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New Approach for E-Commerce Stock Prices Prediction: Combination of Machine Learning and Technical Analysis

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Abstract
Forecasting stock market is always a challenge task for the investors. This study aimed to develop a new approach for forecasting the price movements of e-commerce stocks. The signals emitted by the technical indicators are used as the features for two machine learning algorithms in predicting the stocks movements. The technical indicators used in this study were Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI) and Stochastic Oscillator (SO). Meanwhile, the machine learning algorithms used in this study were Random Forest (RF) and K-Neighbor Nearest (KNN). The findings of this study indicated that the inclusion of signals emitted by MA rule with 5-days short MA and 20-days long MA helps to reduce the error values for the prediction model. Besides that, this study also found that the signals from MA, MACD, RSI and SO fit the prediction model well. The investors are recommended to use machine learning algorithms to predict the price movements of e-commerce stocks. Lastly, investors are recommended to consider the signals from these four technical indicators, MA (5-days short MA & 20 long-MA), MACD, RSI and SO as the reference for their investment strategies in e-commerce stocks.
Keywords: Technical Analysis, Machine Learning, Random Forest, K-Neighbor Nearest

Introduction
The stock market is one of the most appealing creations since it can reflect the financial performance of listed companies, investors' behavioral biases, and capital flow in a market. Most of the time, investors only use two primary analyses -fundamental and technical analysis- to analyze the stock market movements (Kumar et al., 2022). Over the past decades, researchers also have been trying to predict the future performance of stock prices using different factors, such as macroeconomic factors (Ma et al., 2022), institutional factors (Sonenshine, 2022), and environmental factors (Mhadhbi et al., 2021). However, stock market prediction remains a challenging task because it depends on various factors, many of which are unknown (Picasso et al., 2019). In addition, Ayala et al (2022) argued that the stock market data are non-stationary and do not show any linear relationship with other factors, causing the prediction task to be difficult. The assumptions of all the conventional linear statistical models limit the prediction model in capturing the features of stock data (Han et al., 2023).

In contrast, machine learning models could work better in stock market prediction since they do not have any presumptions and able to estimate a function to link both the inputs and outputs (Kumbure et al., 2022).
Previous studies have offered techniques and ideas to solve the enormous problem of predicting the rise and fall of stock prices in specific companies (Mndawe et al., 2021). The prediction of stock prices is generally done by analyzing headlines or financial ratios (fundamental analysis) and signals coming from technical indicators (technical analysis). In the aspect of technical analysis, investors only make their buy or sell decisions based on the signals emitted by the technical indicators. Noteworthy, fund managers tend to use technical analysis as one of their analytical tools in managing the complex portfolio investments (Ahmad et al., 2017). Previous studies have also shown that certain technical indicators are capable in producing abnormal returns in the stock market (Tapa et al., 2016; Ling et al., 2020). However, the main drawback of the previous findings is that they are database specific and may not generalized to other stocks. In addition, the technical indicators may not send the same signals at a given time.

To overcome these drawbacks, this study aims to fill the knowledge gap by combining the technical analysis with machine learning algorithms to predict stock price movements. The main objectives of this study are below:

(i) To identify whether signals of technical indicators are appropriate features for the machine learning model.
(ii) To identify the appropriate machine learning model for the prediction of e-commerce stocks price movements.

The outcomes of this study are expected to contribute to the existing literature in two ways. Firstly, by identify the suitable machine learning algorithms for stock price prediction. Secondly, by identifying the suitable features to be included in the prediction mode. These findings shall be used as useful reference for the investors in setting up their investment strategies. The remainder of this study is organized as follows. Section 2 discusses the previous research related to technical analysis and machine leaning algorithms. Section 3 mainly discusses the data, types of technical indicators and machine leaning algorithms. Section 4 presents the results and discussion. Lastly, Section 5 provides the conclusion, limitations and recommendations for future studies.

