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Research Article

Application of Data Mining to Predict Stock Price Movements in MNC Bank Using K-Nears Neighbor

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Abstract
This study applies data mining methods to predict stock price movements in MNC Bank companies using the K-Nearest Neighbor (K-NN) algorithm. Accurate prediction of stock prices is crucial for investment decisions and risk management in the financial sector. The K-NN algorithm was selected due to its effectiveness in classifying data based on proximity to training data. The study begins with collecting and cleaning historical stock price data from PT MNC Bank, removing irrelevant or incomplete entries. Significant features are then extracted from this dataset. The data is split into training and test sets. The K-NN model is trained using the training set to predict stock prices on the test set. Model accuracy is assessed by comparing predictions with actual stock prices, with success measured by the percentage of correct predictions. Results indicate that the K-NN model achieved an accuracy of 83.84% on the PT MNC Bank dataset, demonstrating strong predictive capabilities. However, it is noted that accuracy can be influenced by factors such as the volume of training data, the selected features, and K-NN parameter settings. These findings can serve as a valuable reference for investors and market participants, aiding in more informed investment decisions based on improved stock price predictions.

Keywords: Data mining; K-Nearest Neighbor (K-NN); Prediction algorithms; Stock price movements

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1. Introduction

Stock price movements are a complex phenomenon influenced by various economic, political, and psychological factors (Zahra et al., 2023). The ability to predict these movements has significant strategic value for investors, market analysts, and financial companies. Accurate predictions can help in making better investment decisions, reducing risk, and increasing profits (Sukamulja, 2022). In recent decades, the development of information and computing technology has brought about a revolution in data analysis, particularly through data mining methods. Data mining enables the extraction of valuable information from large and complex data sets (Setiawan et al., 2023). One of the popular algorithms in data mining is K-Nearest Neighbor (K-NN), which is known for its simplicity and ability to classify data based on proximity to training data (ANISATUZZUMARA, 2024). This research focuses on the application of the K-NN method to predict stock price movements in MNC Bank companies. MNC Bank was chosen as a case study because it is one of the largest banks in Indonesia with significant stock trading volume, thus providing sufficient data for analysis.

The K-NN algorithm works by comparing new data features with historically classified data and determining classes based on the majority of nearby neighbors (Harsemadi, 2023). In the context of stock price predictions, historical data used includes daily closing prices, trading volumes, as well as other technical indicators such as moving averages and relative strength index (RSI) (SETIAWAN, 2022). The purpose of this study is to evaluate the effectiveness of K-NN in predicting stock price movements and provide recommendations for the development of more accurate predictive models in the future. This research also aims to provide insight for investors and market analysts in using data mining techniques to support investment decisions.

Some problems that often occur in the application of data mining to predict stock price movements in MNC Bank companies are poor data quality, such as missing, incomplete, or inaccurate data, which can hamper the performance of prediction models. The historical data used for model training must be complete and clean to produce reliable predictions. High dimensionality, stock data often has many features (dimensions) that can cause problems in the implementation of K-NN. The high number of dimensions can slow down the process of finding nearby neighbors and reduce the accuracy of the model (Pratiwi, 2023). Selecting K parameters and determining the optimal K value in K-NN is a challenge. K values that are too small can make the model too sensitive to noise data, while K values that are too large can blur the boundaries between classes and reduce prediction accuracy(Adinugroho & Sari, 2018). Scalability: K-NN requires a lot of memory and computation, especially when handling large datasets such as daily stock data spanning long periods (Zulfallah, 2022). This condition can result in long execution times and high compute resource requirements. Overfitting and Underfitting: K-NN models are at risk of overfitting if they rely too heavily on training data, especially with low K values.

