EMITTER International Journal of Engineering Technology
Vol. 10, No. 2, December 2022, pp. 279~293
DOI : 10.24003/emitter.v10i2.740

Technical Analysis Based Automatic Trading Prediction System for Stock Exchange using Support Vector Machine

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Received August 25, 2022; Revised September 27, 2022; Accepted October 30, 2022

Abstract

Stock exchange trading has been utilized to gain profit by constantly buying and selling best-performing stocks in a short term. Deep knowledge, time dedication, and experience are essential for optimizing profit if stock price fluctuations are analyzed manually. This research proposes a new trading prediction system that has the ability to automatically predict the accurate time for buying and selling stock using a combination of technical analysis and support vector machine (SVM). Technical analysis is used to analyze stock price fluctuation based on historical data by utilizing technical indicators such as moving average, Bollinger bands, relative strength index, stochastic oscillator, and Aroon oscillator. SVM maps inputs into higher dimensional spaces using non-linear kernel functions, making it suitable for various technical indicators implementation as inputs in stock trading prediction. Experimentation on five Indonesian stocks reveals that the combination of technical analysis and support vector machine is best suited for continuously fluctuated stocks, with the highest accuracy of 77.8%.

Keywords: stock trading prediction, technical indicators, support vector machine, buy-sell signal.

1. INTRODUCTION

Advances in technology have had a huge impact on various aspects of human life, including the trade sector. In this globalization era, the tendency of trade has led to free trade [1]. A major impact of free trade is a borderless movement of funds from one sector to another. In terms of this free trade, the stock market is one important constituent of the capital market. The stock exchange is a place to trade shares systematically. In general, this trade is either carried out by investing stocks or trading stocks. Stock investment and stock trading are both activities of buying, selling, and holding shares until the asset's price rises [2]. However, investment aims to create wealth in a long term by buying companies that have performed well and holding them for a long period, whereas trading aims to generate profits by buying and selling stocks in a short term.

Based on the Indonesia Stock Exchange Press Release, as of December 29, 2020, the number of capital market partakers reached 3.87 million [3]. This number has increased by 42 percent compared to conditions as of December 31, 2019, with a total of 2.48 million participants. One of the most popular types of trading in capital market trading is stock trading. The reason for this is that trading is more beneficial due to the need of only low capital contribution for a short period. This is in contrast to investments that require a large capital contribution for a long period. In addition, a large number of people turned to the trading business due to the big loss in the economic sector caused by the COVID-19 pandemic [3]. Thus, citizens are gradually becoming familiar with the term trading. Nevertheless, a trader must have in-depth knowledge of the stock market before participating in trading. Furthermore, time dedication is essential if the fluctuation of stock prices is analyzed manually. Stocks that have been purchased must be sold within a short period, ranging from hours to weeks based on the stock price fluctuations [2].

With the rapid development of technology, especially in computer science, research focusing on stock price movement prediction, especially in stock trading, has been widely carried out. Various types of technical indicators such as moving average and relative strength index have been used in predicting stock price movements [4]. However, the selection of technical indicators under certain price conditions needs to be considered for high predictive accuracy.

Technical analysis has been used to analyze stock price fluctuation based on historical data by utilizing technical indicators. The use of a single technical indicator will never produce a truly accurate buy and sell signal; this is due to the difference in timeliness in Bollinger bands, relative strength index (RSI), and moving average convergence divergence (MACD). This implies that the combination of several types of indicators will perform better than using a single indicator [5]. This study looks into the performance of various technical indicator combinations.

Hence, this study proposes a new trading prediction system that can automatically predict the accurate time to buy and sell stocks by combining technical analysis and support vector machine. With the support of this system, traders are able to determine the best time for performing buy and sell transactions without the necessity of monitoring and analyzing stock price fluctuation manually and continuously.

2. RELATED WORKS

In trading, technical analysis has become the leading tool for predicting stock price movements [6]. Technical analysis examines stock price fluctuations based on historical data. From those fluctuations, traders observe certain trends or price patterns that can be used as a basis for determining a buy or sell signal. Fluctuation of stock price can also be represented in a more complex form by utilizing several technical indicators such as moving average, Bollinger bands, relative strength index, stochastic oscillator, and Aroon oscillator. These various indicators aim to further refine the data representation of stock price movement. In addition, these indicators can avoid extreme data values such as outliers or certain conditions that affect stock prices at a certain time.