Literature Review

Technical Analysis and Efficient Market Hypothesis (EMH)

Technical analysis (TA) is widely used by the investor for stock prices prediction based on the signals emitted by technical indicators (Murphy & Gebbie, 2021). Regardless of the types of technical indicators, the logic behind the prediction is always the same, since it makes the stock price prediction based on the historical price movements (Hashemi et al., 2022). Moving average (MA) is also one of the well-known technical indicators and widely used by the investors. MA also considers the contemporary scenario that happened over a specific period of time, and reflect the stock market performance (Barghouthi & Ehsan, 2017). Noteworthy, the choice of different MA lengths also affects the technical analysis's profitability and predictability. Khand et al (2020) revealed that the best MA rule consists of a short MA of 1 day and a long MA of 50 days. On the other hand, Ling et al (2020) provides new evidence to show that majority of the TA strategies able to generate more abnormal returns in Shariah-compliant stock, rather than conventional stocks.

However, using the technical indicator to generate abnormal return is basically against the well-known finance theory, name weak form efficient market hypothesis (EMH). The EMH assumed that stock price fully reflects all the information gleaned from historical market transaction data, rendering technical analysis meaningless (Gerritsen, 2016). Under such a circumstance, it will always be costless for investors to collect the essential information because historical stock price information is readily available to the public. The weak-form EMH also contends that all investors will already know how to interpret the signal if these data provide any meaningful indication of future performance (Kang et al., 2021).

Machine Learning

This section starts with the discussion of some recent studies that use machine learning for stock price prediction. Weng et al (2018) applied four different machine learning methods for the stock price prediction of twenty largest companies in US market. They revealed that random forest (RF) and boosted regression trees methods had the higher accuracy in stock prices prediction, as compared to artificial neural networks (ANN) and support vector machine (SVM). Basak et al (2019) applied the RF and extreme gradient boosting (XGBoost) to predict the stock price movements of ten technology stocks. They found that the RF and XGBoost could predict the stock prices movements accurately, as compared to the ANN. On the other hand, Lohrmann and Luukka (2019) used the opening and closing stock price of S&P 500 as the classification for stock price prediction. They also found that RF was the best prediction method. Khan et al (2020) also predicted the stock prices movements of eight technology stocks by using twelve machine leaning methods. It was worth noting that they constructed the specific sentiment indices for the technology stocks and realized that it was an important feature for the stock price prediction. Similarly, they also found that RF had the highest accuracy of stock price prediction. Ampomah et al (2020) predicted the stock prices of six US stocks by using five different machine learning methods. They found that the accuracy for the stock price prediction was more than 80%, in which the ExtraTrees method had the highest accuracy. In summary, the random forest tends to be suitable machine learning method for stock price prediction.

Data and Methodology

This section discusses the data and methodology to be applied in this study. Figure 1 shows the analysis procedure which start with data collection and followed by various analyses. First, this study collects the daily stock prices of the 5 largest market capitalization e-commerce listed companies from Yahoo Finance. Thereafter, this study applies four well-known technical indicators including moving average (MA), moving average convergence divergence (MACD), relative strength index (RSI), and stochastic oscillator (SO) to identify the buy and sell signals.

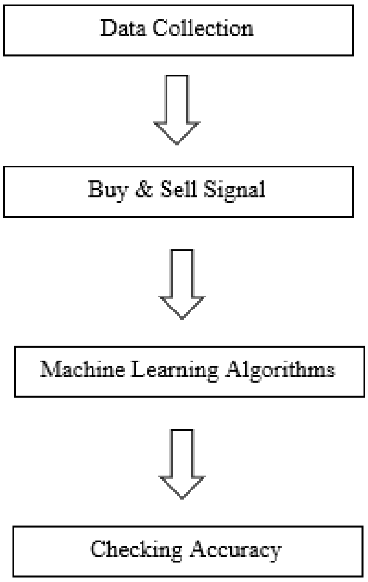

Figure 1: Research Procedure

Technical Indicators

Moving Average (MA)

The moving average (MA) refers to the average of stock price over the period of n-days. The short- and long-MA can be calculated as below

n-day MA = $\frac{\sum_{i=1}^{n} SP_n}{n}$, where the n = 1, 2, 3, 4, 5, 10, 20, 30, 40, and 50.

