Integrating Machine Learning Algorithms into Decision Support Systems for Predicting BBNI Stock

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A B S T R A C T

This study focuses on integrating machine learning models into a Decision Support System (DSS) for predicting BBNI stock prices and generating actionable investment recommendations. The research aims to address the challenges of stock price prediction by evaluating the performance of four models: Multiple Linear Regression (MLR), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). The methodology involves collecting and preprocessing BBNI stock data from 2019 onward, training and evaluating the models using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared, and incorporating the best-performing model into the DSS. The findings reveal that MLR outperformed other models, achieving an MAE of 18.29, RMSE of 23.73, and an R-squared value of 0.9995, indicating high predictive accuracy. RF performed slightly worse but remained competitive, while SVM and ANN exhibited poor results due to limitations in handling complex patterns or tuning issues. The DSS, powered by MLR, successfully generated buy, sell, or hold recommendations based on stock price predictions, with investment simulations confirming its reliability. This study contributes to the field of financial decision-making by demonstrating the effectiveness of MLR in stock price prediction and DSS integration. However, limitations include reliance on historical data and potential model bias. Future research should explore hybrid models and advanced techniques such as deep learning to enhance predictive capabilities. The proposed DSS offers a practical tool for investors, combining robust machine learning insights with user-friendly decision-making support.

1. Introduction

The Indonesian stock market has seen significant growth in recent years, with large companies like Bank Negara Indonesia (BBNI) becoming key players attracting both domestic and international investors. As the fourth-largest bank in Indonesia by total assets, BBNI's stock is one of the major investment instruments in the country. However, predicting the price movements of BBNI's stock is challenging due to the volatile nature of the market, which is influenced by various complex economic, political, and social factors[1]. In this digital age, artificial intelligence (AI) and machine learning (ML) have played a pivotal role in enhancing financial analysis and predictions. The use of Decision Support Systems (DSS) integrated with machine learning techniques provides innovative ways for investors to make more informed and strategic decisions[2]. This research aims to develop a system that leverages historical BBNI stock data, including open price, close price, high price, low price, volume, and other historical data to forecast stock price trends and provide guidance to investors. The application of AI-based predictive models and decision support systems (DSS) for BBNI's stock can offer deeper insights into potential future price movements. Therefore, this research focuses on developing a system that assists investors in optimizing their investment decisions through data-driven analysis of BBNI's stock and more accurate predictions using machine learning.

Previous research in stock price prediction has largely relied on traditional methods such as technical analysis, fundamental analysis, and statistical models. Additionally, while some studies have applied machine learning models, their use has been limited and not fully optimized, especially in integrating decision support systems (DSS) that provide real-time, dynamic analysis. Many existing DSS do not fully leverage AI or machine learning to deliver more accurate and up-to-date insights. Furthermore, most studies focus on general market analysis rather than specific stocks like BBNI, which has unique characteristics influenced by Indonesia's financial market. This research aims to address these gaps by integrating machine learning models within a DSS to more accurately and dynamically forecast BBNI's stock price trends.

The research aims to address the challenges associated with accurately predicting the price movements of BBNI stock. While various methods such as technical and fundamental analysis have been used to predict stock prices, they often fail to capture the uncertainties and complexities of the market. One major issue is how to effectively integrate machine learning algorithms to predict stock trends using the available historical data[3]. Moreover, although decision support systems (DSS) are already used in stock investment, many existing systems have not fully utilized AI and machine learning to provide dynamic, data-driven recommendations[4]. In this context, the research aims to develop an AI-based Decision Support System (DSS) that integrates BBNI stock data to help investors make more strategic decisions.

2. Literature Review

Conducted research on stock market trend prediction using machine learning and deep learning algorithms, analyzing Tehran stock market data from 2009 to 2019. They employed nine machine learning models Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, K-Nearest Neighbors (KNN), Logistic Regression, and Artificial Neural Network (ANN)—and two deep learning models, namely Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Their findings indicated that RNN and LSTM outperformed the other models. This study also compared continuous and binary data as inputs, revealing that binary data significantly improved prediction accuracy. The experiments achieved an average F1-score of 86% for continuous data and 90% for binary data, showcasing LSTM's superior ability to predict stock trends with non-stationary data compared to traditional machine learning methods[5].

