijih Nikel Laterit Antara Data Bor dan Produksi Penambangan: Implikasinya Terhadap Pengolahan Bijih Pada Blok X, PT. Vale Indonesia, Tbk. Sorowako," *J. Penelit. Enj.*, vol. 24, no. 1, pp. 93–99, 2020, doi: 10.25042/jpe.052020.13.

[15] M. & Zaidan, W. Garinas, and K. …… Bahan Baku Mineral Nikel………, "Kajian Bahan Baku Mineral Nikel Untuk Baterai Listrik Di Daerah Sulawesi Tenggara," *J. Rekayasa Pertamb.*, vol. 1, no. 1, p. 49, 2021.

[16] M. Vijh, D. Chandola, V. A. Tikkiwal, and A. Kumar, "Stock Closing Price Prediction using Machine Learning Techniques," *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 599–606, 2020, doi: 10.1016/j.procs.2020.03.326.

[17] N. A. Zabidi *et al.*, "Jo ur na l P," *Int. J. Biol. Macromol.*, vol. 2, no. 2, pp. 33–47, 2022, doi: 10.1016/j.bir.2023.08.005.

[18] Z. Rustam and P. Kintandani, "Application of Support Vector Regression in Indonesian Stock Price Prediction with Feature Selection Using Particle Swarm Optimisation," *Model. Simul. Eng.*, vol. 2019, 2019, doi: 10.1155/2019/8962717.

[19] D. Maulud and A. M. Abdulazeez, "A Review on Linear Regression Comprehensive in Machine Learning," *J. Appl. Sci. Technol. Trends*, vol. 1, no. 4, pp. 140–147, 2020, doi: 10.38094/jastt1457.

[20] W. R. U. Fadilah, D. Agfiannisa, and Y. Azhar, "Analisis Prediksi Harga Saham PT. Telekomunikasi Indonesia Menggunakan Metode Support Vector Machine," *Fountain Informatics J.*, vol. 5, no. 2, p. 45, 2020, doi: 10.21111/fij.v5i2.4449.

[21] Hilman Winnos, Richashanty Septima, and Husna Gemasih, "Perbandingan Metode Regresi Linier Berganda dan Autoregressive Integrated Moving Average (ARIMA) Untuk Prediksi Saham PT. BSI, Tbk.," *Ocean Eng. J. Ilmu Tek. dan Teknol. Marit.*, vol. 1, no. 4, pp. 15–23, 2022, doi: 10.58192/ocean.v1i4.350.

[22] J. Grudniewicz and R. Ślepaczuk, "Application of machine learning in algorithmic investment strategies on global stock markets," *Res. Int. Bus. Financ.*, vol. 66, 2023, doi: 10.1016/j.ribaf.2023.102052.

[23] C. El Morr, M. Jammal, H. Ali-Hassan, and W. El-Hallak, “Support Vector Machine,” *Int. Ser. Oper. Res. Manag. Sci.*, vol. 334, pp. 385–411, 2022, doi: 10.1007/978-3-031-16990-8_13.

[24] C. Shoko and C. Sigauke, “Short-term forecasting of COVID-19 using support vector regression: An application using Zimbabwean data,” *Am. J. Infect. Control*, vol. 000, 2023, doi: 10.1016/j.ajic.2023.03.010.

[25] B. A. Nugroho, A. K. A. Pradana, and E. Nurfarida, “Prediksi Waktu Kedatangan Pelanggan Servis Kendaraan Bermotor Berdasarkan Data Historis menggunakan Support Vector Machine,” *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 1, p. 25, 2021, doi: 10.26418/jp.v7i1.42964.

[26] P. Sadorsky, “Using machine learning to predict clean energy stock prices: How important are market volatility and economic policy uncertainty?,” *J. Clim. Financ.*, vol. 1, no. October, p. 100002, 2022, doi: 10.1016/j.jclimf.2022.100002.

[27] D. Anggraeni, K. Sugiyanto, M. I. Z. Zam, and ..., “Stock price movement prediction using supervised machine learning algorithm: KNIME,” *J. Akun Nabelo ...*, no. January, 2022, [Online]. Available: http://jurnal.untad.ac.id/jurnal/index.php/jan/article/view/18153%0Ahttp://jurnal.untad.ac.id/jurnal/index.php/jan/article/viewFile/18153/pdf

[28] P. Chhajer, M. Shah, and A. Kshirsagar, “The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction,” *Decis. Anal. J.*, vol. 2, no. June 2021, p. 100015, 2022, doi: 10.1016/j.dajour.2021.100015.

[29] Z. Liao, S. Dai, and T. Kuosmanen, “Convex support vector regression,” *Eur. J. Oper. Res.*, no. xxxx, 2023, doi: 10.1016/j.ejor.2023.05.009.

[30] I. Rezaei, S. H. Amirshahi, and A. A. Mahbadi, “Utilizing support vector and kernel ridge regression methods in spectral reconstruction,” *Results Opt.*, vol. 11, no. March, p. 100405, 2023, doi: 10.1016/j.rio.2023.100405.

[31] N. Tripathy, “Stock Price Prediction Using Support Vector Machine Approach,” 2019, doi: 10.33422/conferenceme.2019.11.641.

[32] V. R. Prasetyo, H. Lazuardi, A. A. Mulyono, and C. Lauw, “Penerapan Aplikasi RapidMiner Untuk Prediksi Nilai Tukar Rupiah Terhadap US Dollar Dengan Metode Linear Regression,” *J. Nas. Teknol. dan Sist. Inf.*, vol. 7, no. 1, pp. 8–17, 2021, doi: 10.25077/teknosi.v7i1.2021.8-17.

[33] S. J. Kim, S. J. Bae, and M. W. Jang, “Linear Regression Machine Learning Algorithms for Estimating Reference Evapotranspiration Using Limited Climate Data,” *Sustain.*, vol. 14, no. 18, 2022, doi: 10.3390/su141811674.

[34] Rasyidah, R. Efendi, N. M. Nawi, M. M. Deris, and S. M. A. Burney, “Cleansing of inconsistent sample in linear regression model based on rough sets theory,” *Syst. Soft Comput.*, vol. 5, no. December 2022, p. 200046, 2023, doi: 10.1016/j.sasc.2022.200046.

[35] M. Bansal, A. Goyal, and A. Choudhary, “Stock Market Prediction with High Accuracy using Machine Learning Techniques,” *Procedia Comput. Sci.*, vol. 215, no. 2022, pp. 247–265, 2022, doi: 10.1016/j.procs.2022.12.028.

[36] M. K. Islam, M. M. Rahman, M. S. Ali, S. M. Mahim, and M. S. Miah, “Enhancing lung abnormalities detection and classification using a Deep Convolutional Neural Network and GRU with explainable AI: A promising approach for accurate diagnosis,” *Mach. Learn. with Appl.*, vol. 14, no. July, p. 100492, 2023, doi: 10.1016/j.mlwa.2023.100492.

[37] H. Henderi, “Comparison of Min-Max normalization and Z-Score Normalization in the K-nearest neighbor (kNN) Algorithm to Test the Accuracy of Types of Breast Cancer,” *IJIIS Int. J. Informatics Inf. Syst.*, vol. 4, no. 1, pp. 13–20, 2021, doi: 10.47738/ijiis.v4i1.73.