The short-MA refers to the 1-, 2-, 3-, 4-, 5-days MA, while the long-MA refers to the 10-, 20-, 30-, 40-, 50-days MA.

Figure 2 shows the formation of buy and sell signals under MA. The buy signal is emitted when the short-MA is above the long-MA, while the sell signal is emitted when the long-MA is below the sell-MA.

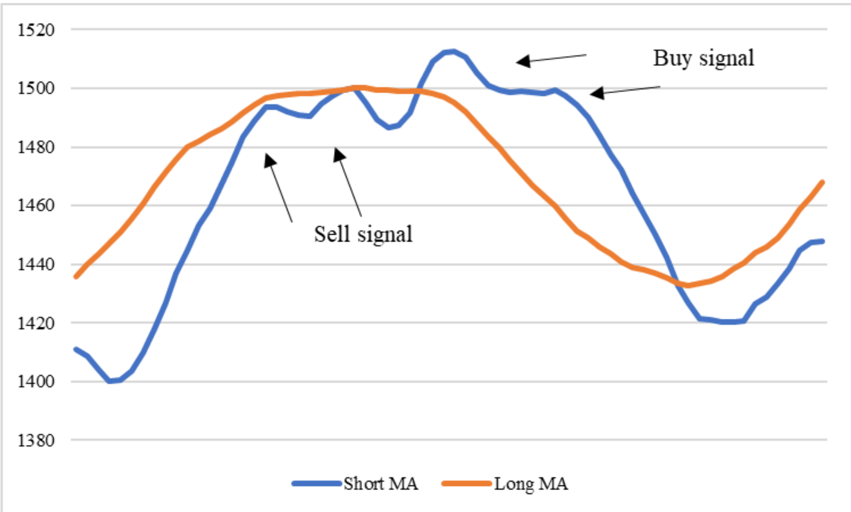

Figure 2: Formation of Buy and Sell Signal (Moving Average)

This study also used ratio of short MA to the long MA as the features for the prediction model. This ratio able to reflect the strength of the buy and sell signals. The ratio of more than 1 simply refers to the buy signal, whereas the ratio of less than 1 refers to the sell signal.

Moving Average Convergence Divergence (MACD)

MACD shows the relationship between two EMA. The MACD can calculated by subtracting the 26-days period EMA from the 12-days period EMA. Then, the 9-days EMA is used as the signal line. Figure 3 shows the bullish confirmation under MACD. The bullish condition is confirmed when the MACD cross above the 9-days EMA, while the bearish condition is confirmed when the MACD cross below the 9-days EMA.

Figure 3: Bullish Confirmation - MACD

This study also used ratio of MACD to the 9-days EMA as the features for the prediction model. This ratio able to reflect the strength of the bullish and bearish condition. The ratio of more than 1 simply refers to the bullish condition, whereas the ratio of less than 1 refers to the bearish condition.

Relative Strength Index (RSI)

The calculation of ESI involved with many steps. Firstly, the up-close (UC) or down-close (DC) should be determined and calculated:

If the $C_{i,t} > C_{i,t-1}$, then $UC_{i,t} = C_{i,t} - C_{i,t-1}$, otherwise $UC_{i,t} = 0$.

If the $C_{i,t-1} > C_{i,t}$, then $DC_{i,t} = C_{i,t-1} - C_{i,t}$, otherwise $DC_{i,t} = 0$.

Where $C_{i,t}$ refers to the closing price of stock *i* at day *t*; C_{t-1} refers to the closing price of stock *i* one day before day *t*; $UC_{i,t}$ refers to the difference between the $C_{i,t}$ and $C_{i,t-1}$ if $C_{i,t} > C_{i,t-1}$. $DC_{i,t}$ refers to the difference between the $C_{i,t-1}$ and $C_{i,t}$ if $C_{i,t-1} > C_{i,t}$.