According to current research, technical variables have two distinct advantages. One is that technical indicators have statistical and economic significance predictive capabilities that match or exceed macroeconomic variables. Technical indicators, on the other hand, primarily use stock price changes to capture and evaluate stock trends. Dai et al. [7] use three well-known trading technical indicators, including exponential moving average rules, relative strength index, and stochastic oscillator, to generate buy or sell signals based on simple or more complex mathematical functions of past and current data. In-sample results show that technical indicator combinations can predict stock returns for the entire sample period. As a result, combining technical indicators gives much more weight to recent observations and can better capture stock market trends.

When compared to a single technical indicator signal, the combination of several technical indicators provides a stronger signal. Pramudya et al. [8] combined several technical indicators to produce a more accurate prediction. Individually, the experiment showed that Bollinger bands and moving average performed better than relative strength index. However, when all three are combined, the prediction result had slightly higher accuracy compared to a single indicator.

Table 1. Comparison of related research

Research	Stock Dataset	Technical Indicator	Predictive Mining
[8]	Indonesia	MACD, BB, RSI	-
[9]	China	SMA, EMA, RSI	Support Vector Machine
[10]	Thailand	RSI, Stoch, MACD	Support Vector Machine
[11]	China	Stoch, RSI	Decision Tree
[12]	USA	RSI	Neural Network
Current	Indonesia	SMA, RSI, Stoch, BB, Aroon	Support Vector Machine

Table 1 summarizes this study's position in terms of dataset and methods used. There are numerous variations in the use of technical indicators in related studies. Some of them are used alone or in combination. Several predictive mining methods have also been explored in the use of predicting stock price fluctuation. Jaiwang et al. [10] implemented support vector machine (SVM) to five stocks on the Stock Exchange of Thailand. Using the SVM's default parameters, the average accuracy achieved was 72.45%. Apart from SVM, studies have researched other methods such as decision tree [11] and neural network [13].

3. ORIGINALITY

The use of technical analysis to forecast stock price fluctuations is rapidly expanding. Most previous research has used technical indicators to conduct this type of analysis. Some use a single indicator, while others use a combination of indicators. However, these studies only look at the price movement. New traders, in particular, require the buy, sell, or hold recommendations. As a result, there is a pressing need to create a system that can produce these recommendations based on technical analysis.

The novelty of this study is that we implement the combination of five technical indicators: simple moving average, relative strength index, stochastic oscillator, Bollinger bands, and Aroon oscillator. The stock prices are transformed using these indicators, which are used as features for the modeling. On the other hand, the class labeling for the model is implemented based on the current conduct of real traders. The class label is determined using three parameters: maximum profit, maximum loss, and maximum hold duration. These features and class labels are used as the training data to create a model used for providing the buy, sell, or hold prediction using support vector machine. The combination of technical analysis and support vector machine produces promising accuracy. Hence, it is truly applicable in real-time trading to optimize profits.