Focus on stock price prediction using machine learning methods, specifically Long Short-Term Memory (LSTM) and Support Vector Machine (SVM), to enhance prediction accuracy. They stated that LSTM, with its ability to manage sequential data and time-related attributes, effectively predicts stock trends with higher accuracy than other methods. Additionally, they incorporated news sentiment analysis into the prediction system to account for the impact of external information on stock movements. This study demonstrated that integrating historical price data with real-time news analysis yields more comprehensive predictive results, helping investors make optimized investment decisions[6].

Researched stock price prediction using a multiple linear regression (MLR) model, focusing on NVDA, AMD, and INTC stocks. This model incorporated independent variables such as stock indices and historical price data to forecast daily closing prices. Evaluation results showed that the

MLR model yielded an R-squared (R^2) score of 0.83697 for NVIDIA, 0.75209 for AMD, and 0.59556 for Intel. These findings indicate that the MLR model performed best for NVIDIA, followed by AMD, while the performance for Intel was comparatively weaker. The model was further refined through correlation analysis, which helped remove insignificant independent variables, reducing complexity and minimizing overfitting risks. The researchers concluded that increasing the sample size could further enhance the model's performance, supporting the utility of multiple linear regression for daily stock price prediction[7].

Patalay and Bandlamudi (2021) developed a Decision Support System (DSS) for stock portfolio selection using Artificial Intelligence (AI) and Machine Learning (ML). This DSS was designed to assist individual investors in creating stock portfolios by integrating fundamental financial analysis with ML techniques. The system can analyze the financial health of stocks and predict stock prices based on AI/ML models. The study results indicate that the DSS can generate a portfolio with a Return on Investment (ROI) of over 11% in the short term and more than 61% in the long term, significantly outperforming the market index by 15%. This research concludes that AI/ML-based DSS can help individual investors make more accurate investment decisions, thereby enhancing the efficiency of the financial system[8].

Applied the Fuzzy Simple Additive Weighting (FSAW) method in group decision-making for capital investment, specifically targeting the selection of cars for rental purposes. This approach addresses the need for optimal decision-making under uncertain conditions by using fuzzy logic to weigh multiple criteria. In this study, four criteria: quality, comfort, reliability, and safety were evaluated by a group of experts to rank three vehicle options. The results demonstrated that the FSAW method effectively handles subjective preferences and fuzzy data, offering a robust framework for group decision-making in environments with high ambiguity. The authors concluded that this methodology enhances decision accuracy and consistency, particularly in complex investment scenarios where traditional crisp methods may fall short[9].

Investigated stock price prediction using multiple linear regression (MLR), exponential weighted moving average (EWMA), extreme gradient boosting (XGBoost), and long short-term memory (LSTM) models, analyzing 730 daily data points from nine companies across three Chinese industries. The study found that MLR and EWMA provided the highest prediction accuracy, with R-squared values up to 0.971 and 0.983, respectively, while XGBoost and LSTM models underperformed, particularly due to limited data. XGBoost showed inconsistent R-squared results, ranging from -0.738 to 0.920, and LSTM yielded poor accuracy with several negative R-squared scores. The results suggest that MLR and EWMA are more effective in stock prediction with smaller datasets, whereas XGBoost and LSTM may require larger data volumes for optimal performance[10].

Investigated portfolio optimization by integrating return predictions with machine learning and deep learning models. They tested models including Random Forest (RF), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), Deep Multilayer Perceptron (DMLP), and Convolutional Neural Network (CNN) on historical stock data from the China Securities 100 Index. The results indicated that the RF-enhanced Mean-Variance model (RF+MVF) yielded the highest performance, with an excess return of 274.88% and an information ratio of 0.8131, though high turnover (155.36%) impacted overall profitability. The Omega model enhanced with SVR (SVR+OF) also performed strongly, achieving an excess return of 133.18% and a relatively lower turnover rate, making it suitable for cost-sensitive investments. These findings suggest RF+MVF is optimal for daily trading, especially when transaction costs are minimized, while SVR+OF offers a balanced alternative for sustained investment strategies[11].