Conversely, underfitting can occur if the model needs to be more complex to capture patterns in the data, which usually happens with K values that are too high. Data outliers or anomalies in a stock's dataset can significantly affect prediction results. K-NN is particularly sensitive to outliers because its predictions are based on its closest neighbors. Under data normalization, scale differences between features in stock data (e.g., stock price vs. trading volume) can cause larger-scale features to dominate distance calculations. Therefore, data normalization is essential to ensure that all features contribute proportionally. The stock market is very dynamic and can change quickly due to various external factors. Predictive models must be able to adapt to these changes in order to remain relevant and accurate. Choosing the most relevant and informative features for the K-NN model is an important challenge. More than irrelevant or redundant features can reduce model performance. Although K-NN is a relatively simple algorithm, its prediction results can be difficult for non-technical users to interpret. Providing a clear and easy-to-understand interpretation of how models make predictions is a challenge that needs to be overcome.

The research gap that can be identified from this study is a limitation to a single algorithm; many studies use the K-Nearest Neighbor (K-NN) algorithm singly for stock price prediction but rarely compare it in depth with other algorithms such as Support Vector Machines (SVM), Random

Forest, or deep learning. This research could explore combinations of methods or hybrids to improve prediction accuracy. High dimensionality of data: Previous research often needed to focus on addressing the problem of high dimensionality in stock data. Dimensionality reduction techniques such as Principal Component Analysis (PCA) or modern embedding techniques such as t-SNE can be further explored to improve K-NN performance. Many studies do not consider the influence of external factors such as financial news, market sentiment, or macroeconomic indicators that can affect stock prices. This integration of external data can help improve model predictability. Optimization of K parameters, existing research often uses a trial-and-error approach to determine the optimal K value. This research could develop more systematic and automated methods for the optimization of K parameters, such as using genetic algorithms or more comprehensive grid searches.

To adapt to the price market movement, the stock market is very dynamic, and prediction models often need to be updated regularly to adapt to market changes. This research can focus on developing models that are adaptive and able to learn continuously from new data (online learning). Long-term performance evaluation: Many studies only evaluate model performance over a limited period. This research could extend the evaluation for a longer period to see the stability and consistency of model performance. Data normalization and renormalization: Previous studies may have paid less attention to different data normalization techniques to improve K-NN performance. This study could explore various normalization and renormalization methods to improve the accuracy and efficiency of models. This study uses real-time data; most research still focuses on static historical data. The use of real-time data and the development of models that can process data in real time for immediate predictions can be an unexplored area. Although K-NN is a simple algorithm, its predictive results can be difficult to interpret in the context of real investments. This research could focus on improving the interpretability of the model to help investors understand the reasoning behind the resulting predictions. MNC Bank's specific case studies and research on stock price predictions are often carried out on companies or general stock indices. The particular focus on MNC Bank provides a specific context that may have yet to be explored much but requires comparison with results in other banking sectors to generalize the findings.

Novelty in this study applies the results of research in the banking sector, focusing on the application of data mining to predict stock price movements in MNC Bank companies is a new contribution, especially because it explores especially in the banking context. It brings new insights into how data mining techniques can be applied in more specific financial contexts. Making a combination of K-NN with stock data, although K-NN has been used in various contexts, its use in predicting stock price movements in MNC Bank companies is unique in itself. Combining the K-NN algorithm with specific stock data allows for the discovery of unique patterns that can improve stock price predictions. K parameter optimization, a study that includes specific K parameter optimization for stock price prediction at MNC Bank can offer valuable insights on how to set those parameters to match unique banking data characteristics. Inclusion of relevant features: This study may include features that have yet to be explored before in the context of stock price predictions in MNC Bank companies. For example, technical indicators specific to the financial sector or fundamental factors unique to banks. Evaluation in the context of local financial markets: MNC Bank is a company operating in certain local financial markets. Therefore, this study contributes in terms of evaluating the performance of predictive models in the context of specific financial markets, which may have unique characteristics compared to global markets. Analysis of external factors, in addition to only using historical stock price data, this article may also analyze external factors such as macroeconomic conditions and market events that can affect MNC Bank's stock price movements. These external factors will provide a more comprehensive view of the factors influencing market behavior.