4. SYSTEM DESIGN

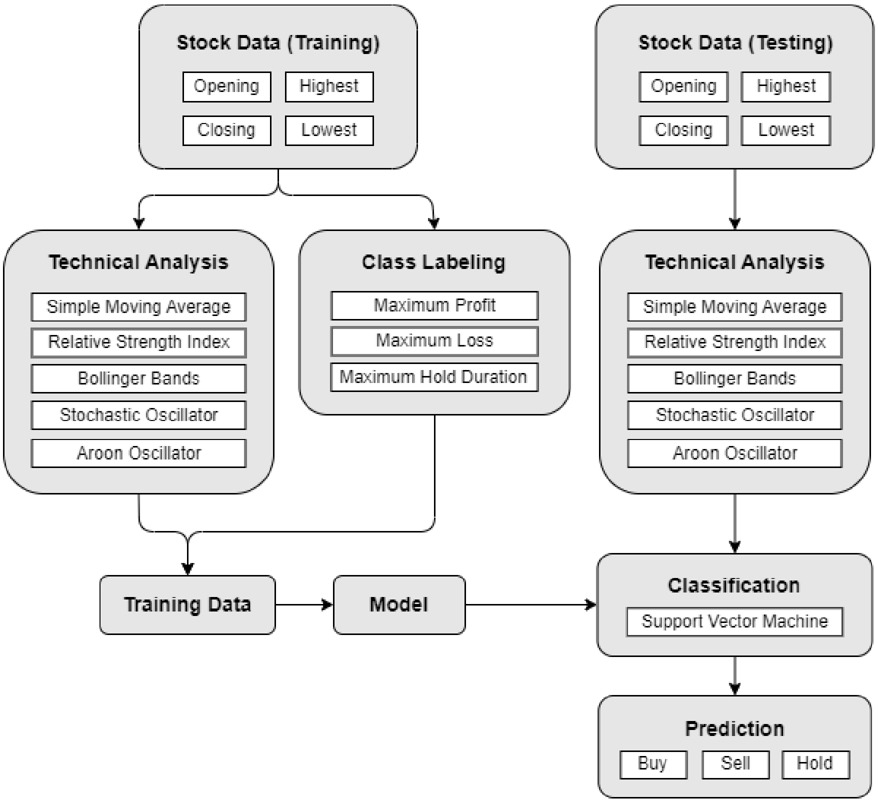

Figure 1. Methodology of the stock exchange trading prediction

This section explains the stock dataset and methodologies used in stock prediction, including technical indicators and support vector machine. This section also defines the evaluation criteria for the prediction result.

The methodology used in this study can be seen in Figure 1. There are two processes, namely training and testing. The training stock data containing the opening, closing, highest, and lowest prices, are transformed into features using five technical indicators. The class label for the training data is determined by three parameters, namely maximum profit, maximum loss, and maximum hold duration. These features and class labels are then randomly divided into training and validation data. The resulting model will be used for the buy, sell, or hold prediction using support vector machine.

4.1 Stock Dataset

Data discovery was implemented for the collection of stock data in this study. The data discovery technique is the process of searching for new datasets as more datasets become available on the web and in corporate data lakes [14]. There are two stages to data discovery. The generated data must first be indexed and made publicly accessible. Many collaborative systems are built with the goal of making this process as simple as possible. The datasets can then be searched for machine learning tasks by researchers in the following step. The crucial challenge, in this case, is determining how to scale the search and whether a dataset is suitable for a given machine learning task.

After the discovery process, the stock dataset for this paper was eventually obtained from Yahoo Finance which provides daily stock price movement data for various stocks [15]. The data collection process includes daily retrieving the stock prices: open, close, high, low, and volume. Yahoo Finance provides a Python library for accessing stock data by setting the stock code, start date, and end date, which can be handled by writing the code shown in Figure 2.

```
import yfinance as yf
stockPrices = yf.download('StockCode', start='StartDate', end='EndDate')
```

Figure 2. Yahoo Finance library for retrieving stock data

Stock data is a type of time series data. Data that is not stationary in the form of a collection of observations made chronologically is referred to as time series data [16]. Stock data contains stock information such as open, close, high, low, and volume. The open and close variables represent the opening and closing prices of a market at a certain period, respectively. The high and low variables are the highest and lowest prices that occur during a trading period, respectively. Lastly, the volume variable is the number of assets traded in a specified period [17].

Table 2. Price information in stock dataset

Date	Open	High	Low	Close	Volume
04/04/22	3350	3370	3330	3360	17373500
05/04/22	3360	3480	3360	3480	38725700
06/04/22	3520	3530	3480	3490	60587800
07/04/22	3510	3510	3440	3500	28540400
08/04/22	3500	3600	3480	3600	40875900
11/04/22	3600	3670	3550	3550	44012000
12/04/22	3550	3570	3490	3510	27267200
13/04/22	3570	3760	3540	3760	93553600
14/04/22	3760	3790	3720	3770	40945400

This research focuses on stocks from the Indonesian Stock Exchange. Five stock data are used: PT Indo Tambangraya Megah (ITMG), PT Bukit Asam (PTBA), PT Kabelindo Murni (KBLM), PT Bank Rakyat Indonesia (BBRI), and PT Bank Central Asia (BBCA). The dataset's stock history data ranges from January 2013 to May 2022, which can be accessed by running the code shown in Figure 2. Table 2 depicts a sample of the retrieved stock data for PT Bukit Asam (PTBA).

The five stock data used are divided into two categories: continuously and infrequently fluctuated data. Continuously fluctuated data is stock data that constantly increases or decreases in a short period. Infrequently fluctuated data, on the other hand, rarely changes and, when it does, it fluctuates slowly. ITMG, PTBA, and KBLM are continuously fluctuated stocks, whereas BBRI and BBCA are classified as infrequently fluctuated stocks. The visualizations of each stock data category are shown in Figure 3 and Figure 4.

