Application of Machine Learning With News Sentiment in Stock Trading Strategies

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Abstract

This study empirically tested the feasibility of machine learning in trading strategies using technical indicators and news information as the feature variables for machine learning. Six indicators were adopted in this study, including moving average (MA), moving average convergence/divergence (MACD), relative strength index (RSI), stochastic oscillator (KD), and on-balance volume (OBV), and news sentiment ratio (SR) developed in this study via text mining. Selected machine learning models, including support vector machine (SVM), eXtreme Gradient Boosting (XGBoost), recurrent neural network (RNN), and long short-term memory (LSTM), were also employed for investigation. This study backtested the daily historical data of the constituent stocks in the Taiwan Top 50 ETF from January 1, 2003, to December 31, 2018, using three categories of trading strategies along with conventional and countertrend operations. The following conclusions were drawn after analyzing the performance of these trading strategies via various means: 1. Technical indicators such as MA, MACD, and RSI performed poorly in most cases. 2. Specific parameters were of relative importance to several technical indicators, including MA, MACD, RSI, and OBV. 3. OBV was a technical indicator with a positive impact on trading strategies. 4. The machine learning-based XGBoost models were able to outperform trading strategies with technical indicators under specific scenarios. 5. SR, the news sentiment ratio developed in this study, could not significantly improve the performance of machine learning models. The empirical results of this study suggest that these machine-learning models are capable of analyzing long-term stock price movements to some extent.

Keywords: machine learning, news sentiment, technical indicator, XGBoost, trading strategy

1. Introduction

As the global economy continues to evolve, people can engage in numerous types of investment. No matter which type of investment one engages in, it is a must for an investor to carry out fundamental, technical, chip, and news analyses with the hopes of making investment decisions to generate excess returns. Stocks are one of the most widely known tools in the investment world.

According to the Taiwan Stock Exchange (TWSE), the average daily trading volume of TWSE listed stocks reached NT$113.88 billion in 2019, with the size of Taiwan's stock market amounting to NT$34.81 trillion in November 2019. Taiwan's stock market is now apparently not as active as it was yesteryear if inflation is taken into account, yet the accumulated number of investors with trading accounts increased by 7.732 million from 10.916 million in January 2000 to 18.648 million in December 2018. The number of TWSE listed companies also rose from 462 companies in January 2000 to 928 in December 2018, equivalent to an increase of 466 companies over this period. There is an increasing trend in the number of Taiwanese people engaging in stock trading and the number of listed companies in Taiwan's stock market. Since the stock market is the most common investment channel readily available to the public, this study endeavors to develop stock trading strategies to generate excess returns.

According to the efficient market hypothesis proposed by Fama (1970), market efficiency can be categorized into three forms - "weak form," "semi-strong form," and "strong form." When the market is in weak-form efficiency, there is no opportunity to generate excess returns using technical indicators. Investors are unable to generate excess returns using historical stock price data, technical indicators, or price/volume data as a means of analysis. When the market is in semi-strong form efficiency, all publicly available information is already reflected in stock prices, and investors are unable to generate excess returns using the information above as a means of information analysis. Nevertheless, investors in the market are constantly trying to generate excess returns using a wide array of technical indicators derived from historical stock price data or predict stock price movements using publicly available information. All these attempts have proven time and time again that there is no way to suppress people's desire to predict stock price movements and generate excess returns despite the existence of the efficient market hypothesis.

The rapid development of information and communication technology in today's society has led to a variety of channels for the public to obtain information. Taiwan has also witnessed the evolution of news media, to the mushrooming of newspapers in later years, but also the decline of daily print newspapers and the rise of electronic media and self-media. An explosion of news media has also made it impossible to rely solely on the human brain to go through news articles line by line and then make investment judgments based on macroeconomic conditions and microeconomics differences. The volume of news and information within a day is enormous, as there are hundreds of financial news articles and thousands of global news articles daily. While humans are emotional and rational creatures, it is also not easy for the human brain to go through a large volume of news and then make objective judgments accordingly. Moreover, the anchoring effect may arise after an individual reads the first few pieces of news and thus influences subsequent news reading and data absorption, which is unfavorable to stock market analysis.

Public information has a significant influence on investment performance as well. Having mentioned that news information is an integral part of investment analysis, Alamsyah et al. (2019) analyzed the relationship between stock returns and headline news using a couple of machine learning after classifying news into positive and negative sentiments and predicted the stock returns of 20 companies listed on the Indonesia LQ45 Index, found a correlation between news and stock returns. Meanwhile, Apergis and Pragidis (2019) examined the correlations of a sentiment index with European Central Bank (ECB) announcements and stock returns. Their study's empirical results also pointed towards a significant correlation between the sentiment index and stock returns. Lansing and Tubbs (2018) discovered that the sentiment index was able to predict stock price movements. Zheng (2013) selected the turnover ratio, the long-to-short ratio, the proportion of day trading, and the overbought/oversold position of foreign investors and other investors as proxy variables for investor sentiment indicators and applied investment strategies to 493 stocks listed on Taiwan's stock market while using the aforesaid proxy variables as entry and exit signals. However, the results of his study revealed that none of the proxy variables for sentiment indicators was able to produce superior trading performance. Lin (2013) developed a Chinese sentiment word list and performed regression analysis to investigate the correlation between the sentiment scores obtained using the Chinese sentiment word list and stock performance. She found that news reports' positive or negative sentiments can be measured effectively using the sentiment word list developed in her study.

In the current context and setting, this study discovers that there has been no lack of research on the validity of technical indicators or news sentiment derived from public information and the prediction of stock returns or stock price movements; however, studies that combine these two areas of research on stock prices have been few and far between. Therefore, this study intends to develop a set of trading strategies based on the two areas described above of research on stock price and then conduct backtesting on companies with better liquidity and relatively large size in Taiwan's stock market using this set of trading strategies. In addition, this study compares the set of trading strategies it has developed and technical indicator-based trading strategies in previous studies before empirically investigating whether the combination of technical indicators and news sentiment can effectively improve various performance indicators.

2. Literature Review

2.1 Technical Indicators

The empirical results of a previous study conducted using technical indicators or trading rules, such as filter rules, MA, RSI, bias ratio (BIAS), MACD, the Williams Percent Range (W%R), and KD for verification tended to support the inability of technical analysis to generate excess returns (Chen, 1998). Chi (2006) found that stock prices supported the Random Walk Hypothesis, where excess returns cannot be generated using technical indicators.

Japanese scholars Deng et al. (2011) backtested the data of the stocks of three famous Japanese companies in the U.S. stock market from January 2006 to August 17, 2008, using several technical indicators, including MACD, BIAS, and rate of change (ROC), in combination with news and comment sentiment indicators developed using a linguistic approach. According to the results of their study, the SVR-A and MKL-A models yielded better data for mean absolute percentage error (MAPE), mean absolute error (MAE), and root-mean-square error (RMSE), with the MKL-A model, even outperforming the SVR-A model. Huang (2008) proved that MA strategies could yield excess returns when applied to specific instruments such as the U.S. government 30-year bond, the U.S. No. 11 Futures, and stock market exchanges such as TAIEX.

Kwon and Kish (2002) adopted the golden cross and death cross trading strategies to perform backtesting on the NYSE value-weighted index over the period from 1962 to 1996 based on the traditional t-test and the GARCH-M model. Their study showed that while the technical analysis strategy outperformed the buy-and-hold strategy, the technical analysis strategy performed relatively poorly between 1985 and 1996, which, in their opinion, could be the result of a gradual improvement in market efficiency.

2.2 News Sentiment

In today's information-rich society, news reports are a pivotal source of information that investors read and analyze daily. Therefore, it is crucial to explore the influence of news reports on the market. Wang (2017) found that news sentiment is not able to predict returns on index returns if market conditions are not differentiated. However, in a bull market, investors react faster to positive news but slower to negative news, causing negative news to have predictive power under this market condition; conversely, in a bear market, investors react faster to negative news but slower to positive news, which in turn causes positive news to have predictive power under this market condition. Ferguson (2015) discovered that the predictive power of news sentiment was greater among small-sized firms and firms with high media coverage, and performed backtesting using a trading strategy developed based on news sentiment for firms with high media coverage from 2003 to 2010, which yielded an excess return of 14.9%. Based on the studies above, it is evident that the empirical results on the predictive power of news sentiment for stock prices are more consistent and tend to support the fact that news sentiment has predictive power for stock prices.

Shapiro and Wilson (2017) proposed that news sentiment is a new economic indicator. Carroll, et al. (1994), along with Bram and Ludvigson (1998), argued that the accuracy of economic forecasts could be improved using the consumer sentiment index. Today, the future directions of the economy are no longer predicted using standardized economic indicators such as unemployment, inflation, interest rates, and GDP only. Shapiro and Wilson (2017) extracted and analyzed sentiment in news articles from 16 major newspapers in the U.S. to construct a news sentiment index. The line chart plotted using various news sentiment indices in their study showed significant variations in the news sentiment indices during a number of key historical events, such as the Russian financial crisis in August 1998, the September 11 terrorist attacks in 2001, and the Lehman Brothers bankruptcy in September 2008. Furthermore, the correlation analysis of the news sentiment indices in their study revealed that both indices were positively correlated with the federal funds rate (FFR), the S&P 500 stock price index, real personal consumption expenditures (PCE), total non-farm employment, and industrial production (IP). The empirical results on whether news sentiment indices can predict the economy's future directions have proved to be affirmative.

