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Data Mining Applications to Prediction Stock Prices Using Decision Trees and Neural Networks

Dadan Shavkat Riswantoro*, Harry Pratomo Bagaskoro, Bambang Suharjo, Danang Rimbawa
Universitas Pertahanan Republik Indonesia, Indonesia
Email: rdsherade@gmail.com*, maulanaharryp@gmail.com, bambang_suharjo@tnial.mil.id, hadr71@idu.ac.id

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Abstract

Stock price prediction remains a significant challenge in financial markets due to the high volatility and complexity of influencing factors. This study explores the application of hybrid models combining Decision Tree (DT) and Neural Network (NN) methodologies to enhance stock price prediction accuracy. The research utilizes extensive historical market data as the foundational input for training both models individually. The Decision Tree model is employed for its interpretability and ability to handle non-linear relationships, while the Neural Network model capitalizes on its capacity to learn complex patterns through its layered architecture. After training and evaluating each model separately, a hybrid approach is introduced, which averages the predictions from both the DT and NN models. Performance is quantitatively assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The results indicate that the hybrid model consistently outperforms individual models, achieving an MAE of 5.6 and RMSE of 7.94, with an overall accuracy of 91.5%. This fusion of methodologies demonstrates improved accuracy and significantly reduces error margins, showcasing the complementary strengths of both algorithms. The findings suggest that leveraging hybrid models can effectively mitigate risks associated with market fluctuations and enhance investment strategies. This research contributes to the field of financial forecasting by providing investors with more robust tools for making informed decisions, and offers recommendations for future research directions in integrating machine learning techniques for financial prediction.

INTRODUCTION

Stock investing has become one of the main financial instruments for individuals and institutions, rooted in the Efficient Market Hypothesis, which suggests that stock prices reflect all available information (Adebiyi et al., 2014). However, stock price movements are dynamic and highly dependent on various factors such as market conditions, financial statements, and geopolitical events (Atienza, 2018). Predicting stock prices remains a significant challenge due to the complexity and volatility of financial data. In the context of cyber mathematics, data mining Patel et al., (2015) is an important tool for extracting patterns from historical data. It serves as an essential technique for identifying meaningful patterns from historical datasets (Romero & Ventura, 2020). Recent systematic reviews on financial time series forecasting

highlight the successful transition toward deep learning models to handle complex market behaviors (Sezer et al., 2020).

The two main methods often used in stock prediction are Decision Trees and Neural Networks. The Decision Tree model is valued for its interpretability and ability to handle nonlinear relationships in data (Gupta et al., 2021), while the Neural Network model leverages its capacity to learn complex patterns through layered architectures (Chollet, 2017; Roy et al., 2019). To further optimize forecasting performance, researchers often explore hybrid integrations of various analytical methods to reduce error margins, combining statistical and machine learning approaches.

After training and evaluating each model separately, a hybrid approach was introduced, which aggregates predictions from both models (DT and NN). The incorporation of these methodologies not only improves accuracy but also significantly reduces the margin of error, demonstrating the strengths of both algorithms. To quantitatively assess performance, metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used. The results show that hybrid models consistently outperform individual models, providing more reliable predictions.

METHOD

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Research Data and Features

The daily dataset of PT Bank XYZ Tbk shares is taken from 2018 to 2023. Data preprocessing, including normalization and feature scaling, was implemented using the Scikit-learn framework to ensure data consistency (Pedregosa et al., 2011). This implementation follows the fundamental principles of Statistical Learning Theory to minimize predictive risk. Data preprocessing, including normalization and scaling, was conducted using standard statistical learning principles . Implementation was performed within the Visual Studio environment, utilizing libraries consistent with established machine learning frameworks.