Proposed an automated stock market trading system based on deep reinforcement learning (DRL), integrating both historical and forecasted stock price trends to improve trading decisions. Using a Gated Recurrent Unit (GRU) network for future price predictions, the DRL agent was tested on stocks such as Tesla, IBM, and Amazon. Results showed that the GRU model achieved low error rates, with Tesla's single step forecasting yielding RMSE of 0.05, MSE of 0.003, and MAE of 0.04. Additionally, the DRL agent's trading performance generated substantial profits, with average portfolio gains exceeding traditional static methods. This study highlights the model's adaptability and effectiveness in enhancing profitability under volatile market conditions by equipping the DRL agent with future trend insights, leading to better buy-sell-hold decisions across varied stock datasets[12].

Conducted a comparative analysis of Linear Regression, Polynomial Regression, and the ARIMA model for short-term stock price forecasting using data from Apple, Tesla, Amazon, and Nike stocks over 1.5 years. The study found that ARIMA performed best, accurately predicting seven out of eight scenarios by capturing temporal patterns effectively, despite its assumption of linearity and stationarity. Polynomial Regression, particularly at degree six, provided a good fit with R-squared values reaching up to 0.902 for Nike, but showed instability in forecasting future trends. Linear Regression, although straightforward, proved to be less accurate with lower R-squared values, such as 0.025 for Tesla, due to its inability to capture complex market dynamics. This study highlights ARIMA's strength in short-term stock forecasting compared to simpler linear methods[13].

Proposed a stock price prediction model that combines regression analysis and Support Vector Machine (SVM) to enhance prediction accuracy. In this approach, a multivariate regression analysis is first employed to predict stock prices based on several independent variables. Then, the prediction errors are corrected using an SVM model. Through empirical studies, the combined prediction results demonstrated that this hybrid model provides more accurate predictions than using either regression analysis or SVM alone. In simulations with stock dataset for a specified period, this combined method proved effective in reducing relative error, achieving a mean absolute percentage error (MAPE) of 0.61%, compared to linear regression (1.33%) and standalone SVM (1.08%)[14].

3. Methodology

The first step in the process is Data Collection (https://finance.yahoo.com/quote/BBNI.JK, source: Yahoo Finance PT Bank Negara Indonesia (Persero) Tbk (BBNI.JK)), where historical stock data for BBNI is gathered. This includes daily information such as the open price, close price, high price, low price, volume, and other relevant stock metrics from January 2019 to the present. This dataset forms the foundation for the predictive modeling and decision support system. The data can be seen in Table 1 below:

Table 1. BBNI datasets

Date	Open	High	Low	Close	Volume
2019-01-01 00:00:00+07:00	3718.354	3718.354	3718.354	3718.354	0
2019-01-02 00:00:00+07:00	3718.354	3718.354	3665.536	3686.663	15681200
2019-01-03 00:00:00+07:00	3665.536	3707.79	3654.973	3686.663	21416600

2019-01-04 00:00:00+07:00	3686.663	3718.354	3665.536	3686.663	41078600
2019-01-07 00:00:00+07:00	3728.917	3771.171	3728.917	3750.044	48108200
2019-01-08 00:00:00+07:00	3750.044	3781.735	3718.354	3760.608	45945800
2019-01-09 00:00:00+07:00	3781.735	3781.735	3728.917	3739.481	50484000
2019-01-10 00:00:00+07:00	3771.171	3771.171	3718.354	3739.481	44421400
…	…	…	…	…	…
2024-11-12 00:00:00+07:00	4960	5000	4870	4930	70220900
2024-11-13 00:00:00+07:00	4930	5025	4910	4960	64548800
2024-11-14 00:00:00+07:00	4960	4970	4910	4950	33431400

Table 1 shows the daily data showing the open, high, low, close prices, and trading volume of an asset from January 1, 2019, to November 14, 2024. Each row represents a single trading day, with the opening price (open), highest price (high), lowest price (low), closing price (close), and trading volume (the number of shares or assets traded) for that day. For example, on January 1, 2019, the highest, lowest, and closing prices were 3718.354, with a trading volume of 0. Meanwhile, on November 14, 2024, the opening price was 4960, the closing price was 4950, and the trading volume was recorded at 33,431,400. This data can be used for trend analysis or to assess the performance of the asset over time.