Figure 3. Visualization of continuously fluctuated stock data

Figure 4. Visualization of infrequently fluctuated stock data

4.2 Data Preprocessing

Notable differences between feature values, such as the maximum and minimum values, frequently occur in various stock datasets. This issue is undesirable and necessitates careful intervention to perform a scaling-down transformation that ensures all attribute values are appropriate and acceptable. This is known as feature scaling or data normalization, and it is required and critical for various classifiers, including support vector machine (SVM), which cannot perform well if feature values in the dataset differ significantly. Min-max normalization and standardization were used in the study.

Min-Max Normalization

The min-max normalization is a method that performs a linear transformation of the original data to produce a balance of comparison values between data [18]. This normalization method is used on stock datasets before the technical analysis transformation to avoid huge differences between feature values. Equation (1) is the min-max normalization formula in which *v* denotes the initial feature value, *min* the minimum feature value, and *max* the maximum feature value.

$$v' = \frac{v - min}{max - min} \tag{1}$$

Standardization

Standardization, also known as z-score, is a normalization method based on the data's average value and standard deviation [18]. If the minimum and maximum actual values of the data are unknown, this method is extremely useful. This method ensures the distance between the values produced by the technical indicators is uniform. Because the data's minimum and maximum actual values are uncertain, this method is suitable in this case. The standardization formula is given in Equation (2), where v is the initial feature value, $\bar{x}$ is the average feature value, and σ is the data's standard deviation.

$$v' = \frac{v - \bar{x}}{\sigma} \quad (2)$$

4.3 Class Labeling

The class labeling process is used to produce the training label. In order to determine the class label, three parameters are used: maximum profit, maximum loss, and maximum hold duration. Maximum profit and maximum loss are the maximum profit and loss values preferred by a trader, respectively, before performing a transaction. The maximum hold duration is the maximum length of time stock can stay in a hold position. Figure 5 depicts the algorithm of this process.

```
if percentage > maximum profit :
    then buy
elif percentage < - (maximum loss) :
    then sell
else :
    if count hold > maximum hold duration :
        then sell
    else :
        then hold
```

Figure 5. Class labeling algorithm

Percentage represents how much a stock price has risen or fallen since the last transaction, whereas count hold is the length of time a stock has been in a hold position. The resulting label can take one of three categories: buy, sell, or hold. The labels buy and sell represent recommendations to purchase and sell a specific stock, respectively. The hold label, on the other hand, represents a recommendation to neither purchase nor sell a stock.

4.4 Technical Analysis

Technical analysis is a tool for analyzing price fluctuations over a specific period. Certain patterns can be derived from these price movements and used as a basis to buy or sell stock. Technical analysis analyzes prices based on previous price data [19].

Stock price movement data can be represented in a more complex form by utilizing various trading indicators [20]. These various indicators can be developed to improve the representation form of stock price movement data. Furthermore, these indicators can avoid trading models that are influenced by extreme data values, such as the presence of outliers or the presence of certain conditions that affect the unit price of a stock on certain days.

For high predictive accuracy, the selection of technical indicators under specific price conditions must be considered [21]. Using a single technical indicator will never result in a truly accurate buy and sell signal. According to previous research, combining technical indicators gives much more weight to recent observations and can better capture stock market trends. In comparison to a single technical indicator signal, a combination of several technical indicators provides a stronger signal.

This paper implements the combination of five technical indicators: simple moving average, relative strength index, stochastic oscillator, Bollinger bands, and Aroon oscillator. The stock prices transformed using these indicators are used as features for the modeling.

Simple Moving Average

Simple moving average is used to filter out market noise and determine price direction [22]. It is calculated by adding the stock prices over the last *n* days and dividing by *n*. Equation (3) is the formula, where *N* is the period and $S_{i,close}$ is the *i*-day closing price.

$$SMA(N) = \frac{1}{N}\sum_{i=1}^{N} S_{i,close} \tag{3}$$

Relative Strength Index

Relative strength index compares the magnitude of the stock's recent gains to its recent losses and produces a number ranging from 0 to 100 [22]. It is calculated using Equation (4), where *AU* is the total upwards price changes and *AD* is the total downwards price changes during the past *n* days.

$$RSI = 100 - \left(\frac{100}{1 - RS}\right) = 100 \cdot \left(\frac{RS}{1 + RS}\right); RS = \frac{AU}{AD} \tag{4}$$