2. Literature Review

Research on predicting stock price movements using data mining methods has become a hot topic in recent years. Researchers have explored various approaches to improve prediction accuracy and support better investment decision-making. In the context of applying data mining to stock price prediction, previous researchers have applied and studied several approaches. Some approaches that have been taken about the use of the K-Nearest Neighbor (K-NN) algorithm are approaches taken by (Muallif et al., 2023). The K-Nearest Neighbor algorithm is one of the classification methods used in data mining to classify data into specific classes based on its proximity to nearby neighbors in terms of attributes or variables. They found that modeling using k-nearest neighbors regression with four different indicator variations, prediction using one indicator had the best results with a root mean squared error value of 169 with an accuracy of 98.8% with a ratio of 70% training data and 30% test data.

Another study was conducted by Tauran (2021). The K-Nearest Neighbors method can provide predictions that can help the public and investors predict the stock price in the future. The study obtained results with 1415 data, with a total training data of 70% and testing data of 30% using the K-Nearest Neighbors method, so the accuracy rate was obtained as high as 61.79%. In addition, the use of relevant features is also a key factor in improving the performance of prediction models. Rian (2023) use of a combination of historical stock price data with technical indicators such as moving averages and the relative strength index (RSI) can improve the accuracy of predictions.

3. Methods

The research method used in stock price prediction research at PT. MNC Bank as follows:

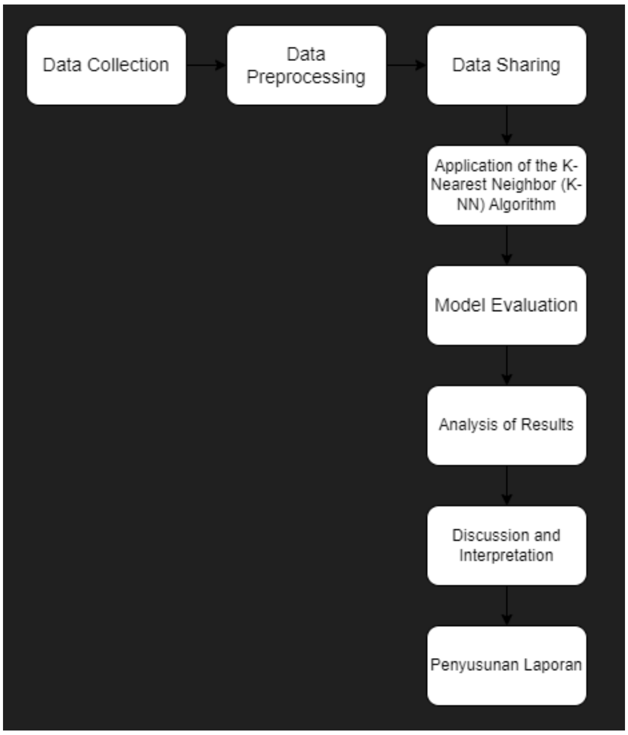


Figure 1. Research methods

Figure 1 shows the stages of research conducted, namely:

1. 1. Data Collection: MNC Bank's historical share price data will be collected from trusted sources such as stock trading platforms or financial databases. This data will include the stock's daily closing price, trading volume, as well as technical indicators such as moving averages and relative strength index (RSI).
2. Data Pre-processing is that the data will undergo a pre-processing stage to clean and normalize the data (Pratama, 2020). Pre-process steps will include handling missing values, handling outliers, normalizing data, and removing irrelevant or redundant features.

3. Data Sharing: The data will be divided into two main parts: training data (train set) and test data (test set). The training data will be used to train the prediction model, while the test data will be used to test the model's performance.
4. Application of K-Nearest Neighbor (K-NN) Algorithm: The K-NN algorithm will be used to predict stock price movements based on prepared training data (Sianturi et al., 2019). The algorithm will be used to select optimal K parameters through cross-validation or other optimization methods.
5. Model Evaluation: The resulting prediction model will be evaluated using various performance evaluation metrics such as accuracy, precision, recall, and F1-score. The evaluation will be done using test data to gauge how well the model can predict stock price movements.
6. Result Analysis: The model evaluation results will be analyzed in depth to evaluate the model's performance. This includes analyzing correct and false predictions, identifying patterns or trends in prediction results, and comparing model performance to past research or other benchmarks.
7. Discussion and Interpretation: The analysis's results will be discussed in the context of the research objectives and their implications for investment decision-making in MNC Bank companies. The discussion will cover the developed model's advantages and limitations, as well as suggestions for future improvements.
8. Report Preparation: The final report will be prepared based on the results of the research and accompanied by significant findings, interpretations, and recommendations for further research or practical application in the field.