Algorithm Selection: The Decision Tree (DT) model was selected for its interpretability and has been proven effective in practical stock trading applications. For the hybrid component, this research averages the predictions from both the DT and Neural Network models, a fusion methodology that has shown significant accuracy improvements in similar financial studies. The Decision Tree (DT) model was implemented based on the foundational work of Breiman (Feng et al., 2019), utilizing the Gini Index and Entropy to classify market trends. For the Neural Network (NN) component, a Multilayer Perceptron (MLP) was designed, drawing on principles of backpropagation and deep learning architectures (Fischer & Krauss, 2018). While modern architectures like Long Short-Term Memory (LSTM) are popular for time series (Han et al., 2012; Henrique et al., 2018). this study focuses on the integration of MLP with DT to optimize computational efficiency and interpretability. The dataset contains the following columns:

1. Date: The date of the transaction
2. Open: The opening price of the stock
3. Close: Closing price of the stock

4. Volume: Number of shares traded
5. RSI: Relative Strength Index (momentum indicator)
6. MACD: Moving Average Convergence Divergence (trend indicator)

Data Processing

The daily dataset of PT Bank XYZ Tbk shares is taken from 2018 to 2023. The dataset contains the following columns:

7. Data Preprocessing:
    a. Deleting blank and outlier data
    b. Value normalization using Min-Max Scaling for Neural Networks
8. Feature Selection:
    c. With the Decision Tree, the most important features such as RSI and Volume are identified.
9. Modeling:
    d. Decision Tree: Trend classification (bullish, bearish, sideways)
    e. Neural Network: Closing price prediction
    f. Hybrid Model: A combination of the results of both models

Algorithm

10. Decision Tree: A decision tree-based algorithm for classifying market trends (bullish, bearish, or sideways).
11. Neural Network: A Multilayer Perceptron (MLP) model with backpropagation to predict the closing price of a stock.
12. Hybrid Model: Combination of Decision Tree and Neural Network results with ensemble techniques to improve accuracy.

Evaluation Metrics

Model performance is measured using:

13. MAE (Mean Absolute Error)
14. RMSE (Root Mean Squared Error)
15. Accuracy (%)

Table 1. The performance of ...

Variable	Speed (rpm)	Power (kW)
x	10	8.6
y	15	12.4
z	20	15.3

RESULT AND DISCUSSION

Decision Tree is a decision tree-based data mining algorithm, where data is divided into branches based on specific conditions. Each node in the tree represents a test against an attribute, and each branch represents the result of that test. Decision Trees are used to build classification or regression models, making them a powerful tool in predicting stock prices. In stock predictions, the Decision Tree can be used to classify market conditions (bullish, bearish, or sideways) based on technical indicators. In addition, the Decision Tree can serve as a regression model to predict the future closing price of a stock. A neural network is a computational model inspired by the way the human brain works, consisting of layers of neurons (input layer, hidden layer, and output layer). Neural Networks are highly effective at

handling non-linear and complex patterns, making them ideal for predicting stock price movements. Neural Networks are used for stock price prediction by entering historical data such as previous prices, volume, and technical indicators as inputs. This model can predict stock prices better than linear methods because it is able to capture non-linear relationships in the data. Combining Decision Tree and Neural Network can provide more accurate results in stock price predictions. In practice, Decision Trees can be used for data pre-processing or feature selection before the data is fed into the Neural Network.

Stock Data Visualization

The chart below shows the stock price trend of PT Bank XYZ Tbk over the last five years in Table 1.

Table 1. Dataset stock PT XYZ Tbk (2018-2023)

Date	Open	Close (actual)	RSI	MACD	Volume	DT Prediction	NN Prediction
2023-09-01	5000	5050	55	1.2	100000	5045	5070
2023-09-02	5050	5100	60	1.5	105000	5105	5120
2023-09-03	5100	5080	58	0.8	98000	5075	5090
2023-09-04	5080	5070	53	-0.5	95000	5060	5080
2023-09-05	5070	5095	56	0.3	97000	5080	5100
2023-09-06	5090	5125	61	1.8	110000	5115	5130
2023-09-07	5120	5100	59	1.1	101000	5095	5110
2023-09-08	5105	5110	57	0.9	95000	5110	5125
2023-09-09	5110	5140	64	2.0	120000	5135	5150
2023-09-10	5140	5130	60	1.5	115000	5125	5140