Thereafter, the average of $UC_{i,t}$ and $DC_{i,t}$ over a specific period are calculated. The relative strength (RS) of stock *i* at day *t* is equal to the average of UC divided by the average of DC. Lastly, the RSI is calculated as below.

$$RSI_{i,t} = 100 - \frac{100}{1 + RSi,t}$$

RSI ranges from 0 to 100. The RSI below 30 refers to the *oversold* zone, while the RSI value above 70 refers to *overbought* zone.

Stochastic Oscillator (SO)

The Stochastic Oscillator is also known as K value. The K value is calculated as below.

$$K_{i,t} = \left(\frac{C_{i,t} - min(C_{i,1}, C_{i,2}, C_{i,3}, \ldots\ldots C_{i,14})}{max(C_{i,1}, C_{i,2}, C_{i,3}, \ldots\ldots C_{i,14}) - min(C_{i,1}, C_{i,2}, C_{i,3}, \ldots\ldots C_{i,14})}\right) x\ 100$$

Where $C_{i,t}$ refers to the closing price of stock *i* at day *t*; $min(C_{i,1}, C_{i,2}, C_{i,3}, \ldots\ldots C_{i,14})$ refers to the lowest price of stock *i* over the past 14 days; $max(C_{i,1}, C_{i,2}, C_{i,3}, \ldots\ldots C_{i,14})$ refers to the highest price of stock *i* over the past 14 days.

Similar to the RSI, the value of K ranges from 0 to 100. The K value equal or more than 80 refers to the overbought zone, while the K value equal or less than 20 refers to the oversold zone.

Machine Learning (ML)

In this study, the signals emitted by the technical indicators are used as features for the forecasting approach. The signals are used as input to predict the stock prices (see Figure 4). Two different machine learning techniques, namely Random Forest (RF), and K-Nearest Neighbors (KNN) are used to predict the stock price movements. The R^2 is used to measure the goodness of fit for the prediction model. Then, the accuracy of the prediction is then determined using three metrics, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

Random Forest (RF)

A RF algorithm refers to the collection of multiple decision trees (DT) by using a bootstrap sampling from the training dataset. Each of the decision tree is built based on an input random vector, which tend to add the randomness factor to prevent from overfitting the data. For the regression estimation, the output of RF is mainly the continuous variable Y.

K-Nearest Neighbor (KNN)

KNN algorithm is one the simplest machine learning algorithms to be implemented. KNN is a non-parametric algorithm; hence it does not presume an underlying distribution of the data. It is helpful for practical issues where the data frequently deviates from theoretical predictions. Additionally, KNN does not have an explicit training phase, which suggests that relatively little time is needed to train the model. In contrast to other machine learning techniques, the computations of KNN are based on the entire dataset. However, there are temporal and memory costs associated with doing so.