Once the data is collected, the next step is Data Preprocessing & Feature Engineering. In this stage, the dataset is cleaned to handle missing values and outliers that could distort model predictions. Additionally, new features are derived from the existing data, such as Return on Investment (ROI), Volatility. These new features help enrich the dataset, making it more informative and better suited for machine learning models.

Following data preprocessing, the dataset is split into Training and Testing Sets. The training set is used to teach the machine learning models, while the testing set is reserved for model evaluation. This split ensures that the model is tested on data it has not seen before, providing an estimate of how well it will perform on unseen data in real-world scenarios.

In the Application of Machine Learning Models stage, various models are used to predict future stock prices. Multiple Linear Regression (MLR) analyzes the relationship between independent variables like stock price and trading volume, and the dependent variable, which is the future stock price. Support Vector Machine (SVM) identifies the optimal hyperplane for separating data, useful for both classification and regression. Random Forest (RF), an ensemble method, uses multiple decision trees to reduce overfitting and improve accuracy. Finally, Artificial Neural Networks (ANN), a deep learning model, captures complex, nonlinear patterns in data, making it highly effective for stock price prediction.

After the models are applied, the Model Evaluation & Validation stage assesses their accuracy using various performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared. K-fold cross-validation is also used to ensure the models are not overfitting with the training data, providing a more reliable measure of their performance.

$$MAE = \frac{1}{n} = \sum_{i=1}^{n} |y_i - \widehat{y_i}|$$

$$RMSE = \sqrt{\frac{1}{n} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:

n	:	Number of observations.
y_i	:	Actual value of the dependent variable for observation *i*.
$\hat{y}_i$	:	Predicted value of the dependent variable for observation *i*.
$\lvert y_i - \hat{y}_i \rvert$	:	Absolute difference between actual and predicted values.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where:

y_i	:	Actual value of the dependent variable for observation *i*.
$\hat{y}_i$	:	Predicted value of the dependent variable for observation *i*.
$\bar{y}$	:	Mean of the actual values ($\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$)
$(y_i - \hat{y}_i)^2$	:	Sum of squared residuals (SSR) or errors.
$(y_i - \bar{y})^2$	:	Total sum of squares (TSS), representing total variability in the data.

Once the models have been evaluated, the Selection of the Best Model takes place. The best-performing model, based on evaluation metrics, is selected for integration into the Decision Support System (DSS). This model is chosen because it provides the most accurate and reliable predictions of stock prices. The Decision Support System (DSS) is then developed, integrating into the best-performing model. This system uses the selected machine learning model to provide daily stock price predictions for BBNI and offer investment recommendations, such as whether to buy, hold, or sell the stock. The DSS serves as a tool to assist investors in making more informed, data-driven decisions.

The next step is Investment Decision Simulation, where the DSS is used to simulate potential investment decisions. This simulation applies the predictions from the model to a hypothetical portfolio, showing the potential impact of these decisions on the investor’s returns. It helps investors understand how the model’s predictions would affect real-world investment strategies.

Finally, Decision Support provides the concluding investment recommendations based on the predictions and simulation results. The DSS generates specific recommendations such as buy, hold, or sell, guiding investors in their decision-making process. These recommendations are based on the combined insights into the machine learning model and the results of the simulation, ensuring that the decisions are informed and strategic.

4. Results and Discussion

The performance of each model was evaluated based on the MAE, RMSE, and R-squared values, and the results highlight distinct differences in accuracy and predictive power. Multiple Linear Regression (MLR) performed the best across all metrics, achieving an MAE of 18.29, RMSE of 23.73, and an R-squared value of 0.9995, indicating that MLR was able to closely predict stock prices with minimal errors. Support Vector Machine (SVM), on the other hand, showed the poorest performance, with an MAE of 872.79, RMSE of 1051.26, and a very low R-squared value of 0.0071, suggesting that the model failed to capture the underlying patterns in the stock data, leading to highly inaccurate predictions. Random Forest (RF) performed reasonably well, with an MAE of 22.17, RMSE of 29.47, and an R-squared value of 0.9992, which was very close to MLR's performance, though slightly worse in terms of MAE and RMSE. Finally, Artificial Neural Networks (ANN) demonstrated the weakest results, with an MAE of 3403.64, RMSE of 3710.19, and a significantly negative R-squared value of -11.3679, indicating a very poor fit to the data and extremely high prediction errors. The following can be seen in Table 2:

Table 2. Model Results

Model	MAE	RMSE	R-squared
Multiple Linear Regression (MLR)	18.29	23.73	0.9995
Support Vector Machine (SVM)	872.79	1051.26	0.0071
Random Forest (RF)	22.17	29.47	0.9992
Artificial Neural Networks (ANN)	3403.64	3710.19	-11.3679

Table 2 shows the performance of the models varied based on their ability to capture patterns in stock price data. Multiple Linear Regression (MLR) performed the best, with low MAE, RMSE, and high R-squared, as it effectively modeled the linear relationship between features and stock prices. Support Vector Machine (SVM) struggled, showing poor results due to its inability to handle complex, non-linear data patterns, resulting in high errors. Random Forest performed well, capturing both linear and non-linear patterns, but slightly lagged behind MLR. Artificial Neural Networks (ANN) performed the worst, with a negative R-squared, likely due to overfitting and improper model tuning. The model evaluation and validation can be seen in Table 2:

Table 3. Model Evaluation and Validation Results

Model	Cross-validation Mean MSE	Cross-validation SD
Multiple Linear Regression (MLR)	-563.9	26.6
Support Vector Machine (SVM)	-1,037,209.33	86,780.77
Random Forest (RF)	-884.50	63.98
Artificial Neural Networks (ANN)	- 10,880,404.86	8,007,065.19

Table 3 shows the Mean MSE (K-fold) and Std Dev MSE (K-fold) values for each model providing insights into their performance and stability during cross-validation. For Linear Regression, the mean MSE is -563.90 with a standard deviation of 26.60, indicating a relatively stable and good performance across the folds. The Support Vector Machine (SVM) model, however, has a very high mean MSE of -1,037,209.35 and a large standard deviation of 86,780.78, suggesting that it struggles significantly with high errors and is highly unstable across different folds. The Random Forest shows a mean MSE of -884.50 and a standard deviation of 63.98, reflecting a consistent and reasonable performance, but with slightly more variability compared to Multi Linear Regression. Lastly, the ANN exhibits a very poor performance with a mean MSE of -10,880,404.86 and an extremely high standard deviation of 8,007,065.19, indicating both poor predictive accuracy and extreme instability across the cross-validation folds. These results highlight the variability and reliability of each model in terms of error consistency and performance. The DSS using MLR can be seen in Table 3:

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Table 4. DSS Using MLR Results

Date	Predicted Price	Current Price	Recommendation
9/27/2023	3774.01	3865.59	Sell
9/29/2023	4363.46	4357.36	Buy
10/2/2023	4354.86	4311.61	Buy
10/3/2023	5631.06	5600.00	Buy
10/4/2023	3328.31	3331.54	Sell
…	…	…	…
11/8/2024	3841.50	3829.10	Buy
11/11/2024	2417.64	2380.64	Buy
11/12/2024	2172.11	2232.41	Sell
11/13/2024	2107.81	2111.14	Sell
11/14/2024	3893.79	3922.77	Sell

Table 4 presents the results of the Decision Support System (DSS). Initially, the dataset consisted of 1,440 entries, which was reduced to 1,338 entries after preprocessing to remove rows with missing values or zero volume. The processed data was then divided into training and testing datasets in an 80:20 ratio, resulting in 1,070 training samples and 268 testing samples. Using Multiple Linear Regression (MLR), identified as the best-performing model among the evaluated machine learning models, the DSS generated predictions and recommendations. These recommendations serve as guidance for Sell, Buy, or Hold decisions, as displayed in the table. The investment simulation Decision can be seen in Table 4:

Table 5. Invesment Simulation Decision Results

Date	Predicted Price	Current Price	Recommendation
11/18/2024	4927.73	4950	Sell

Table 5 presents the results of a stock price prediction and investment recommendation simulation using Multiple Linear Regression (MLR) for November 18, 2024. The predicted price of the stock is 4927.73, which was forecasted by the model based on historical data, considering features such as Open, High, Low, and Volume. The current price, or the real market value, is 4950, which is slightly higher than the predicted value. Based on this comparison, the recommendation is to Sell the stock. The model suggests selling because it predicts a potential decrease in the stock price, as the predicted value is lower than the current market price. This indicates that holding or buying the stock at this point could lead to a loss, hence the recommendation to sell to avoid possible declines.