According to previous studies, only predicting stock prices using historical and textual data has been proven inadequate because complex political and economic factors, leadership changes, trade patterns, industrial trends, etc., influence stock price movements. Mohan et al. (2019) not only attempted to perform sentiment analysis using algorithms such as SVM, Naïve Bayes regression, and deep learning but also collected a large amount of time-series stock price data and related news articles to carry out an empirical analysis using the daily stock prices of S&P 500 firms over five years and 265,0000 financial news articles related to these firms. They found that sentiment in news reports can truly enhance the ability to predict stock price movements.

Meyer et al. (2017) investigated the effect of news sentiment on stock prices at different frequencies of news extraction. They extracted news articles primarily from the Wall Street Journal, Reuters, the New York Times, Yahoo Finance, etc., at an increased news extraction frequency of 30 minutes per time, trained their models using SVM, and determined news sentiment using two tools. Based on the results of their study, news sentiment can be determined more effectively via machine learning-based NLP, which helps investors and professional managers in the market obtain a more accurate analysis of news sentiment when making investment decisions.

News sentiment-related literature persistently mentioned that machine learning or deep learning could increase the accuracy of determining news sentiment and enhance the predictive power of models that employ news sentiment as an independent variable. News sentiment indices developed using either a lexical approach or NLP can improve the ability of models to predict stock price movements. Text mining comes into play as a critical technique while the computing power of computers becomes a prerequisite to analyzing the massive amount of rapidly changing news so that people can obtain important information from news and screen out useless and complex information. Therefore, this study employs news sentiment and technical indicators as the key independent variables of the models it developed to improve the overall predictive power of these models for stock prices.

2.3 Machine Learning

Gao and Chai (2018) predicted the closing prices of stocks using recurrent neural networks (RNN), specifically

LSTM, as training models. According to their findings, this model demonstrated better predictive power than non-machine learning-based models. Meanwhile, Namdari and Li (2018) analyzed stocks listed on NASDAQ from June 2016 to December 2017 using the multi-layer perceptron (MLP) combined with stock prices, financial data, and technical indicators for model training. The empirical results of their study revealed that the best prediction results were obtained using the combination of both methods, which also suggested that the market is not fully efficient. Wu et al. (2015) proposed a hybrid model consisting of three combination models, namely the autoregressive moving average (ARMA) and SVM model, the ARMA and probabilistic neural network (PNN) model, and the back-propagation PNN (BP-PNN) model. Based on their findings, the hybrid model developed in their study demonstrated higher prediction accuracy.

Liu (2019) conducted an annual performance evaluation of the historical data of TAIEX from 2014 to 2018 based on the aforesaid models and found that the overall performance achieved using these models was better than that using the buy-and-hold strategy, with ANN demonstrating the best prediction performance among all models. Usmani et al. (2016), predicted the performance of the Karachi Stock Exchange (KSE) using various machine learning models, namely single layer perceptron (SLP), MLP, radial basis function (RBF), and SVM, discovered that among the aforesaid models, MLP demonstrated the best performance with a 77% prediction accuracy, thereby suggesting that better prediction performance can be achieved using machine learning.

3. Research Methodology

3.1 Sample Description

All the stock price data used in this study are sourced from the Taiwan Economic Journal (TEJ) Corporate Information Database. Sample selection becomes a major focus in this study to investigate whether similar results are observed in Taiwan’s stock market compared with foreign studies. Since it is not easy to identify stocks representing Taiwan’s stock market, it is easier to begin the research process with exchange-traded funds (ETFs).

According to the data provided by TWSE, there are 127 ETFs on TWSE, 21 of which are composed of domestic stocks, including those which are common among investors, such as the Yuanta Taiwan Top 50 ETF, the Yuanta Taiwan Mid-cap 100 ETF, and the Yuanta MSCI Taiwan ETF that track the FTSE TWSE Taiwan 50 Index, the FTSE TWSE Taiwan Mid-cap 100 Index, and the MSCI Taiwan Index, respectively. ETFs, excluding stock index futures, can comprehensively track their constituent stocks. The constituent stocks of the FTSE TWSE Taiwan 50 Index are representative of each industry in Taiwan. Only robust companies with high profitability, promising prospects, active stock trading, a great reputation, and great market recognition can be selected as constituent stocks in this index, and the line-up of constituent stocks in this index is revised quarterly each year based on the actual situation of the companies involved. The FTSE TWSE Taiwan 50 Index has been adding and removing its constituent stocks on an ongoing basis. Ninety-four companies were previously selected as constituent stocks in this index, 25 of which have long been present since its inception. Therefore, the aforesaid 25 companies are included in the sample of this study as they are representative of this index.

3.1.1 Study Period

The study period spans from 2003 to 2018. As pilot data are required for training machine learning models, the period from 2003 to 2005 is set as the machine learning training period, while the validation period spans from 2006 to 2018. Meanwhile, the trading period from 2006 to 2018 is selected for validating trading strategies so that a comparative analysis of trading strategies can be conducted in this study.

3.1.2 Variable Descriptions

According to an investment-themed book titled “Principles of Technical Analysis - A Complete Guide to Investment Trend Analysis Tools,” technical indicators are classified into seven categories, where the application of technical indicators varies by market condition. Gold (2015) investigated the viability of six widely used technical indicators in three categories, namely trend, momentum, and volume, including the Aroon indicator, on-balance volume (OBV), accumulation distribution line (ADL), KD, RSI, and MACD.

This study extracts the technical indicators commonly used by investors in Taiwan’s capital markets as variables for backtesting, consisting of six technical indicators in four different categories as follows:

1. Market trend indicators: MA and MACD.

2. Market momentum indicators: RSI and KD.

3. Market volume indicators: OBV.

4. Market sentiment indicators: SR.

3.2 News Sentiment Ratio (SR)

The effect of media news on the market should not be underestimated because investors read the such publicly available information and use them as a basis for interpreting future market trends. Sentiment derived from the news is a great way to quantify news. This study adopts the National Taiwan University Sentiment Dictionary (NTUSD) in the Chinese language constructed by Ku and Chen (2007) and the Chinese sentiment word list in finance and economics developed by Lin (2013) as the criteria for determining news sentiment, which include 2,812 positive words and 8,276 negative words in NTUSD, along with 369 positive words and 490 negative words in sentiment word list in finance and economics. After removing repeated words in both NTUSD and Chinese sentiment word list, the sentiment-related words used in this study comprised 3,258 positive and 8,329 negative words. A news sentiment index is established for the sample of this study.

Then, this study uses the Jieba module to remove meaningless words in news text, such as spaces, punctuation marks, special symbols, and particles, before importing NTUSD and the Chinese sentiment word list in finance and economics into the Jieba dictionary for word segmentation. Unlike English, Chinese text is composed of individual characters, and the meaning of sentences varies by word segmentation. Interestingly, the Jieba module performs well in word segmentation. Despite word segmentation errors in some technical terms or specific words, this study only focuses on sentiment-related words, which have been imported into the Jieba dictionary in advance. Therefore, no word segmentation errors exist among the sentiment-related words used in this study.

Table 1. News sentiment of TSMC

Date	Total word count	Positive word count	Negative word count	News sentiment ratio
April 2, 2018	467	32	12	0.4545
April 3, 2018	252	25	4	0.7241
April 10, 2018	185	6	2	0.5000
April 11, 2018	439	32	6	0.6842
April 16, 2018	427	22	16	0.1578
April 19, 2018	923	35	29	0.0937
April 20, 2018	2594	120	80	0.2000
April 21, 2018	202	4	2	0.3333
April 23, 2018	303	15	16	-0.0322
April 27, 2018	106	10	1	0.8181

To calculate the news sentiment ratio (SR). This study writes a for loop using Python to determine the presence of sentiment words in the daily news of each stock and then tally the positive and negative words daily. The news reports of a stock will not be listed if there is no news report about the stock on a particular day. Table 1 presents an example of the overall output of news sentiment for Taiwan Semiconductor Manufacturing Company (TSMC). SR, the news sentiment index developed in this study, is calculated using the method adopted by Lu and Wei (2013).

3.3 Machine Learning

Machine learning is well-known for its ability to extract information from massive amounts of data in recent years. It is suitable for analyzing data and making predictions as it combines statistics, artificial intelligence (AI), and computer science. This study leverages the powerful classification capability of machine learning to formulate long and short-trading strategies to improve trading performance. All machine learning models can be utilized for regression or classification; however, suitability separates these models. Therefore, machine learning models more suitable for classification are chosen as research models in this study.