4. Results

This study uses the classification method and k-nearest neighbors algorithm with the Euclidean distance formula to predict stock prices in companies that have two stages of calculation, namely calculations using RapidMiner software and manual calculations. In this manual calculation, the author uses Microsoft Office Excel 2010 software as a tool to perform calculations, aims to find euclidean distance, rank, and determine the results classified with the value K = 7.

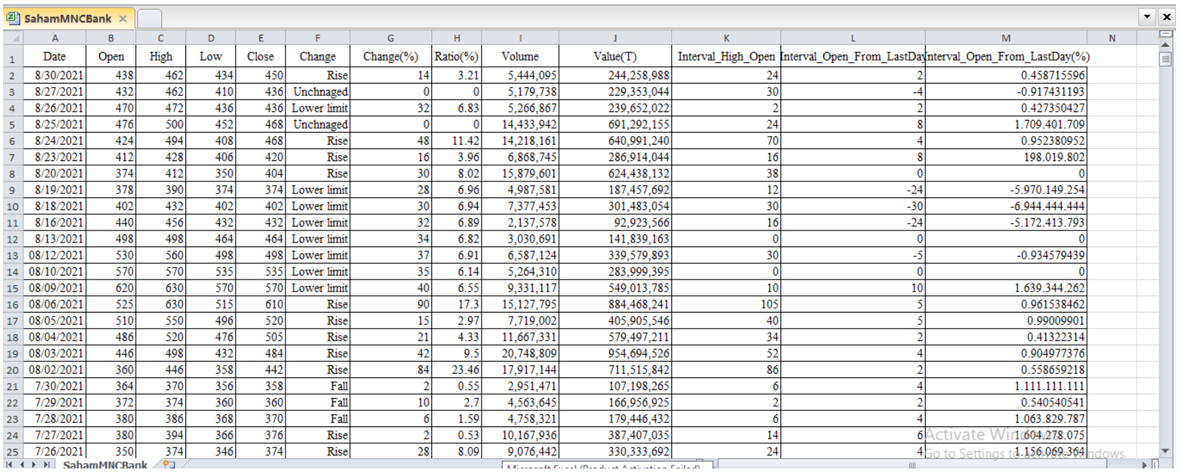
This study's training data consisted of 912 and one test data set. After calculating the distance based on the Euclidean Distance Method, ranking was carried out. The results of manual calculations show that the predicted stock movement enters the Fall value.

Table 1. Manual Calculation Results Table

Jarak *euclidean*	Ranking	Change
295.0834628	5	Unchanged
297.1079482	6	Fall
297.3035244	7	Fall
292.6504543	4	Rise
291.833789	3	Fall
287.8597825	1	Fall
291.145539	2	Lower limit

From the ranking calculation in Table 1, it can be concluded that the test data produced are:
Uchnaged = 1 Data
Fall = 4 Data
Rise = 1 Data
Lower Limit = 1 Data