Stochastic Oscillator

Stochastic oscillator is an oscillator that measures the relative position of the closing price within a previous high-low range [23]. The indicators produced by the Stoch measurement are known as *%K* and *%D*. The *%K* indicator defines a price range by comparing the lowest low and highest high of a determined period. The most recent closing price is then calculated as a percentage of that range. Meanwhile, the *%D* indicator represents a moving average of *%K*. Calculation of these indicators for day *t* is formulated in

Equation (5), where C_t is today's closing price, $L_t(m)$ is the lowest price of the last t days, and $R_t(m)$ is the price range of the t days.

$$\%K = 100 \cdot \frac{C_t - L_t(m)}{R_t(m)}, \%D = \frac{\sum_{i=t-n}^{t} \%K_i}{n} \tag{5}$$

Bollinger Bands

Bollinger bands applies price volatility by calculating the standard deviation of the prices themselves [24]. The indicator consisted of three bands: an n-day moving average band and the value of two standard deviations of price changes plotted above and below the n-day moving average. The *%b* indicator represents Bollinger bands by reflecting the closing price as a percentage of the lower and upper bands. Equation (6) is the formula, where *upperBB* is the upper Bollinger band, *lowerBB* is the lower Bollinger band, and *last* is the last price value.

$$\%b = \frac{last - lowerBB}{upperBB - lowerBB} \tag{6}$$

Aroon Oscillator

Aroon oscillator is used to assess the strength of a trend and predict when it will change direction [25]. It is calculated using Equation (7), where t_{high} is periods since n-period high and t_{low} is periods since n-period low.

$$Aroon = 100 \cdot \left(\frac{(n - t_{high}) - (n - t_{low})}{n} \right) \tag{7}$$

4.5 Support Vector Machine

Machine learning can be approached in four ways: supervised, unsupervised, semi-supervised, and reinforcement learning [26]. Classification is a type of supervised learning in which input data is mapped to output data based on a large number of example input-output pairs determined during a training phase. Using classification, features from a set of example observations can be used to train a classifier, which generates class assignments with a given accuracy. Once built on these features, this classifier can automatically assign class labels to previously unseen observations using the previously established patterns.

Support Vector Machine (SVM) is a machine learning classification method [26]. SVM has a concept in classification modeling that is systematically clearer than other classification algorithms. Equation (8) represents the formula for the SVM linear model as a decision boundary, where x is the input vector, w is the weight parameter, $\emptyset(x)$ is the basis function, and b is a bias value.

$$y(x) = w^T \emptyset(x) + b \tag{8}$$

SVM, like all machine learning algorithms, seeks to maximize the accuracy of predicted labels. By maximizing the distance between classes, the SVM algorithm finds the best hyperplane. A hyperplane is a function that serves as a feature-based separator between classes. In general, the features used to determine the hyperplane are not raw data, but rather data that have been processed through the feature selection stage. These features are referenced using coordinates, and a support vector is formed based on the distance between them.

SVM uses non-linear kernel functions to map inputs into higher-dimensional spaces [27]. As a result, SVM is suitable for stock forecasting with a variety of technical indicators as inputs. The model is created by fitting the training data, containing the technical indicators and class labels.

4.6 Evaluation Criteria

The dataset of technical indicators and class labels is divided into random train and test subsets first. The SVM model is then fit to the given training data. The classification accuracy is used to evaluate the stock prediction algorithm. This accuracy is calculated by dividing the number of true predictions by the total number of samples, resulting in the mean accuracy of the given test data and labels.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

The accuracy formula used in this study is shown in Equation (9). *TP* and *TN* stand for true positive and true negative, respectively, and represent the conditions in which the model correctly predicts the positive and negative classes. *FP* and *FN*, on the other hand, stand for false positive and false negative, respectively, and represent the conditions when the model incorrectly predicts the positive and negative classes.

5. EXPERIMENT AND ANALYSIS

This section analyzes the performance of the stock exchange trading prediction system using technical analysis and support vector machine. This method is experimented on five Indonesian stocks, namely PT Indo Tambangraya Megah (ITMG), PT Bukit Asam (PTBA), PT Kabelindo Murni (KBLM), PT Bank Rakyat Indonesia (BBRI), and PT Bank Central Asia (BBCA). ITMG, PTBA, and KBLM are classified as continuously fluctuated stocks, whereas BBRI and BBCA are infrequently fluctuated stocks.