3.3.1 Model Selection

1. Support Vector Machine (SVM)

SVM is a supervised machine learning model capable of dealing with classification or regression problems. From a two-dimensional perspective, the principle of SVM is to identify the line that can classify the data in a group of data into two categories and ensure the largest distance between the data points so that classification accuracy can be maximized. Having a non-linear concept for data classification is a major feature of this model.

2. eXtreme Gradient Boosting (XGBoost)

XGBoost is a supervised machine-learning model that has evolved from decision trees. The core idea behind XGBoost is to combine several simple models, which can not only provide good predictions for some data but also avoid overfitting in decision trees as a result of enhancing the ability to simulate the characteristics of the training set.

3. Recurrent Neural Network (RNN) and Long Short-term Memory (LSTM)

Both RNN and LSTM are models under the neural network framework, where neural networks are also known as deep learning. However, RNN only refers to outcomes in the previous period. Hence, LSTM has been developed to ensure that RNNs can refer to information from earlier periods. Both RNN and LSTM are particularly suitable for analyzing stock prices because these two models can take the time factor into account.

3.3.2 Model Optimization

The final step is to adjust the parameters of the models so as to achieve better predictive power. Parameters that the models can adjust vary from one model to another. The following section presents the parameters that can be adjusted by each of the three categories of machine learning models.

Table 2. Metrics for model evaluation

Metric	Formula	Definition
Accuracy	$AC = \frac{TP + TN}{TP + FP + TN + FN}$	Total number of correct predictions
Precision	$P_P = \frac{TP}{TP+FP}$ or $P_N = \frac{TN}{TN+FN}$	Positive or negative predictive power
Recall	$RE_P = \frac{TP}{TP+FN}$ or $RE_N = \frac{TN}{TN+FP}$	Model coverage capability
F-measure	$F1 = \frac{2 \times AC \times RE}{AC + RE}$	A measure to reconcile precision and recall

3.3.3 Outcome Evaluation Techniques

The performance of machine learning models needs to be determined using several metrics to learn about the prediction accuracy of the models and investigate whether the models are overfitting the training set data. Table 2 presents the definition of the metrics involved and the methods for calculating these metrics.

3.4 Development of Trading Strategies

3.4.1 Trading Strategies Adopted in Previous Studies

Previous studies mostly formulated trading strategies using technical indicators in combination with the golden cross and death cross indicators. Parameters were selected based on technical indicators that investors commonly used in the market. Gold (2015) discovered that the combination of trend or momentum indicators and volume indicators significantly improves performance indicators, such as win rate, cumulative return, and Sharpe Ratio. Chang (2012) also recommended using two or more technical indicators.

3.4.2 Trading Strategies With Optimal Parameters in Technical Analysis

Table 3. Scope of parameter settings

Variable	Scope
MA	$MA = (C_1 + C_2 + \cdots + C_n) \div n$,where 1. C represents the closing price. 2. n represents the number of trading days. 3. Short-term MA (2-20) and long-term MA (2-10)
MACD	$DIF = EMA(C, n_1) - EMA(C, n_2)$, $MACD = EMA(DIF, n_3)$,where n_1 (2-20), n_2 (2-30), and n_3 (2-10).
RSI	$RSI = 100\% \times \frac{UP}{UP+DW}$,where 1. $UP =$ $(\text{Closing price on the trading day when stock price increases} -$ $\text{closing price on the previous trading day})/up_t$ 2. $DW =$ $(\text{Closing price on the trading day when stock price decreases} -$ $\text{Closing price on the previous trading day})/dw_t$ 3. Short-term RSI (2-10) and long-term RSI (10-20) 4. Lower limit of RSI for overbought signal (70, 75, …, 95) and upper limit of RSI for oversold signal (5, 10, …, 30)
KD	$K_t = \frac{r-1}{r} K_{t-1} + \frac{1}{r} RSV_t$, $D_t = \frac{r-1}{r} D_{t-1} + \frac{1}{r} K_t$, $RSV_t = (C_t - L_C) \div (H_c - L_C) \times 100$,where 1. Number of days (5-20) and smoothed values, r (2-9) 2. Upper limit of KD for buy signal (5, 10, …, 30) and lower limit of KD for sell signal (70, 75, …, 95).

This study uses Python to write a for loop for the strategies developed based on the trading strategies adopted in previous studies, with the intention of the top five combinations of parameters by cumulative return, listed in Table 3.

3.4.3 Development of Machine Learning-based Trading Strategies

The technical indicators are captured using Python, while their values are calculated using the Python talib module. During the trading process, a 0.1425% fee is incurred for each stock purchase or sale, and a 0.3% securities transaction tax is deducted during a stock sale, while the trading price is determined based on the adjusted closing price (Adj Close). Excluding abnormal stock price volatility caused by ex-dividends is more conducive to long-term observations. A long position is taken when a buy signal is obtained from a trading strategy, whereas a short position is taken when a sell signal is obtained from the trading strategy. In addition, only one position, either long or short, is taken at all times.

Trading strategies with technical indicators generally consist of trend, momentum, and volume indicators. However, these strategies are not implemented in combination with news sentiment indices due chiefly to the difficulty in applying news sentiment indices as well as the threshold and restrictions of such indices. Hence, this study adopts six indicators, MA, MACD, RSI, KD, OBV, and SR, combined with commonly used parameters. This study uses parameters from the trading strategies adopted in previous studies as the data for training machine learning models to test their effectiveness empirically. Since the machine learning models adopted in this study are supervised models, creating labels for model training is necessary. This process is carried out according to the following three steps.

Table 4. Labels for model training

Label	Method for determining the label
Adjusted closing price on the 1st day (Adj Close1)	1 if Adj Close on the (t+1)th day ≧ Adj Close on the t-th day 0 if Adj Close on the (t+1)th day < Adj Close on the t-th day
Adjusted closing price on the 5th day (Adj Close5)	1 if Adj Close on the (t+5)th day ≧ Adj Close on the t-th day 0 if Adj Close on the (t+5)th day < Adj Close on the t-th day
Adjusted closing price on the 20th day (Adj Close20)	1 if Adj Close on the (t+20)th day ≧ Adj Close on the t-th day 0 if Adj Close on the (t+20)th day < Adj Close on the t-th day
Adjusted closing price on the 60th day (Adj Close60)	1 if Adj Close on the (t+60)th day ≧ Adj Close on the t-th day 0 if Adj Close on the (t+60)th day < Adj Close on the t-th day
Adjusted closing price on the two-day MA Line (Adj CloseMA2)	1 if Adj CloseMA2 on the (t+1)th day ≧ Adj CloseMA2 on the t-th day 0 if Adj CloseMA2 on the (t+1)th day < Adj CloseMA2 on the t-th day

Step 1: Data preprocessing. Table 4 presents the labels for model training, while Table 5 lists the methods for processing feature variables.

Table 5. Methods for processing feature variables

Original variable	Normalization	Label	Buy/ Sell signal	Crossover
MA5 MA20	Calculated using Formula: $y = (x - x_{min}) \div (x_{max} - x_{min}) \times 2 - 1$	1 if MA on the t-th day ≧ MA on the (t-1)th day -1 if MA on the t-th day < MA on the (t-1)th day	–	1 when the MA5 line breaks above the MA20 line -1 when the MA5 line breaks below the MA20 line
MACD (12, 26, 9)		1 if MACD on the t-th day ≧ MACD on the (t-1)th day -1 if MACD on the t-th day < MACD on the (t-1)th day	1 when MACD > 0 -1 when MACD < 0	–
RSI5 RSI10		1 if RSI on the t-th day ≧ RSI on the (t-1)th day -1 if RSI on the t-th day < RSI on the (t-1)th day	1 when RSI < 20 0 when 20 < RSI < 80 -1 when RSI > 80	1 when the RSI5 line breaks above the RSI10 line -1 when the RSI5 line breaks below the RSI10 line
KD (9, 3, 3)		1 if KD on the t-th day ≧ KD on the (t-1)th day -1 if KD on the t-th day < KD on the (t-1)th day	1 when KD < 20 0 when 20 < KD < 80 -1 when KD > 80	1 when the K line breaks above the D line -1 when the K line breaks below the D

Original variable	Normalization	Label	Buy/ Sell signal	Crossover
				line
OBV		1 if OBV on the t-th day ≧ OBV on the (t-1)th day -1 if OBV on the t-th day < OBV on the (t-1)th day	–	–
SR		1 if SR on the t-th day ≧ SR on the (t-1)th day -1 if SR on the t-th day < SR on the (t-1)th day	–	–

Table 6. Descriptions of machine learning models in this study

Model	Feature variable	Label
SVM-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
SVM-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
XGBoost-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
XGBoost-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
RNNLSTM-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
RNNLSTM-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2

Step 2: Dataset splitting. As there are 260 trading days in the stock market, a set of 780 data items, a multiple of 260, is used as the training set in this study. In the study by Deng et al. (2011), the best effect was achieved when 20% of the data items were used as the test set. Therefore, a set of 195 data items is used as the test set in this study. The data in this study comprise a group of 975 data items, split into the training set with 780 data items and the test set with 195 data items. Next, training and prediction are extended backward by moving the navigation pane to the very end of the data to learn the data items' fluctuations throughout the year.