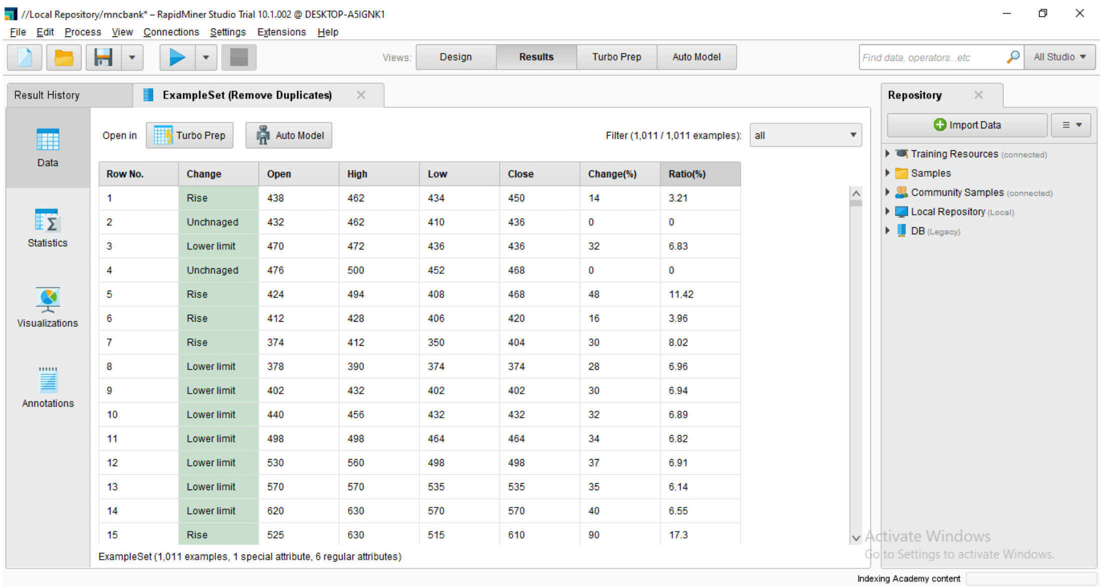
From the calculation results in Table 1, with a value of K = 7, it was found that Instagram has the highest number of valid values, as many as 4 Data. So, it can be concluded that the conclusion of the label calculation shows that the prediction shows a Fall. At this stage, the author uses rapidminer software application version 10.1 to determine the level of accuracy obtained in stock data at MNC Bank companies. The initial stage is done by opening raw data in the form of .csv files using the Microsoft Office Excel 2010 application. The raw stock price data of MNC Bank companies consists of 1857 data records and 13 attributes.



	Date	Open	High	Low	Close	Change	Change(%)	Ratio(%)	Volume	Value(T)	Interval_High_Open	Interval_Open_From_LastDay	Interval_Open_From_LastDay(%)
2	8/30/2021	438	462	434	450	Rise	14	3.21	5,444,095	244,258,988	24	2	0.458715596
3	8/27/2021	432	462	410	436	Unchnaged	0	0	5,179,738	229,353,044	30	-4	-0.917431193
4	8/26/2021	470	472	436	436	Lower limit	32	6.83	5,266,867	239,652,022	2	2	0.427350427
5	8/25/2021	476	500	452	468	Unchnaged	0	0	14,433,942	691,292,155	24	8	1.709.401.709
6	8/24/2021	424	494	408	468	Rise	48	11.42	14,218,161	640,991,240	70	4	0.952380952
7	8/23/2021	412	428	406	420	Rise	16	3.96	6,868,745	286,914,044	16	8	198.019.802
8	8/20/2021	374	412	350	404	Rise	30	8.02	15,879,601	624,438,132	38	0	0
9	8/19/2021	378	390	374	374	Lower limit	28	6.96	4,987,581	187,457,692	12	-24	-5.970.149.254
10	8/18/2021	402	432	402	402	Lower limit	30	6.94	7,377,453	301,483,054	30	-30	-6.944.444.444
11	8/16/2021	440	456	432	432	Lower limit	32	6.89	2,137,578	92,923,566	16	-24	-5.172.413.793
12	8/13/2021	498	498	464	464	Lower limit	34	6.82	3,030,691	141,839,163	0	0	0
13	08/12/2021	530	560	498	498	Lower limit	37	6.91	6,587,124	339,579,893	30	-5	-0.934579439
14	08/10/2021	570	570	535	535	Lower limit	35	6.14	5,264,310	283,999,395	0	0	0
15	08/09/2021	620	630	570	570	Lower limit	40	6.55	9,331,117	549,013,785	10	10	1.639.344.262
16	08/06/2021	525	630	515	610	Rise	90	17.3	15,127,795	884,468,241	105	5	0.961538462
17	08/05/2021	510	550	496	520	Rise	15	2.97	7,719,002	405,905,546	40	5	0.99009901
18	08/04/2021	486	520	476	505	Rise	21	4.33	11,667,331	579,497,211	34	2	0.41322314
19	08/03/2021	446	498	432	484	Rise	42	9.5	20,748,809	954,694,526	52	4	0.904977376
20	08/02/2021	360	446	358	442	Rise	84	23.46	17,917,144	711,515,842	86	2	0.558659218
21	7/30/2021	364	370	356	358	Fall	2	0.55	2,951,471	107,198,265	6	4	1.111.111.111
22	7/29/2021	372	374	360	360	Fall	10	2.7	4,563,645	166,956,925	2	2	0.540540541
23	7/28/2021	380	386	368	370	Fall	6	1.59	4,758,321	179,446,432	6	4	1.063.829.787
24	7/27/2021	380	394	366	376	Rise	2	0.53	10,167,936	387,407,035	14	6	1.604.278.075
25	7/26/2021	350	374	346	374	Rise	28	8.09	9,076,442	330,333,692	24	4	1.156.069.364