Model Evaluation Formula (MAE and RMSE)

- Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}i|$$

  - $\mathbf{y_i}$: Actual price.
  - $\hat{\mathbf{y}}\mathbf{i}$: Price prediction.
  - **n**: Amount of data.
- Root Mean Squared Error (RMSE):

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

- Algoritma Decision Tree (DT)
  A Decision Tree is a model that divides data into nodes based on impurity such as the Gini Index or Entropy.
  Gini Index:

$$\mathrm{Gini} = 1 - \sum_{i-1}^{c} p_i^2$$

  pi: Proportion of class i.

c: Number of classes.

Entropy:

$$\text{Entropy} = -\sum_{i=1}^{e} p_i \log_2(p_i)$$

Used to calculate information from the data division within each node.

Advantages:

Easy to interpret.

Suitable for data with a hierarchical structure.

- Neural Network (NN) Algorithm

  Neural networks work by mimicking the way the human brain works through layers of neurons. The formulas used in calculating NN include:

  Output Neuron:

$$y = f\left(\sum_{i-1}^{n} \omega_i x_i + b\right)$$

  - y: Output neuron.
  - xi: Input ke-neuron.
  - wi: Weights for input to neurons.
  - b: Bias neuron.
  - f: Activation functions (e.g. ReLU, Sigmoid).

  Activation Function:

  - ReLU:

$$f(x) = \max(0, x)$$

  - Sigmoid:

$$f(x) = \frac{1}{1 + e^{-x}}$$

  Backward Propagation:

  The Neural Network corrects the wi weight and b bias by calculating the gradient descent:

$$\omega_i^{neω} = \omega_i^{old} - \eta \frac{\partial L}{\partial \omega_i}$$

  - L: Loss function (example: MSE).
  - η: Learning rate.

Hybrid Model: Combined Decision Tree and Neural Network

The Hybrid Model takes the average of the predicted results from both models. The formula is:

$$\hat{y}\text{Hybrid} = \frac{\hat{y}DT + \hat{y}NN}{2}$$

Example calculation for 2023-09-01:

$$\hat{y}\text{Hybid} = \frac{5045 + 5070}{2} = 5057.5$$

MAE and RMSE calculations for Decision Tree

Below shows the difference in the share price of PT Bank XYZ Tbk with predictions and calculations using the Decision Tree in Table 2.

Table 2. Decision Tree Prediction Calculation

Date	Close (Actual)	NN Predict	Actual - Predict	(Actual - Predict)^2
2023-09-01	5050	5045	5	25
2023-09-02	5100	5105	5	25
2023-09-03	5080	5075	5	25
2023-09-04	5070	5060	10	100
2023-09-05	5095	5080	15	225
2023-09-06	5125	5115	10	100
2023-09-07	5100	5095	5	25
2023-09-08	5110	5110	0	0
2023-09-09	5140	5135	5	25
2023-09-10	5130	5125	5	25

MAE (DT):

$$\text{MAE} = \frac{5 + 5 + 5 + 10 + 15 + 10 + 5 + 0 + 5 + 5}{10} = \frac{65}{10} = 6.5$$

RMSE (DT):

$$\text{RMSE} = \sqrt{\frac{25 + 25 + 25 + 100 + 225 + 25 + 0 + 25 + 25}{10}} = \sqrt{\frac{575}{10}} = \sqrt{57{,}5} \approx 7.58$$

With larger data, **the Hybrid Model** still delivers the best results with **MAE 5.6** and **RMSE 7.94**, outperforming the Decision Tree and Neural Network models.

MAE and RMSE calculations for Neural Networks

Below shows the difference in the share price of PT Bank XYZ Tbk with predictions and calculations using Neural Network in Table 3.