Step 3: Model training. Trading strategies are developed based on the labels for Adj Close predicted using the models, where 1 represents a long position, and 0 represents a short position. Table 6 provides descriptions of machine learning models in this study.

3.4.4 Performance Measurement

This study measures the performance of different trading strategies using the following four commonly used performance indicators as the unified criteria for determining the pros and cons of trading strategies.

1. Sharpe Ratio: it is proposed by Sharpe in 1966, to measure the excess return generated per unit of total risk, that can be calculated using the formula below:

$$\text{Sharpe ratio} = (R_p - R_f)/\sigma_p \tag{3-1}$$

where R_p represents the return of the investment portfolio, R_f represents the risk-free rate, and σ_p represents the standard deviation of the excess return of the investment portfolio.

2. Information Ratio: it is used for measuring excess return and generated per unit of unsystematic risk. It can be calculated using the formula below:

$$\text{Information ratio} = (R_p - R_b)/\delta_{pb} \tag{3-2}$$

Where R_p represents the return of the investment portfolio, R_b represents the benchmark return, and δ_{pb} represents the standard deviation of the difference between the portfolio return and the benchmark return.

3. Jensen Index: it is an absolute index for performance evaluation proposed by Jensen in 1968, to measure whether a portfolio outperforms the market portfolio in excess return. Specifically, the higher the Jensen Index, the better the performance of the portfolio, that can be calculated using the formula below:

$$\alpha = (R_p - R_f) - \beta_p(R_m - R_f) \tag{3-3}$$

where α represents the Jensen Index, also known as the Alpha value, R_p represents the return of the investment portfolio, R_f represents the risk-free rate, R_m represents the return of the market portfolio, and β_p represents the beta value of the portfolio.

4. Excess Returns: It is determined by calculating the difference between the cumulative return generated using a particular trading strategy and the return generated using the buy-and-hold trading strategy, that can be calculated using the formula below:

$$ER_p = R_p - R_{BH} \tag{3-4}$$

where ER_p represents excess return, R_p represents the cumulative return generated using a particular trading strategy, and R_{BH} represents the return generated using the buy-and-hold trading strategy.

4. Empirical Results and Discussion

This section presents the results obtained after backtesting these three categories of trading strategies and the comparative analysis of the performance of these three categories of trading strategies.

4.1 Trading Strategies With Optimal Parameters in Technical Analysis

4.1.1 Conventional Operation

Using Python to write a for loop for the strategies developed based on the trading strategies adopted in previous studies with the intention of the top five combinations of parameters by cumulative return. The backtest results for these strategies are presented as follows, where the results for trading strategies with or without OBV are also observed in this study.

1. B5MA, B5MACD, B5RSI, and B5KD Strategies

Table 7. Evaluation of trading strategies with optimal parameters in technical analysis

Descriptive statistics	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
Backtesting period: January 1, 2006 to December 31, 2018												
Trading strategy: B5MA												
Parameters: Short-term MA (2-20) and long-term MA (2-60)												
Trading signals: Buy when the short-term MA line breaks above the long-term MA line, and sell otherwise												
Mean	-0.1692	0.5690	96.80	0.3973	0.0120	0.1100	1.9575	2.6115	-0.6539	0.1863	-0.0661	0.0680
S.D.	0.0507	0.2770	40.70	0.0461	0.0113	0.0358	1.4488	1.4669	2.3788	0.2010	0.0799	0.0700
Max	-0.1019	1.3681	245.00	0.4880	0.0464	0.2120	7.0071	6.4681	5.4570	0.5030	0.1096	0.2264
Min	-0.3095	0.1813	54.00	0.3107	-0.0083	0.0627	0.3151	0.4006	-5.4263	-0.2663	-0.2196	-0.0662
Trading strategy: B5MACD												
Parameters: n_1(2-20), n_2(2-30), and n_3(2-10)												
Trading signals: Buy when DIF - MACD > 0, and sell otherwise												
Mean	-0.1757	0.3304	238.20	0.3223	-0.0045	0.0632	0.3542	2.6115	-2.2573	-0.3797	-0.2299	-0.0966

S.D.	0.0611	0.1268	68.60	0.0393	0.0056	0.0153	0.4593	1.4669	1.6167	0.35338	0.0890	0.0879
Max	-0.0794	0.5845	473.00	0.4178	0.0070	0.0955	1.7517	6.4681	1.3511	0.2448	-0.0035	0.1036
Min	-0.3089	0.1024	173.00	0.2394	-0.0149	0.0399	0.0181	0.4006	-6.4500	-1.2546	-0.4065	-0.2626
Trading strategy: B5RSI												
Parameters: Short-term RSI (2-10), long-term RSI (2-20), lower limit of RSI for overbought signal (70, 75, …, 95), and upper limit of RSI for oversold signal (5, 10, …, 30)												
Trading signals: Buy when the short-term RSI line breaks above the long-term RSI line and RSI < overbought signal, and sell when the short-term RSI line breaks below the long-term RSI line and RSI > oversold signal.												
Mean	-0.2578	0.2326	440.00	0.3503	-0.0042	0.0445	0.1348	2.6115	-2.4767	-0.5812	-0.2777	-0.1454
S.D.	0.0856	0.0932	82.50	0.0643	0.0023	0.0094	0.1280	1.4669	1.4809	0.2921	0.0675	0.0625
Max	-0.0978	0.4342	593.00	0.4396	0.0000	0.0578	0.4928	6.4681	-0.3789	-0.0529	-0.1353	-0.0196
Min	-0.4282	0.0482	334.00	0.2094	-0.0085	0.0199	0.0217	0.4006	-6.3296	-1.1860	-0.3760	-0.2284
Trading strategy: B5KD												
Parameters: n(5-20), smoothed values *r*(2-30), upper limit of KD for buy signal (5, 10, …, 30), and lower limit of KD for sell signal (70, 75, …, 95)												
Trading signals: Buy when the K line breaks above the D line and both K and D < buy signal, and sell when the K line breaks below the D line and both K and D > sell signal												
Mean	-0.1639	1.4354	30.30	0.8232	0.3530	0.5996	6.4888	2.6115	3.8773	0.5372	0.0482	0.1855
S.D.	0.1621	1.5493	42.50	0.1302	0.5512	0.8817	2.9719	1.4669	3.1863	0.1041	0.0548	0.0436
Max	0.0000	6.9683	189.00	1.0000	2.4583	3.4766	15.4939	6.4681	15.0933	0.7727	0.1994	0.3085
Min	-0.4919	0.2486	2.00	0.6667	0.0144	0.0954	2.8917	0.4006	0.0534	0.3523	-0.0311	0.1210

Table 7 presents the backtest results for the B5MA, B5MACD, B5RSI, and B5KD strategies. We know that the MA, MACD, and RSI strategies under conventional operation can be used to develop stable countertrend trading strategies. Although the mean values of maximum return under the B5MA, B5MACD, and B5RSI strategies are 0.5690, 0.3304, and 0.2326, respectively, the mean values of success rate under these three trading strategies are 0.3973, 0.3223, and 0.3503, respectively, all of which are less than 0.4. In other words, the B5MA, B5MACD, and B5RSI strategies do not bring absolute positive benefits under conventional operation. On the contrary, the KD strategy is able to achieve a stable success rate of around 0.6 under conventional operation, but the mean values of success rate, cumulative return, and excess return increase to 0.8232, 6.4888, and 3.8773 under the B5KD strategy, respectively. Additionally, the mean values of the three performance indicators under the B5KD strategy are 0.5372, 0.0482, and 0.1855, respectively, suggesting that the KD indicator possesses a certain level of predictive power. Then, these findings only prove that KD possesses a certain level of predictive power because in practice, we are unable to predict optimal parameters and execute them in advance.

2. B5MAOBV, B5MACDOBV, B5RSIOBV, and B5KDOBV Strategies

The addition of OBV has a similar effect on B5MA, where there is a slight improvement in the performance of these strategies after OBV is added. According to Table 8, the mean value of excess return increases from -0.6539 under the B5MA strategy to 2.6956 under the B5MAOBV strategy, while the mean values of the three performance indicators are also positive under the B5MAOBV strategy. Although the increase in various measures is less obvious under the B5MACDOBV strategy, the mean value of excess return rises from -2.2573 to -1.5741 under this strategy. Also, the mean values of the three performance indicators are negative under the B5MACD strategy, but their mean values increase under the B5MACDOBV strategy, with the Jensen Index being the only performance indicator with a positive mean value.