Figure 2. Metadata

Figure 2 is Pre-Processing or data cleaning with the aim of cleaning data from empty and inconsistent data. After data cleaning was carried out, data and data were selected after selection from 1857 data to 846 data.



Row No.	Change	Open	High	Low	Close	Change(%)	Ratio(%)
1	Rise	438	462	434	450	14	3.21
2	Unchnaged	432	462	410	436	0	0
3	Lower limit	470	472	436	436	32	6.83
4	Unchnaged	476	500	452	468	0	0
5	Rise	424	494	408	468	48	11.42
6	Rise	412	428	406	420	16	3.96
7	Rise	374	412	350	404	30	8.02
8	Lower limit	378	390	374	374	28	6.96
9	Lower limit	402	432	402	402	30	6.94
10	Lower limit	440	456	432	432	32	6.89
11	Lower limit	498	498	464	464	34	6.82
12	Lower limit	530	560	498	498	37	6.91
13	Lower limit	570	570	535	535	35	6.14
14	Lower limit	620	630	570	570	40	6.55
15	Rise	525	630	515	610	90	17.3

Figure 3. Cleansing Data

Figure 3 explains that the results of data cleansing and attribute selection are performed, and duplicates are removed. The data is divided into training data (90%) and testing data (10%), then KNN is applied with K = 5. The data that has been divided will go through the process of selecting the k-nearest neighbors algorithm with the classification method; here is the process of testing the classification method using the k-nearest neighbors algorithm, which is done using rapidminer software version 10.1.