Table 3. Composition of training and testing data

Data Type	Percentage (%)	Amount
Training Data	80	1867
Testing Data	20	467
Total	**100**	**2334**

Each stock dataset contains 2334 rows of price history data from January 2013 to May 2022. After transformed using technical indicators and class labeling algorithm, the features and labels are split into training and testing data with a random state value of 4. Table 3 represents the composition of training and testing data used for evaluation. 1867 rows or 80% of the dataset are used for training, while the rest are used for testing.

Table 4. SVM parameters used for experiment

SVM Parameters	Value
Kernel Type	Radial Basis Function (RBF)
Regularization Parameter (C)	1.0
Kernel Coefficient (γ)	$1\ /\ (n\_features * X.var()) = 0.34191$

The model is created by fitting the training data using SVM. Table 4 shows tuning of the SVM parameters used in this experiment. The radial basis function (RBF) kernel computes the similarity and proximity of features. RBF overcomes the space complexity problem by only storing the support vectors during training rather than the entire dataset. This kernel is associated with two hyperparameters: C for SVM and γ for the RBF Kernel. As γ increases, the model tends to overfit for a given value of C. Therefore, the C and γ values are set using the calculation depicted in Table 4.

Table 5. Prediction accuracy without any trading parameters

Stock Exchange	Classification Accuracy (%)
ITMG	56.2
PTBA	55.9
KBLM	57.2
BBRI	52.5
BBCA	54.1

Table 6. Prediction accuracy with trading parameters

Trading Parameters			Classification Accuracy of Each Stock (%)				
Max Profit	Max Loss	Max Hold	ITMG	PTBA	KBLM	BBRI	BBCA
10	2	20	72.2	71.3	68.7	62.6	51.8
10	2	25	73.5	75.9	69.6	60.4	51.0
10	2	30	77.4	77.8	67.4	62.4	50.4
10	5	30	74.8	71.1	61.7	61.1	47.0
15	2	25	70.4	70.9	68.3	57.8	56.4
15	2	30	74.8	73.0	67.4	59.1	53.0
15	5	30	71.1	66.3	62.8	58.5	52.8
20	2	30	72.2	71.5	66.1	59.8	52.6
25	2	25	69.1	68.7	68.0	62.4	57.7
25	2	30	71.1	69.6	65.7	61.7	52.0
30	2	30	72.6	67.8	65.4	61.5	52.2
Highest Accuracy (%)			**77.4**	**77.8**	**69.6**	**62.6**	**56.4**

First, the experiment is carried out without any trading parameters therefore the class label is determined solely by the price difference from the previous day. As indicated in Table 5, the highest accuracy is 57.2%, as shown by KBLM, a continuously fluctuated stock. The lowest accuracy, on the other hand, is 52.5%, as shown by BBRI, an infrequently fluctuated stock. Based on these numbers, there is still room for improvement. Modifying the class labeling process can improve accuracy.

Table 6 displays the trading parameters implementation for the class labeling process, including maximum profit, maximum loss, and maximum hold duration. These parameters allow traders to determine the maximum desired profit and loss. Furthermore, it specifies the preferred time limit for traders to hold stock after purchasing it. These parameters are evaluated in 11 different scenarios with varying values.

When the three trading parameters are implemented, there is a significant increase in accuracy compared to the results in Table 5. The continuously fluctuated stocks: ITMG, PTBA, and KBLM, reveals accuracies above 69%, with the highest accuracy of 77.8%. On the contrary, the infrequently fluctuated stocks: BBRI and BBCA, depicts accuracies below 69%, with the lowest accuracy of 56.4%. Thereby, the proposed method is best suited for stocks that have a continuous fluctuation, which corresponds to stocks that are suitable for trading.

6. CONCLUSION

This study proposes a new trading prediction system that automatically predicts the best time to buy and sell stocks by combining technical analysis and support vector machine. Technical indicators used in this paper are simple moving average, relative strength index, stochastic oscillator, Bollinger bands, and Aroon oscillator. SVM is suitable for this proposed method due to the implementation of various technical indicators as inputs, whereas SVM uses non-linear kernel functions to map inputs into higher-dimensional spaces.

Experimentation on five Indonesian stocks compares the performance of the proposed method with and without class labeling parameters in the derivation. The accuracy enhances significantly when the parameters are implemented. The proposed method is suitable for trading as it shows high accuracy on continuously fluctuated stocks, with the highest accuracy of 77.8%.

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