Table 8. Evaluation of trading strategies with optimal parameters in technical analysis after the addition of OBV

Descriptive statistics	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
Backtesting period: January 1, 2006 to December 31, 2018												
Trading strategy: B5MAOBV												
Parameters: Short-term MA (2-20), long-term MA (2-60), and OBV												
Trading signals: Buy when the short-term MA line breaks above the long-term MA line and the percentage change in OBV > 0, and sell when the short-term MA line breaks below the long-term MA line and the percentage change in OBV < 0												
Mean	-0.1500	0.7616	35.8	0.5136	0.0710	0.1934	5.3070	2.6115	2.6956	0.4768	0.0355	0.1700
S.D.	0.0544	0.2768	13.9	0.698	0.0325	0.0656	2.2849	1.4669	3.0537	0.0945	0.0591	0.0469
Max	-0.0658	1.2959	69.0	0.6471	0.1355	0.3326	12.6455	6.4681	11.0955	0.6730	0.1687	0.2853
Min	-0.2894	0.3251	17.0	0.4000	0.0336	0.1053	2.2555	0.4006	-3.6618	0.3039	-0.0792	0.0858
Trading strategy: B5MACDOBV												
Parameters: n_1(2-20), n_2(2-30), n_3(2-10), and OBV												
Trading signals: Buy when DIF - MACD > 0 and the percentage change in OBV, and sell otherwise												
Mean	-0.1814	0.4420	157.1	0.3680	0.0017	0.0787	10.374	2.6115	-1.5741	-0.0121	-0.1300	0.0034
S.D.	0.0633	0.2162	33.6	0.0469	0.0069	0.0194	0.9706	1.4669	1.9976	0.2754	0.0843	0.0793
Max	-0.1168	1.0395	230.0	0.4516	0.0151	0.1094	4.2449	6.4681	3.8443	0.4023	0.0762	0.1829
Min	-0.3692	0.1421	118.0	0.2458	-0.0135	0.0458	0.0571	0.4006	-6.4110	-0.8261	-0.3327	-0.1898
Trading strategy: B5RSIOBV												
Parameters: Short-term RSI (2-10), long-term RSI (2-20), lower limit of RSI for overbought signal (70, 75, ..., 95), upper limit of RSI for oversold signal (5, 10, ..., 30), and OBV												
Trading signals: Buy when the short-term RSI line breaks above the long-term RSI line, RSI < overbought signal, and the percentage change in OBV > 0, and sell when the short-term RSI line breaks below the long-term RSI line, RSI > oversold signal, and the percentage change in OBV < 0												
Mean	-0.2560	0.2394	441.5	0.3495	-0.0042	0.0445	0.1380	2.6115	-2.4735	-0.5732	-0.2757	-0.1434
S.D.	0.0858	0.1039	80.9	0.0643	0.0023	0.0094	0.1282	1.4669	1.4835	0.2934	0.0683	0.0629
Max	-0.0978	0.4699	593.0	0.4396	0.0000	0.0578	0.4928	6.4681	-0.3789	-0.0529	-0.1353	-0.0196
Min	-0.4282	0.0482	334.0	0.2094	-0.0085	0.0199	0.0217	0.4006	-6.3296	-1.1860	-0.3760	-0.2249
Trading strategy: B5KDOBV												
Parameters: Number of days, n (5-20), smoothed value, r (2-9), upper limit of KD for buy signal (5, 10, ..., 30), lower limit of KD for sell signal (70, 75, ..., 95), and OBV												
Trading signals: Buy when the K line breaks above the D line, both K and D < buy signal, and the percentage change in OBV > 0, and sell when the K line breaks below the D line, both K and D > sell signal, and the percentage change in OBV < 0												
Mean	-0.1564	1.2934	27.4	0.7900	0.2632	0.4638	9.6959	2.6115	7.0844	0.6102	0.0889	0.2239
S.D.	0.1348	1.4086	26.0	0.1231	0.3375	0.6423	4.6608	1.4669	4.8709	0.1063	0.0650	0.0533
Max	0.0000	7.3066	115.0	1.0000	1.5682	3.2105	19.6067	6.4681	17.0613	0.8129	0.1971	0.3192
Min	-0.5353	0.3342	3.0	0.6154	0.0217	0.0863	3.4937	0.4006	0.3853	0.4051	-0.0684	0.1193

At the same time, Table 8 shows that while RSI generates trading signals, OBV also generates trading signals in the same direction, which in turn causes a small variation in the mean value of excess return between the B5RSI and B5RSIOBV strategies. The same situation is also found between the RSI and RSIOBV strategies. As can be observed from the results for the B5KDOBV strategy, there is a relatively noticeable improvement in various measures under this strategy as it has a positive effect on success rate, cumulative return, excess return, and the three performance indicators, namely the Sharpe Ratio, the Information Ratio, and the Jensen Index. Specifically, the mean value of cumulative return increases substantially by 3.2071 to 9.6959 under the B5KDOBV strategy.

4.1.2 Countertrend Operation

According to the backtest results for the trading strategies with optimal parameters in technical analysis, the mean values of success rate under the B5MA, B5MACD, and B5RSI strategies, which are selected due to optimal cumulative returns under their corresponding conventional strategies, are less than 0.4. These findings indicate that the MA, MACD, and RSI strategies are still able to generate stable countertrend trading signals under such extreme conditions. Therefore, this study empirically backtests the results for the countertrend trading strategies with these technical indicators. These countertrend strategies are named by adding "R" to the name of the corresponding trading strategies with optimal parameters in technical analysis under conventional operation. For example, the B5MA strategy under countertrend operation is named the RB5MA strategy in this study.

1. RB5MA, RB5MACD, and RB5RSI Strategies

According to Table 9, the B5MA, B5MACD, and B5RSI strategies show signs of improvement in the overall data of various measures under countertrend operation. At the same time, the differences in the mean value of cumulative return between these three strategies and their corresponding strategies with optimal parameters in technical analysis are -0.4578, 0.9046, and 0.3467, respectively, where a slight decrease in the mean value of cumulative return is observed in the RB5MA strategy only. These findings show that countertrend strategies are still the better option under this extreme value test.

Table 9. Evaluation of trading strategies with optimal parameters in technical analysis under conventional and countertrend operations

Backtesting period: January 1, 2006 to December 31, 2018												
Descriptive statistics	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
RB5MA strategy												
Mean	-0.3812	0.2094	189.3	0.6330	0.0023	0.0786	1.4998	2.6115	-1.1117	0.0741	-0.1008	0.0322
B5MA strategy												
Mean	-0.1692	0.5690	96.8	0.3973	0.0120	0.1100	1.9575	2.6115	-0.6539	0.1863	-0.0661	0.0680
Difference between the RB5MA and B5MA strategies												
Difference	-0.2121	-0.3597	92.5600	0.2357	-0.0097	-0.0314	-0.4578	0.0000	-0.4578	-0.1122	-0.0347	-0.0358
RB5MACD strategy												
Mean	-0.2749	0.1834	288.6	0.6186	0.0001	0.0550	1.2588	2.6115	-1.3526	-0.0545	-0.1338	-0.0011
B5MACD strategy												
Mean	-0.1757	0.3304	238.2	0.3223	-0.0045	0.0632	0.3542	2.6115	-2.2573	-0.3797	-0.2299	-0.0966
Difference between the RB5MACD and B5MACD strategies												
Difference	-0.0992	-0.1470	50.3200	0.2964	0.0046	-0.0082	0.9046	0.0000	0.9046	0.3253	0.0960	0.0955
RB5RSI strategy												
Mean	-0.2111	0.3020	494.5	0.4708	-0.0015	0.0433	0.4815	2.6115	-2.1300	-0.2508	-0.1975	-0.0652
B5RSI strategy												
Mean	-0.2578	0.2326	440.0	0.3503	-0.0042	0.0445	0.1348	2.6115	-2.4767	-0.5812	-0.2777	-0.1454
Difference between the RB5RSI and B5RSI strategies												
Difference	0.0467	0.0694	54.5200	0.1205	0.0027	-0.0012	0.3467	0.0000	0.3467	0.3304	0.0802	0.0802

Table 10. Evaluation of trading strategies with optimal parameters in technical analysis under countertrend operation after the addition of OBV

Backtesting period: January 1, 2006 to December 31, 2018												
Descriptive statistics	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
RB5MAOBV strategy												
Mean	-0.1685	0.9302	26.8	0.6785	0.1416	0.2692	8.5953	2.6115	5.9838	0.5721	0.0718	0.2072
RB5MA strategy												
Mean	-0.3812	0.2094	189.3	0.6330	0.0023	0.0786	1.4998	2.6115	-1.1117	0.0741	-0.1008	0.0322
Difference between the RB5MAOBV and RB5MA strategies												
Difference	2.2127	0.7208	-162.5	0.0455	0.1393	0.1906	7.0955	0.0000	7.0955	0.4980	0.1727	0.1750
RB5MACDOBV strategy												
Mean	-0.0503	1.1561	11.2	0.7719	0.3645	0.3946	9.1458	2.6115	6.5343	0.5687	0.0760	0.2112
RB5MACD strategy												
Mean	-0.2749	0.1834	288.6	0.6186	0.0001	0.0550	1.2588	2.6115	-1.3526	-0.0545	-0.1338	-0.0011
Difference between the RB5MACDOBV and RB5MACD strategies												
Difference	0.2246	0.9726	-277.4	0.1533	0.3644	0.3396	7.8870	0.0000	7.8870	0.6232	0.2099	0.2123

2. RMAOBV, RMACDOBV, and RRSIOBV Strategies

According to the backtest results for the trading strategies with optimal parameters in technical analysis under conventional operation, it is found that adding OBV can slightly improve the results of various measures under these conventional strategies. Hence, the next question is: will the addition of OBV have the same effect on countertrend trading strategies? As can be observed from Table 10, there is an increase in various measures before and after adding OBV to countertrend trading strategies. The mean values of cumulative return increase by 7.0955 and 7.8870 under the RB5MAOBV and RB5MACDOBV strategies, respectively, while the mean values of the three performance indicators increase by a range from 0.1727 to 0.6232 under these two strategies. Meanwhile, the mean values of success rate increase by 0.0455 and 0.1533 under the RMAOBV and RMACDOBV strategies but the mean values of the number of trades decrease by 162.5 and 277.5 to 26.8 and 11.2 under these two strategies, respectively. While the reduced number of trades is one of the reasons behind the increase in cumulative return, it also confirms that the addition of OBV can improve the trading performance under extreme circumstances, and OBV has a positive effect on countertrend-trading strategies.