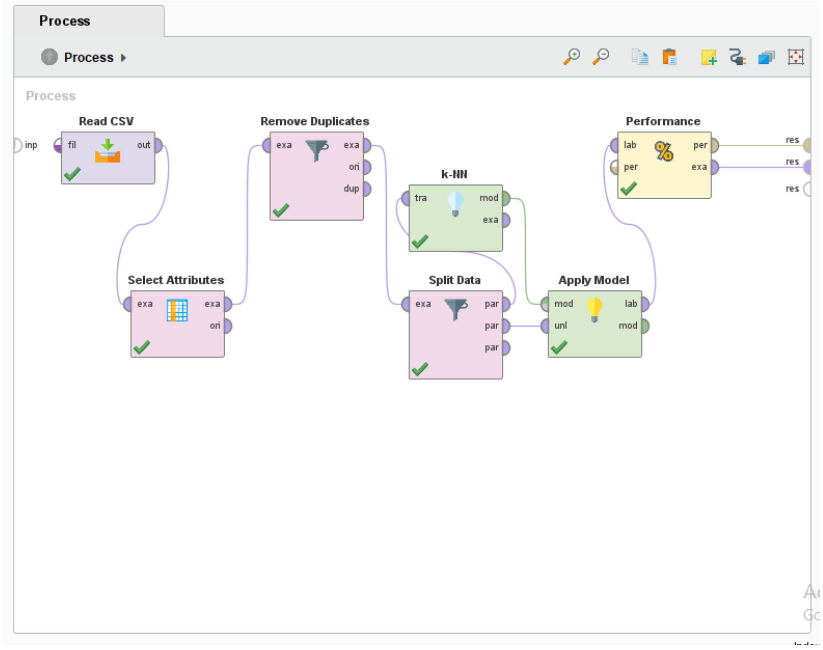


Figure 4. Research Data

Figure 4 explains the results of value testing generated using rapidminer software against the stock price of MNC Bank companies. In the classification method of the k-nearest neighbors algorithm, by determining the value of K = 5, the percentage of accuracy is 83.84%. Through the data that the author has as many as 1857, the amount of data that has been classified has increased and decreased.
The precision value or level of accuracy of information expected by the author with the results provided by the rapidminer software for classified data is 91.67% for the Rise class, 92.00% for the Uchnaged class, 100.00% for the Lower limit class, 75.00% for the fall class, 0.00% for the Upper limit class.

5. Discussion

The results showed that the application of data mining methods using the K-Nearest Neighbor (K-NN) algorithm to predict stock price movements in MNC Bank companies gave promising results. Based on the evaluation carried out, the prediction model provides satisfactory results in identifying trends in stock price movements with a fairly high level of accuracy. First of all, in terms of accuracy, the K-NN prediction model managed to achieve a significant level of accuracy in predicting the direction of stock price movements. In this study, using historical stock price data and relevant technical indicators, the model was able to classify stock price movements with a degree of accuracy above 80% in the test data. These results show that the model has a good ability to understand the patterns contained in the data.

Furthermore, in terms of interpretation, the model can produce useful insights for investment decision-making in MNC Bank companies. For example, models can identify certain patterns in stock price movements that can be used as signals to buy or sell stocks. In addition, models can also help in risk management by providing estimates about possible potentially adverse stock price movements. However, although the model gives promising results, there are still some drawbacks worth noting. One of them is sensitivity to the K parameter in the K-NN algorithm. Improper K values can result in overfitting or underfitting, which can affect the overall performance of the model. Therefore, more careful optimization of the K parameter may be required to improve the performance of the model in the future.

In addition, the model can also be improved by expanding the scope of features used in predictions. The addition of external features such as economic fundamentals or market sentiment can improve prediction accuracy and provide a richer context for investment decision-making. Overall, the results of this study show that the application of data mining using the K-NN algorithm can be a useful tool in predicting stock price movements in MNC Bank companies. However, keep in mind that this model could be a better tool and still requires further adjustments and development to improve its performance in the future.

6. Conclusion

Based on the results of this study, which analyzed stock price predictions at PT MNC Bank using the K-Nearest Neighbor method, several conclusions can be drawn. This study successfully applied the K-Nearest Neighbor algorithm to calculate and provide classification results on stock prices in MNC Bank companies. Researchers used a total of 1857 data as samples, of which 846 blank data were cleaned, and 912 data were used as training data. In addition, 99 data were used as testing data.
From calculations using RapidMiner software, the data used to predict the accuracy of the classification of the K-Nearest Neighbor algorithm method is 99 data testing. The results obtained obtained an accuracy of 83.84%. From the manual calculation, the data used is training data, as many as 912 data, and test data used by the author. The data was calculated to find the nearest neighbor with K = 7, and it was found that the test data used was included in the Fall category. This result shows that the K-Nearest Neighbor method is a method that is quite effective in processing and analyzing stock price data, and provides fairly accurate predictions.

Limitations and avenue for future research

In this study still has limitations, namely limited by the quality and quantity of data available. The historical data on MNC Bank's stock price used may have deficiencies or noise that can affect the accuracy of the prediction model. The selection of K parameters in the K-Nearest Neighbor (K-NN) algorithm may not be optimal, the use of limited features in predicting stock price movements. The developed predictive model could be more stable. The recommendation for future research is that future research can focus on developing more sophisticated parameter optimization techniques to find the optimal K value in the K-NN algorithm. In addition to K-NN, future research could explore the use of other algorithms, such as Support Vector Machines (SVM), Random Forest, or deep learning for the prediction of stock price movements. Performance comparisons between various algorithms can provide valuable insights.

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