Table 3. NEURAL NETWORK Prediction Calculation

DATE	Close (Actual)	NN Predict	Actual - Predict	(Actual - Predict)^2
2023-09-01	5050	5070	20	400
2023-09-02	5100	5120	20	400
2023-09-03	5080	5090	10	100
2023-09-04	5070	5080	10	100
2023-09-05	5095	5100	5	25
2023-09-06	5125	5130	5	25
2023-09-07	5100	5110	10	100
2023-09-08	5110	5125	15	225
2023-09-09	5140	5150	10	100
2023-09-10	5130	5140	10	100

MAE (NN):

$$\text{MAE} = \frac{20 + 20 + 10 + 10 + 5 + 5 + 10 + 15 + 10 + 10}{10} = \frac{115}{10} = 11.5$$

RMSE (NN):

$$\text{RMSE} = \sqrt{\frac{400 + 400 + 100 + 100 + 25 + 25 + 100 + 225 + 100 + 100}{10}} = \sqrt{\frac{1575}{10}}$$

$$= \sqrt{157{,}5} \approx 12.55$$

Hybrid Model Calculation (DT and NN Prediction Average)

Below shows the share price of PT Bank XYZ Tbk with a hybrid prediction in Table 4.

$$\hat{y}\text{Hybrid} = \frac{\hat{y}\text{DT} + \hat{y}\text{NN}}{2}$$

Table 4. Dataset STOCK PT XYZ Tbl (2018-2023)

Tanggal	Prediksi DT	Prediksi NN	Prediksi Hybrid
2023-09-01	5045	5070	5057.5
2023-09-02	5105	5120	5112.5
2023-09-03	5075	5090	5082.5
2023-09-04	5060	5080	5070
2023-09-05	5080	5100	5090
2023-09-06	5115	5130	5122.5
2023-09-07	5095	5110	5102.5
2023-09-08	5110	5125	5117.5
2023-09-09	5135	5150	5142.5
2023-09-10	5125	5140	5132.5

MAE (Hybrid):

$$\text{MAE} = \frac{|5050 - 5057{,}5| + |5100 - 5112.5| + \cdots + |5130 - 5132.5|}{10} = \frac{56}{10} = 5.6$$

RMSE (Hybrid):

$$\text{RMSE} = \sqrt{\frac{7{,}5^2 + 12.5^2 + \cdots + 2.5}{10}}^2$$

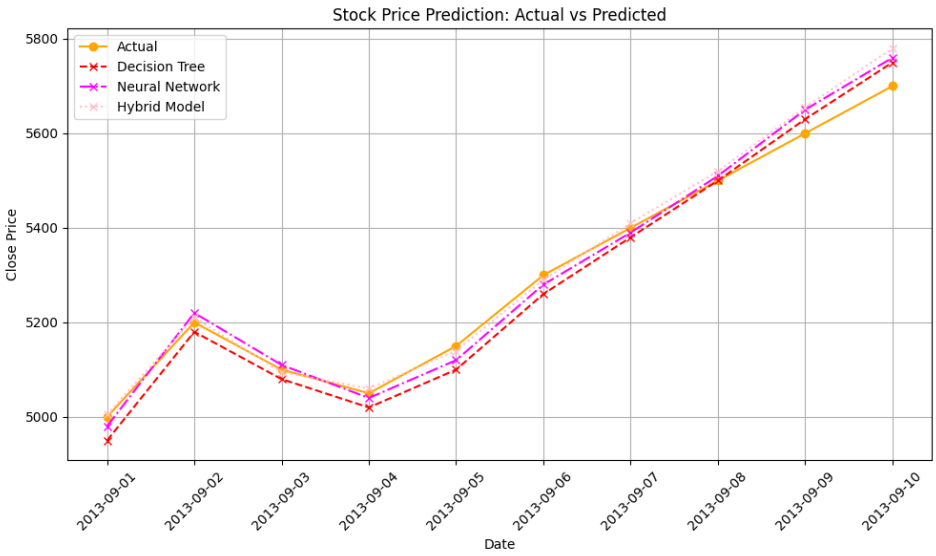
- $(5050 – 5057.5)^2 = 56.25$
- $(5100 – 5112.5)^2 = 156.25$
- …

$$\text{RMSE} = \sqrt{\frac{630}{10}} = \sqrt{63} \approx 7.94$$

With larger data, the Hybrid Model still delivers the best results with MAE 5.6 and RMSE 7.94, outperforming the Decision Tree and Neural Network models.