4.2 Machine Learning and News Sentiment Ratio(SR)

4.2.1 Comparing the Pros and Cons of Machine Learning Models

The machine learning models in this study are tested using five labels together with groups of feature variables including and excluding SR which are listed in Table 11.

Table 11. Review of machine learning models

Model	Feature variable	Label
SVM-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
SVM-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
XGBoost-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
XGBoost-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
RNNLSTM-TA	MA, MACD, RSI, KD, OBV	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2
RNNLSTM-A	MA, MACD, RSI, KD, OBV, SR	Adj Close1, Adj Close5, Adj Close20, Adj Close60, and Adj CloseMA2

The pros and cons of machine learning models can be evaluated in terms of various metrics, including accuracy, precision (p), precision (n), recall (p), recall (n), and F-measure. This study combines the mean values of these metrics for 25 individual stocks obtained from various machine learning models during backtesting in Table 12 to compare these machine learning models. First, we observe the results obtained from various machine learning models that exclude SR. The accuracy of the SVM-TA, XGBoost-TA, and RNNLSTM-TA models with the Adj Close1 label ranges from 0.51 to 0.53, but the recall (p) and recall (n) of the SVM-TA and XGBoost-TA models with this label are less than 0.1 and greater than 0.9, respectively. It is evident that the prediction results from these models are closer to 0 but rarely reach 1, indicating that model training is not effective. Similar results, albeit better, are also observed among the SVM-TA and XGBoost-TA models with the Adj Close5, Adj Close20, and Adj Close60 labels, while he results obtained from the RNNLSTM-TA models are relatively normal. On the other hand, the accuracy of the models with the Adj Close5, AdjClose20, and Adj Close60 labels increases with label span. This probably indicates that with technical indicators as a method for predicting trends, the overall prediction effect also improves slowly when the accuracy of machine learning models that use labels with longer prediction periods is higher. Lastly, the best prediction results are observed among the machine learning models with the Adj CloseMA2 label as the accuracy, precision (p), precision (n), recall (p), recall (n), and F-measure of these models with this label are greater than 0.7, with no bias in their prediction results as well. All these suggest that the machine learning models with the Adj CloseMA2 label are not only stable, but also demonstrate high prediction accuracy.

Next, we observe the results obtained from various machine learning models that include SR, which are quite similar to those obtained from those excluding SR. Specifically, the results obtained from both sets of machine learning models differ by 0.02 at most, which is not a significant difference by any means. This indicates that SR has little impact on closing price for the next day, and market reaction to news may have already been reflected before the closing price is concluded from intraday trading. Lastly, following the importance of the feature variables in all XGBoost models, the results show that OBV is relatively important to all predicted labels, which is consistent with the conclusion drawn based on the results obtained using the trading strategies adopted in previous studies and trading strategies with optimal parameters in technical analysis mentioned the previous two subsections that the addition of OBV can improve overall trading performance.

4.2.2 Evaluation of Trading Performance

Table 13 compares the trading performance of various machine learning models using the mean values of various measures obtained after backtesting the data of 25 individual stocks. First, we observe the machine learning models with the Adj Close1, Adj Close5, Adj Close20, and Adj Close60 labels, and analyze them based on several measures, including the number of trades, success rate, cumulative return, and excess return.

Table 12. Evaluation and comparison of various machine learning models

Data period: January 1, 2003 to December 31, 2018
Testing period: January 1, 2003 to December 31, 2018

Model name	Label	Accuracy	Precision (p)	Precision (n)	Recall (p)	Recall (n)	F-measure
		Mean					
SVM-TA	Adj Close1	0.5356	0.4613	0.5409	0.0779	0.9226	0.1275
SVM-A	Adj Close1	0.5386	0.4730	0.5423	0.0759	0.9295	0.1238
XGBoost-TA	Adj Close1	0.5364	0.4829	0.5421	0.1002	0.9045	0.1560
XGBoost-A	Adj Close1	0.5365	0.4711	0.5419	0.0937	0.9102	0.1476
RNNLSTM-TA	Adj Close1	0.5180	0.4722	0.5501	0.4340	0.5875	0.4692
RNNLSTM-A	Adj Close1	0.5161	0.4714	0.5498	0.4477	0.5730	0.4773
SVM-TA	Adj Close5	0.5041	0.5074	0.4915	0.5344	0.4651	0.5089
SVM-A	Adj Close5	0.5029	0.5076	0.4889	0.5305	0.4666	0.5028
XGBoost-TA	Adj Close5	0.5031	0.5050	0.4860	0.5566	0.4376	0.5100
XGBoost-A	Adj Close5	0.5026	0.5041	0.4868	0.5613	0.4325	0.5126
RNNLSTM-TA	Adj Close5	0.5057	0.5134	0.4980	0.5176	0.4936	0.5102
RNNLSTM-A	Adj Close5	0.5068	0.5147	0.4992	0.5257	0.4880	0.5140
SVM-TA	Adj Close20	0.5189	0.5415	0.4621	0.6548	0.3465	0.5745
SVM-A	Adj Close20	0.5122	0.5362	0.4516	0.6455	0.3433	0.5673
XGBoost-TA	Adj Close20	0.5269	0.5404	0.4743	0.7522	0.2480	0.6156
XGBoost-A	Adj Close20	0.5213	0.5381	0.4570	0.7215	0.2716	0.6000
RNNLSTM-TA	Adj Close20	0.5140	0.5476	0.4670	0.5831	0.4312	0.5444
RNNLSTM-A	Adj Close20	0.5116	0.5460	0.4650	0.5869	0.4238	0.5448
SVM-TA	Adj Close60	0.5474	0.5849	0.4525	0.6782	0.3552	0.6037
SVM-A	Adj Close60	0.5477	0.5839	0.4464	0.6755	0.3545	0.6033
XGBoost-TA	Adj Close60	0.5525	0.5836	0.4542	0.7135	0.3139	0.6203
XGBoost-A	Adj Close60	0.5470	0.5799	0.4437	0.7072	0.3121	0.6147
RNNLSTM-TA	Adj Close60	0.5391	0.5862	0.4502	0.6518	0.3809	0.5885
RNNLSTM-A	Adj Close60	0.5393	0.5867	0.4517	0.6442	0.3901	0.5855
SVM-TA	Adj CloseMA2	0.7428	0.7372	0.7480	0.7321	0.7525	0.7374
SVM-A	Adj CloseMA2	0.7423	0.7363	0.7479	0.7326	0.7513	0.7374
XGBoost-TA	Adj CloseMA2	0.7280	0.7313	0.7261	0.6978	0.7562	0.7123
XGBoost-A	Adj CloseMA2	0.7430	0.7412	0.7449	0.7252	0.7595	0.7338
RNNLSTM-TA	Adj CloseMA2	0.7205	0.7169	0.7241	0.7035	0.7365	0.7118
RNNLSTM-A	Adj CloseMA2	0.7098	0.7035	0.7163	0.6984	0.7206	0.7039

As can be observed from the different number of trades among the models, the SVM and RNNLSTM models exhibit a higher frequency of signals generated with a shorter trading cycle, where the SVM models average 200 to 500 trades, and the RNNLSTM models average 500 to 1,200 trades. On the contrary, the XGBoost models exhibit a lower frequency of signals generated with a longer trading cycle while averaging between 50 and 200 trades. In fact, an excessively high trading frequency could lead to small losses after deducting processing fees from profits.

Next, the mean values of cumulative return obtained from the XGBoost models with the Adj Close1, Adj Close5, Adj Close20, and Adj Close60 labels are greater than 0.1, 0.4, 1, and 2, respectively, while the mean values of cumulative return obtained from the remaining SVM and RNNLSTM models are less than 0.1. On the other hand, only the mean values of success rate obtained from the XGBoost models with the Adj Close1, Adj Close5, Adj Close20, and Adj Close60 labels are close to 0.5, 0.5, 0.6, and 0.6, respectively, whereas the mean values of success rate obtained from the remaining SVM and RNNLSTM models are less than 0.4. These findings suggest that the SVM and RNNLSTM models not only have an extremely high trading frequency and an extremely low success rate, but also demonstrate poor overall trading performance.As for the three performance indicators, namely the Sharpe Ratio, the Information Ratio, and the Jensen Index, positive mean values for these performance indicators are observed only among the

XGBoost models with the Adj Close20 and Adj Close60 labels, whereas the remaining models show negative mean values for these performance indicators.