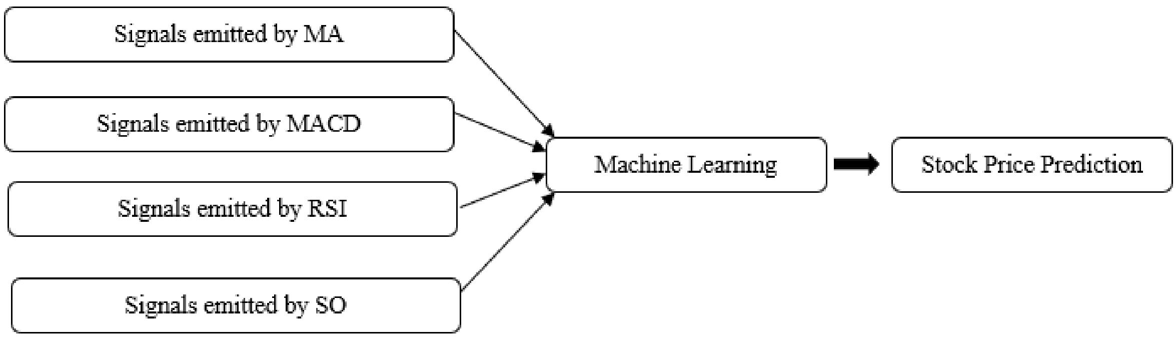

Figure 4: Proposed Approach for Stock Price Prediction

Following Lee et al (2022), this study is using five different evaluation matrices to compared the predicted data and actual data. These five evaluation matrices including (i) coefficient of determination (R^2), (ii) root-mean-square error (RMSE), (iii) mean absolute error (MAE), (iv) mean absolute percentage error (MAPE), and (v) weighted absolute percentage error (WAPE).

Evaluation Matrices

Coefficient of Determination (R^2)

R^2 simply refers to the correlation between the actual data and predicted data. It ranges from 0 to 1, in which higher value is always preferable. The R^2 is calculated as below:

$$R^2 = 1 - \frac{SSE}{SST}$$

where SSE refers to residual sum of square, SST refers to total sum of squares.
However, the R^2 cannot be used to determine whether the prediction model able to fit the actual data. Lee et al (2022) also stated out a good prediction model might have low R^2, while a biased prediction model might have high R^2.

Root Mean Square Error (RMSE)

RMSE refers to the standard deviation of the residuals, and it is calculated based on Euclidean distance between the actual data and predicted data. The RMSE is calculated as below:

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

where y_i refers to the actual data, $\hat{y}_i$ refers to the predicted data.

Mean Absolute Error (MAE)

MAE is basically the calculation of the average for the absolute errors. The MAE is calculated as below:

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

Mean Absolute Percentage Error (MAPE)

MAPE present the accuracy in the form of ratio, and it is calculated as below:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

Weighted Absolute Percentage Error (WAPE)

WAPE is an evaluation matric that weighs heavier on the error values with high realized value. WAPE is calculated as below:

$$\text{WAPE} = \frac{\sum_{t=1}^{n}|y_i - \hat{y}_i|}{\sum_{t=1}^{n}|y_i|} \times 100$$

Lee et al. (2022) also mentioned that there is no single evaluation matric that able to fit all the prediction models. Hence, using various types of evaluation matric to measure the accuracy of prediction model is a better option.

Results and Discussion

This section discusses the results obtained by embedding the signals of technical indicators in machine learning algorithms for the e-commerce stocks. The name of these stocks are replaced with stock A, B, C, D, and E to reduce the unnecessary conflicts. Table 1 presents the descriptive statistics for the five e-commerce stocks. The mean daily return for all the five stocks were low, ranged between -0.0261% to 0.1940%. The standard deviation of the daily returns were relatively high, as compared to the low mean return. Besides that, the range for the daily returns were large, in which the largest range is up to 78.9481%. These results indicated that the stock price of e-commerce stocks is highly fluctuated.

Table 1
Descriptive Statistics

Stock	A	B	C	D	E
Mean	0.0909	-0.0261	0.0603	0.1500	0.1940
Standard Deviation	2.2084	2.8924	3.2233	3.8970	5.1077
Skewness	0.0922	1.7484	1.4884	0.5633	1.6204
Minimum	-14.0494	-13.3422	-15.8333	-17.6570	-22.8880
Maximum	13.5359	36.7639	39.3649	32.0755	56.0601
Range	27.5853	50.1061	55.1983	49.7325	78.9481

Notes: The name of the stocks are not disclosed. Five of the stocks are named as Stock A, B, C, D and E.