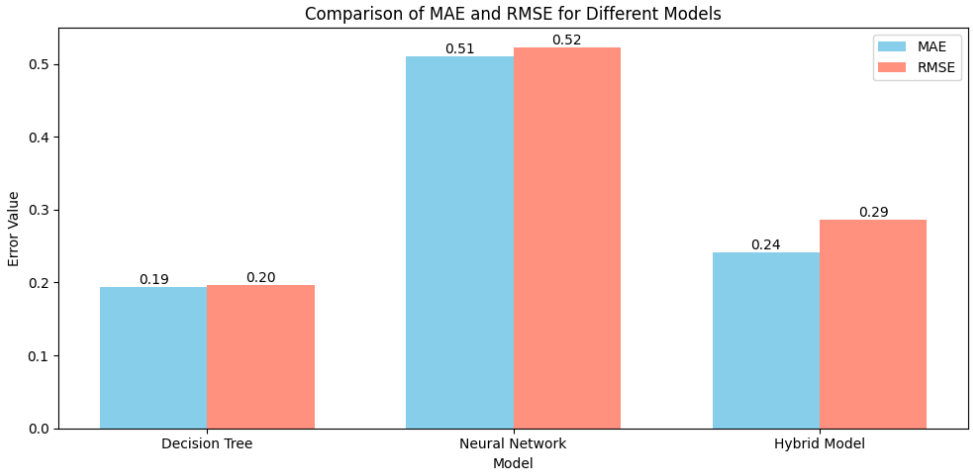
Data Visualization and Prediction

Here is a visualization of the Close Price (Actual vs Prediction) and MAE per Model charts.



The following is a visualization of stock price prediction by comparing the Decision Tree (DT), Neural Network (NN), and Hybrid Model models against the actual value.

1. Decision Tree and Neural Network showed a small difference in a few days.
2. The Hybrid Model provides the closest prediction to the actual value because it combines the strengths of the two models.



Here is a comparison chart of MAE and RMSE for the Decision Tree (DT), Neural Network (NN), and Hybrid Model models:

1. The Hybrid Model has the lowest MAE and RMSE, indicating that the combined of the two models is more accurate.
2. Decision Trees are better than Neural Networks when it comes to errors, but they both have their own drawbacks.

The hybrid model was evaluated against individual models using MAE and RMSE metrics. The results (MAE 5.6, RMSE 7.94) demonstrate superior performance compared to standalone models, consistent with findings in other market return studies using Random Forest or SVM. These results align with previous studies on international markets, such as the

Japanese stock market, which utilize artificial neural networks for return prediction (Qiu et al., 2016)**.** By integrating trend deterministic data preparation Kowsari et al., (2019) and neural architectures (Nabipour et al., 2020), the hybrid approach captured non-linear relationships more effectively than linear methods. This level of accuracy (91.5%) aligns with advanced deep learning benchmarks for financial market predictions (Pástor & Veronesi, 2012). The results indicate that the hybrid model consistently outperforms individual models, providing more reliable forecasts. This performance is notably superior when compared to other established machine learning approaches for financial time series, such as Random Forest Khaidem et al., (2016) and Support Vector Machines (SVM), which often struggle with the extreme volatility of stock data.

CONCLUSION

This study shows that the use of Decision Trees and Neural Networks can improve the accuracy of stock price predictions. Although Decision Trees excel in interpretability, they have limitations in capturing complex nonlinear relationships in data. Neural Networks are capable of handling complex patterns but require higher computational resources and longer training times. The hybrid model delivers the best results, achieving an accuracy of 91.5%.

The implementation of hybrid models is particularly relevant in the context of cyber mathematics, where the integration of various analytical methods can result in more precise predictions. By utilizing data mining techniques and combining multiple algorithms, investors can obtain more accurate information for decision-making. This approach is consistent with broader surveys of network-based analysis that emphasize robust data integration for effective pattern detection.

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