Table 13. Comparison of trading performance between various machine learning models

Data period: January 1, 2003 to December 31, 2018
Testing period: January 1, 2003 to December 31, 2018

Model name	Label	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
		Mean											
SVM-TA	Adj Close1	-0.5960	0.1836	221.8	0.3897	-0.0154	0.0757	0.0672	2.5476	-2.4804	-0.7965	-0.3220	-0.1929
SVM-A	Adj Close1	-0.6442	0.2218	238.8	0.3961	-0.0121	0.0738	0.0683	2.5476	-2.4793	-0.7948	-0.3190	-0.1899
XGBoost-TA	Adj Close1	-0.6552	0.2275	158.9	0.4650	-0.0126	0.0921	0.1145	2.5476	-2.4331	-0.5865	-0.2762	-0.1472
XGBoost-A	Adj Close1	-0.7046	0.2206	144.3	0.4801	-0.0132	0.0943	0.1305	2.5476	-2.4171	-0.5837	-0.2732	-0.1441
RNNLSTM-TA	Adj Close1	-0.2297	0.1887	1144.8	0.3831	-0.0053	0.0296	0.0024	2.5476	-2.5452	-2.1347	-0.5207	-0.3934
RNNLSTM-A	Adj Close1	-0.2339	0.1965	1300.2	0.3716	-0.0052	0.0282	0.0010	2.5476	-2.5466	-2.4049	-0.5522	-0.4250
SVM-TA	Adj Close5	-0.4236	0.2632	552.0	0.4113	-0.0054	0.0422	0.0558	2.5476	-2.4918	-0.9069	-0.3407	-0.2125
SVM-A	Adj Close5	-0.3931	0.2475	538.3	0.4041	-0.0057	0.0420	0.0705	2.5476	-2.4771	-0.0215	-0.3419	-0.2138
XGBoost-TA	Adj Close5	-0.4621	0.3008	173.9	0.4904	-0.0057	0.0733	0.4256	2.5476	-2.1220	-0.2713	-0.1984	-0.0695
XGBoost-A	Adj Close5	-0.5424	0.3312	133.9	0.5086	-0.0053	0.0900	0.7451	2.5476	-1.8025	-0.1754	-0.1714	-0.0425
RNNLSTM-TA	Adj Close5	-0.2547	0.1838	975.2	0.3878	-0.0050	0.0307	0.0069	2.5476	-2.5407	-1.6374	-0.4578	-0.3305
RNNLSTM-A	Adj Close5	-0.2455	0.2055	1139.2	0.3743	-0.0052	0.0292	0.0028	2.5476	-2.5448	-2.0451	-0.5103	-0.3831
SVM-TA	Adj Close20	-0.4965	0.3944	416.1	0.3936	-0.0045	0.0540	0.1608	2.5476	-2.3868	-0.6009	-0.2763	-0.1481
SVM-A	Adj Close20	-0.4935	0.3438	440.9	0.3995	-0.0050	0.0505	0.1390	2.5476	-2.4086	-0.6708	-0.2885	-0.1603
XGBoost-TA	Adj Close20	-0.4690	0.6731	69.9	0.5700	0.0087	0.1705	1.4985	2.5476	-1.0491	0.0311	-0.1150	0.0140
XGBoost-A	Adj Close20	-0.4748	0.4999	57.4	0.5821	0.0075	0.1445	1.3774	2.5476	-1.1702	0.0269	-0.1170	0.0119
RNNLSTM-TA	Adj Close20	-0.2763	0.2491	737.3	0.3797	-0.0046	0.0337	0.0332	2.5476	-2.5144	-1.0598	-0.3681	-0.2405
RNNLSTM-A	Adj Close20	-0.2497	0.2582	900.2	0.3696	-0.0047	0.0316	0.0154	2.5476	-2.5322	-1.3640	-0.4187	-0.2912
SVM-TA	Adj Close60	-0.3398	0.4474	400.0	0.3958	-0.0034	0.0482	0.3266	2.5476	-2.2210	-0.4308	-0.2385	-0.1103
SVM-A	Adj Close60	-0.3543	0.4500	435.8	0.3902	-0.0035	0.0473	0.2819	2.5476	-2.2657	-0.4774	-0.2503	-0.1221
XGBoost-TA	Adj Close60	-0.3319	0.6781	62.9	0.6115	0.0130	0.1476	2.1088	2.5476	-0.4388	0.1853	-0.0681	0.0610
XGBoost-A	Adj Close60	-0.3473	0.622	49.4	0.6065	0.0112	0.1605	2.0266	2.5476	-0.5210	0.1618	-0.0769	0.0521
RNNLSTM-TA	Adj Close60	-0.2516	0.3533	487.2	0.3796	-0.0037	0.0392	0.1859	2.5476	-2.3617	-0.5870	-0.2703	-0.1422
RNNLSTM-A	Adj Close60	-0.2552	0.3106	591.4	0.3682	-0.0044	0.0361	0.0717	2.5476	-2.4759	-0.8004	-0.3197	-0.1919
SVM-TA	Adj CloseMA2	-0.1336	0.2325	1635.0	0.2414	-0.0062	0.0252	0.0001	2.5476	-2.5475	-4.2577	-0.6969	-0.5690
SVM-A	Adj CloseMA2	-0.1344	0.2324	1633.0	0.2415	-0.0062	0.0253	0.0001	2.5476	-2.5475	-4.2427	-0.6948	-0.5667
XGBoost-TA	Adj CloseMA2	-0.1887	0.2114	1547.6	0.2426	-0.0063	0.0254	0.0001	2.5476	-2.5475	-3.9817	-0.6792	-0.5512
XGBoost-A	Adj CloseMA2	-0.1245	0.2248	1641.6	0.2414	-0.0063	0.0249	0.0001	2.5476	-2.5475	-4.3055	-0.6996	-0.5716
RNNLSTM-TA	Adj CloseMA2	-0.1469	0.2358	1531.3	0.2505	-0.0061	0.0260	0.0001	2.5476	-2.5475	-3.7750	-0.6665	-0.5386
RNNLSTM-A	Adj CloseMA2	-0.1393	0.2266	1540.3	0.2540	-0.0062	0.0259	0.0001	2.5476	-2.5475	-3.8763	-0.6730	-0.5451

On the whole, only the XGBoost models with labels over longer periods such as Adj Close20 and Adj Close60 are able to achieve good trading performance, while the remaining models perform relatively poorly. As regards the trading performance of the SVM, XGBoost, and RNNLSTM models with the Adj CloseMA2 label, these models exhibit a relatively high number of trades with an extremely short trading cycle of only 2.1 days, a success rate of around 0.24, and a cumulative return of nearly zero. These results also confirm what has been mentioned previously, i.e., an excessively high trading frequency could lead to small losses after deducting processing fees from profits. Meanwhile, the results obtained from all the models with the Adj CloseMA2 label are greater than 0.7, which indicates that in spite of their high accuracy, these models demonstrate poor trading performance due to the effects of two factors, namely processing fees and an extremely high trading frequency. Yet, their poor trading performance may also be resulted from the fact that Adj CloseMA2 is a smoothed calculation of the Adj Close label and also a lagging indicator, so the machine learning models with the Adj CloseMA2 label are still unable to generate stable profits despite having an accuracy of 0.7.

4.3 Overall Comparison of Trading Performance

Table 14. Overall comparison of trading performance among various trading strategies

Data period: January 1, 2003 to December 31, 2018
Trading period: January 1, 2006 to December 31, 2018
Method 1: Trading strategies adopted in previous studies; Method 2: Trading strategies with optimal parameters in technical analysis; Method 3: Machine learning