Table 2 shows that RF algorithms always have the higher R^2 and lower RMSE, MAE, MAPE and WAPE than KNN algorithms. These results indicated that RF was a better prediction model as compared to KNN. Consistent with findings of Weng et al (2018); Basak et al (2019); Lohrmann and Luukka (2019); Khan et al (2020), RF was better machine learning algorithms for stock price prediction. On the other hand, five different set of features had been used and tested. The first set of features is excluding the signals emitted by MA, while the other four set of features include the signals emitted by four different MA rules. Table 1 further shows that the inclusion of the MA (5,20) signals tends to reduce the RMSE, MAE, MAPE and WAPE for stock A, B and E. Thus, MA with short MA of 5 days and long MA of 20 days should be used by the investor when they are analyzing the e-commerce related stocks. Specifically, the short MA of 5 days would simply capture the stocks' information over the past 5 trading days, whereas the long MA of 20 days would simply capture the stocks' information over the past 20 trading days (equivalent to a month). Investors are recommended to observe and compare the e-commerce stocks movements for the past 5 days with the e-commerce stock movements over the past 20 days. However, investors should not solely focus on the signals of MA, but also the signals emitted by other technical indicators.

Table 2
R-Squared and Error Value for Prediction Model

Stock	ML	Accuracy	Pred1	Pred2	Pred3	Pred4	Pred5
A	RF	R^2	0.9953	0.9959	0.9962	0.9953	0.9966
		RMSE	2.4490	2.3643	2.3014	2.4622	2.2032
		MAE	1.7481	1.6765	1.6070	1.6996	1.4967
		MAPE	1.4673	1.4632	1.3836	1.4298	1.2522
		WAPE	1.4588	1.3802	1.3216	1.4264	1.2205
	KNN	R^2	0.9573	0.9810	0.9471	0.9700	0.9482
		RMSE	7.4847	5.0087	8.1259	6.1441	8.3035
		MAE	3.7116	3.1388	4.5417	3.1942	4.0368
		MAPE	3.4204	2.6752	4.1991	2.8969	3.5448
		WAPE	3.1580	2.5810	3.8026	2.6967	3.4098
B	RF	R^2	0.9903	0.9937	0.9925	0.9936	0.9933

		RMSE	5.1368	4.1976	4.8751	3.9215	4.0823
		MAE	3.4844	3.0843	3.1971	2.9797	2.8501
		MAPE	2.0500	1.8500	1.9471	1.7370	1.5852
		WAPE	1.9111	1.7340	1.7750	1.6140	1.5394
	KNN	R^2	0.9006	0.9526	0.9475	0.9734	0.9362
		RMSE	16.6756	10.3242	11.1208	8.3458	13.3934
		MAE	7.8551	5.5109	5.7599	5.0014	6.9366
		MAPE	5.1730	3.0649	3.5723	3.1248	4.6450
		WAPE	4.3798	2.9614	3.1622	2.7545	3.8555
C	RF	R^2	1.0000	0.9999	0.9997	0.9999	0.9999
		RMSE	0.0882	0.1954	0.3559	0.1915	0.1964
		MAE	0.0595	0.0843	0.1120	0.0819	0.0867
		MAPE	0.1230	0.1717	0.1745	0.1720	0.1792
		WAPE	0.1149	0.1637	0.2017	0.1532	0.1638
	KNN	R^2	0.9077	0.9478	0.9499	0.9316	0.9049
		RMSE	6.6113	4.9545	4.8229	5.7755	6.6337
		MAE	3.1097	2.4989	2.6264	3.0599	2.9679
		MAPE	6.5811	5.5767	6.5758	6.9825	7.3758
		WAPE	5.8708	4.7916	5.0764	5.8428	5.5817
D	RF	R^2	0.9927	0.9952	0.9997	0.9999	0.9999
		RMSE	7.6846	6.3763	0.3559	0.1915	0.1964
		MAE	5.0274	4.3224	0.1120	0.0819	0.0867
		MAPE	2.8105	2.2975	0.1745	0.1720	0.1792
		WAPE	2.8396	2.4061	0.2017	0.1532	0.1638
	KNN	R^2	0.9533	0.9478	0.9499	0.9316	0.9049
		RMSE	19.5535	4.9545	4.8229	5.7755	6.6337
		MAE	9.2978	2.4989	2.6264	3.0599	2.9679
		MAPE	7.1611	5.5767	6.5758	6.9825	7.3758
		WAPE	5.3076	4.7916	5.0764	5.8428	5.5817
E	RF	R^2	0.9957	0.9950	0.9947	0.9940	0.9919
		RMSE	3.0770	3.0331	3.1699	3.3511	4.0552
		MAE	1.8837	1.9154	1.9714	1.9914	2.3260
		MAPE	3.0898	2.8128	3.2478	2.8506	3.2191
		WAPE	2.7036	2.8362	3.0871	3.0142	3.4876
	KNN	R^2	0.9569	0.9541	0.9005	0.9549	0.9545
		RMSE	8.4837	8.6882	13.5389	8.6902	9.7236
		MAE	4.5177	4.8051	6.6857	4.7508	5.0295
		MAPE	10.2830	10.9757	14.1125	10.5235	10.7598
		WAPE	6.8886	7.7390	10.3614	7.5743	7.3451