5. Discussion

The results of the stock price prediction models reveal significant differences in accuracy and predictive power. Multiple Linear Regression (MLR) performed the best, achieving low MAE (18.29), RMSE (23.73), and high R-squared (0.9995), indicating that MLR effectively captured the linear relationships in stock price data. Random Forest (RF) followed closely with slightly higher errors, while Support Vector Machine (SVM) and Artificial Neural Networks (ANN) showed poor performance, particularly ANN, which had a negative R-squared, suggesting poor fit and high errors. The Decision Support System (DSS) utilizing MLR generated reliable investment recommendations with consistent predictions for BBNI stock prices. However, the results also highlight the limitations of the models. SVM struggled with non-linear data patterns, while ANN's performance was significantly affected by overfitting. The MLR model, although the best performer, might not fully account for more complex market behaviors, which could affect long-term predictions.

Several limitations affected this research. First, the dataset was limited to historical stock prices of BBNI and did not incorporate other potentially influential factors such as macroeconomic indicators or global events. Second, some models like ANN showed instability, likely due to improper tuning or overfitting, affecting their overall predictive accuracy. Finally, the models were evaluated based on past data, which may not reflect future market conditions, limiting the generalizability of the results.

Future research could explore incorporating additional features such as sentiment analysis from news articles, or economic indicators, to improve model predictions. Experimenting with more advanced machine learning models, such as ensemble methods or deep learning, could also yield better results, particularly in capturing complex market patterns. Additionally, real-time data integration could enhance the DSS's ability to adapt to market fluctuations, improving its practical application.

6. Conclusion

This study evaluated the performance of machine learning models Multiple Linear Regression (MLR), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) for predicting BBNI stock prices and generating investment recommendations via a Decision Support System (DSS). The results showed that MLR outperformed the other models, with the lowest errors and highest predictive accuracy, followed by Random Forest. SVM and ANN performed poorly, particularly ANN, which struggled with accurate predictions. The DSS using MLR provided reliable investment guidance, showcasing the practical utility of machine learning in stock price prediction. This research contributes to the field by emphasizing the importance of model selection and feature engineering in financial forecasting and offers a basis for future research to improve prediction accuracy and incorporate advanced models.

The key difference in this study is its focus on integrating machine learning (ML) techniques like multiple linear regression (MLR), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) to predict stock price trends more accurately. Unlike previous studies, which may not have fully exploited the potential of AI in stock market predictions, this research aims to combine these advanced ML models within a decision support system (DSS). By leveraging AI-driven predictions, the study seeks to offer more data-driven, reliable recommendations that go beyond traditional methods.

Moreover, the study is specifically focused on BBNI’s stock data, a key player in Indonesia's financial sector, and intends to analyze how machine learning models can improve predictions by utilizing a range of data (open price, close price, high price, low price, and volume). This is a more targeted approach compared to broader market studies, which might not focus on a specific stock or industry.

In summary, the difference in findings lies in the application of machine learning algorithms in combination with AI-powered decision support systems to offer a more accurate and dynamic forecasting system for stock prices, whereas previous studies have been limited to traditional analysis methods.

7. Recommendation

This paper focuses on predicting BBNI stock prices and generating investment recommendations through a Decision Support System (DSS) using machine learning models. The problem addressed was selecting an effective model for accurate stock price prediction. The methodology involved evaluating four models Multiple Linear Regression (MLR), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANN) using performance metrics like MAE, RMSE, and R-squared, as well as cross-validation. The findings revealed that MLR outperformed the other models with the lowest errors and highest predictive accuracy, followed by Random Forest. SVM and ANN showed poor performance, especially ANN, which had a very low R-squared value. The implications of these findings highlight the significance of model selection in financial forecasting and the potential of machine learning to aid investment decisions. This study contributes to the field by demonstrating the effectiveness of MLR in stock price prediction and providing insights for future research to refine predictive models in finance.

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