Notes: ML refers to Machine Leaning; RF refers to Random Forest; KNN refers to K-Neighbor Nearest; R^2 refers to R-squared; RMSE refers to Root Mean Square Error (RMSE); MAE refers to Mean Absolute Error; MAPE refers to Mean Absolute Percentage Error; WAPE refers to Weighted Absolute Percentage Error; Pred1 refers to the first set of features which included the signals of MACD, RSI, SO, and the opening-, highest-, lowest-, closing-price in the previous day; Pred2 refers to the second set of features which included all the features of Pred1 with the signals of MA(1,5); Pred3 refers to the second set of features which included all the features of Pred1 with the signals of MA(2,5); Pred4 refers to the second set of features which included all the features of Pred1 with the signals of MA(5,10); Pred5 refers to the second set of features which included all the features of Pred1 with the signals of MA(5,20).

Conclusion

This study embedded the technical analysis with machine learning algorithms to predict the stock price of five largest market capitalization e-commerce stocks. This study also applied four technical indicators – Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Stochastic Oscillator (OS). The signals of technical indicators are used together with the opening-, highest-, lowest-, and closing-prices from previous day as the features for the machine learning algorithms. This study also applied two machine learning algorithms – Random Forest (RF) algorithms and K-Neighbor Nearest (KNN) algorithms to predict the stock prices. Five different set of features have been included in the prediction models. Lastly, the accuracy of the prediction models are tested by using R-squared (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Weighted Absolute Percentage Error (WAPE). The findings of this study indicated that RF performed better than KNN in predicting the stock price movements of e-commerce stocks. The results of R^2 also indicated that the signals of technical indicators fit the regression model well. Besides that, this study revealed that the inclusion of MA rule (combination of *5 days* short MA and *20 days* long MA) lower down the RMSE, MAE, MAPE, and WAPE. This study recommends the investor to use the machine learning algorithm to predict the stock price prediction. Moreover, investors are suggested to use the compare the 5-days MA with 20-days MA before making any investment decision in e-commerce stocks. Hence, this study contributed to the existing literature by providing new evidence concerning the signals of technical indicator to be used as the features in machine learning model. Secondly, this study also figures out the appropriate technical rules and machine learning model for the prediction of e-commerce stock price.

However, this study faced several limitations. First, this study focuses only on the e-commerce stocks, which limits the generalization of the findings to the stocks from another sector. Secondly, this study only included the signals of four technical indicators as the features in the prediction model. Future study may consider to include more technical indicators for the stock price prediction. Thirdly, this study only tested the accuracy of two machine learning algorithms. Future studies should include other machine learning algorithms. The major practical implication of the findings is that investors should consider machine learning algorithms in stock price prediction, despite it is more complicated. This is due to the reason that machine learning algorithms do not have any assumptions as the conventional statistical model. Thus, the machine learning algorithms able to capture as much potential factors as possible. The findings of this study also underscore the importance of monitoring the signals emitted by different technical indicators to get the more accurate stock price prediction. Lastly, the proposed approach can also serve as a reference for investors before making an investment decision for other stocks.

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