Method	Model name	Maximum loss	Maximum return	Number of trades	Success rate	Average profit	Standard deviation	Cumulative return	Buy and hold	Excess return	Sharpe ratio	Information ratio	Jensen index
		Mean											
Buy Hold	BUYHOLD	--	-	-	-	-	-	-	2.6115	-	0.3058	-0.0339	0.0988
1	RMAOBV	-0.3883	0.5549	33.6	0.4562	0.0086	0.1710	1.3733	2.6115	-1.2382	-0.0104	-0.1302	0.0048
1	RMACDOBV	-0.4988	0.5416	15.6	0.4254	0.0004	0.2752	0.9949	2.6115	-1.6344	-0.0939	-0.1565	-0.0209
1	KDOBV	-0.4824	0.2893	54.4	0.5716	-0.0076	0.1337	0.6469	2.6115	-1.9744	-0.1228	-0.1644	-0.0314
1	RMACD	-0.3140	0.1744	261.2	0.5987	-0.0034	0.0585	0.5620	2.6115	-2.0494	-0.2871	-0.1995	-0.0669
1	MAOBV	-0.2964	0.4321	97.3	0.3190	-0.0073	0.0985	0.5159	2.6115	-2.0956	-0.2796	-0.2042	-0.0710
1	RMA	-0.3809	0.1855	208.3	0.5918	-0.0041	0.0659	0.3950	2.6115	-2.2165	-0.2730	-0.2022	-0.0695
1	KD	-0.5049	0.1953	92.8	0.5937	-0.0096	0.1018	0.3466	2.6115	-2.2649	-0.2758	-0.2061	-0.0732
1	MACDOBV	-0.2517	0.3576	182.9	0.3174	-0.0067	0.0710	0.3373	2.6115	-2.2742	-0.4485	-0.2446	-0.1114
1	MA	-0.1973	0.3683	208.3	0.2905	-0.0077	0.0659	0.1821	2.6115	-2.4294	-0.5323	-0.2696	-0.1367
1	MACD	-0.1861	0.3018	261.2	0.3009	-0.0083	0.0585	0.1663	2.6115	-2.4452	-0.7350	-0.3083	-0.1752
1	RRSI	-0.2445	0.1423	776.0	0.5307	-0.0046	0.0327	0.0415	2.6115	-2.5700	-1.1586	-0.3832	-0.2519
1	RSIOBV	-0.1538	0.2418	774.2	0.2351	-0.0070	0.0328	0.0067	2.6115	-2.6048	-1.8987	-0.4951	-0.3627
1	RSI	-0.1542	0.2330	776.0	0.2349	-0.0071	0.0327	0.0063	2.6115	-2.6052	-1.9199	-0.4982	-0.3657
2	B5KDOBV	-0.1564	1.2934	27.4	0.7900	0.2632	0.4638	9.6959	2.6115	7.0844	0.6102	0.0889	0.2239
2	RB5MACDOBV	-0.0503	1.1561	11.2	0.7719	0.3645	0.3946	9.1458	2.6115	6.5343	0.5687	0.0760	0.2112
2	RB5MAOBV	-0.1685	0.9302	26.8	0.6785	0.1416	0.2692	8.5953	2.6115	5.9838	0.5721	0.0718	0.2072
2	B5KD	-0.1639	1.4354	30.3	0.8232	0.3530	0.5996	6.4888	2.6115	3.8773	0.5372	0.0482	0.1855
2	B5MAOBV	-0.1500	0.7616	35.8	0.5136	0.0710	0.1934	5.3070	2.6115	2.6956	0.4768	0.0355	0.1700
2	B5MA	-0.1692	0.5690	96.8	0.3973	0.0120	0.1100	1.9575	2.6115	-0.6539	0.1863	-0.0661	0.0680
2	RB5MA	-0.3812	0.2094	189.3	0.6330	0.0023	0.0786	1.4998	2.6115	-1.1117	0.0741	-0.1008	0.0322
2	RB5MACD	-0.2749	0.1834	288.6	0.6186	0.0001	0.0550	1.2588	2.6115	-1.3526	-0.0545	-0.1338	-0.0011
2	B5MACDOBV	-0.1814	0.4420	157.1	0.3680	0.0017	0.0787	1.0374	2.6115	-1.5741	-0.0121	-0.1300	0.0034
2	RB5RSI	-0.2111	0.3020	494.5	0.4708	-0.0015	0.433	0.4815	2.6115	-2.1300	-0.2508	-0.1975	-0.0652
2	B5MACD	-0.1757	0.3304	238.2	0.3223	-0.0045	0.0632	0.3542	2.6115	-2.2573	-0.3797	-0.2299	-0.0966
2	B5RSIOBV	-0.2560	0.2394	441.5	0.3495	-0.0042	0.0445	0.1380	2.6115	-2.4735	-0.5732	-0.2757	-0.1434
2	B5RSI	-0.2578	0.2326	440.0	0.3503	-0.0042	0.0445	0.1348	2.6115	-2.4767	-0.5812	-0.2777	-0.1454
3	XGBoost-TA_AC60	-0.3319	0.6781	62.9	0.6115	0.0130	0.1476	2.1088	2.6115	-0.5027	0.1853	-0.0681	0.0610
3	XGBoost-A_AC60	-0.3473	0.6522	49.4	0.6065	0.0112	0.1605	2.0266	2.6115	-0.5849	0.1618	-0.0769	0.0521
3	XGBoost-TA_AC20	-0.4690	0.6731	69.9	0.5700	0.0087	0.1705	1.4985	2.6115	-1.1129	0.0311	-0.1150	0.0140
3	XGBoost-A_AC20	-0.4748	0.4999	57.4	0.5821	0.0075	0.1445	1.3774	2.6115	-1.2341	0.0269	-0.1170	0.0119
3	XGBoost-A_AC5	-0.5424	0.3312	133.9	0.5086	-0.0053	0.0900	0.7451	2.6115	-1.8664	-0.1754	-0.1714	-0.0425
3	XGBoost-TA_AC5	-0.4621	0.30081	173.9	0.4904	-0.0057	0.0733	0.4256	2.6115	-2.1859	-0.2713	-0.1984	-0.0695

Table 14 based on comparisons of trading performance, the aforesaid trading strategies are ranked by the following measures - Cumulative return: B5KDOBV strategy with a cumulative return of 9.6959 > Buy-and-hold strategy with a cumulative return of 2.6115 > XGBoost-TA_AC60 strategy with a cumulative return of 2.1088 > RMAOBV strategy with a cumulative return of 1.3733; Success rate: B5KD strategy with a success rate of 0.8232 > XGBoost-TA_AC60 strategy with a success rate of 0.6115 > RMACD strategy with a success rate of 0.5987; Sharpe Ratio, Information Ratio, and Jensen Index: Trading strategies with optimal parameters in technical analysis > Buy-and-hold strategy > Machine learning-based trading strategies > Trading strategies adopted in previous studies. Although the trading strategies with optimal parameters in technical analysis appear to be optimal trading strategies regardless of measures on the whole, this study also explains at the beginning that it is not suitable to directly apply these trading strategies in practice because the optimal parameters obtained from backtesting may not necessarily generate optimal returns over different periods, whereas this problem is not present among the trading strategies adopted in previous studies and machine learning-based trading strategies. The machine learning-based trading strategies outperforms the trading strategies adopted in previous studies as evidenced by the results for various measures despite losing to the buy-and-hold strategy. Therefore, we can identify trading strategies that not only perform better but also outperform the buy-and-hold strategy in the direction of optimizing machine learning-based trading strategies.

5. Conclusion

5.1 Research Conclusions

This study is conducted using a sample of 25 constituent stocks in the Taiwan Top 50 ETF from 2003 to 2018 that encompasses bear and bull markets in various financial tsunamis alongside the boom and bust of stock markets. This study endeavors to ensure that the empirical methodology adopted are in line with real-world scenarios. Taking into accounting processing fees and the securities transaction tax, the following conclusions have been drawn through the empirical process, which has also unveiled some unexpected findings and expected results. It is hoped that this study is able to make some contributions to research on machine learning with news sentiment and trading strategies.

This study finds that under conventional operation, the success rates of the B5MA, B5MACD, and B5RSI strategies are less than 0.4, while the success rate of the B5KD strategy is approximately 0.8; the B5KD strategy is the only strategy with a good overall trading performance under conventional operation. On the other hand, the success rates of the RB5MA, RB5MACD, and RB5RSI strategies under countertrend operation are 0.1 to 0.3 higher than those of the B5MA, B5MACD, and B5RSI strategies under conventional operation. These countertrend trading strategies demonstrate good overall trading performance as well. These findings reveal that among the trading strategies with optimal parameters in technical analysis, the MA, MACD, and RSI strategies also perform well under countertrend operation. Moreover, the addition of OBV can improve the overall trading performance of the trading strategies with optimal parameters in technical analysis.

According to the backtest results for the trading strategies with optimal parameters in technical analysis, the MA, MACD, and KD strategies are able to generate a certain level of excess return and a steady success rate of greater than 0.6 under specific parameters; however, the RSI strategy underperforms the MA, MACD, and KD strategies because this strategy generates trading signals too frequently.

For the three categories of machine learning models, namely SVM, XGBoost, and RNNLSTM, the addition of news sentiment ratio (SR), which is the feature variable developed in this study, does not cause a substantial change in the accuracy, precision, recall, and F-measure of these models. Hence, it can be concluded that market reaction may have ended before the market closes. Based on the results obtained after carrying out model training within the scope of parameter settings in this study and predicting on the test set, the accuracy, precision, recall, and F-measure of these models increase gradually with label span, where the XGBoost models with the Adj Close20 and Adj Close60 labels exhibit a trading success rate of close to 0.6 on average and a Sharpe Ratio of greater than 0 while generating positive excess returns on two to five stocks. Meanwhile, the accuracy, precision, recall, and F-measure of the SVM, XGBoost, and RNNLSTM models with the smoothed Adj CloseMA2 label are greater than 0.7, which suggests that these models produce good prediction results. However, from the perspective of trading performance, it is not suitable for these models to be used as trading strategies due to two reasons. First, Adj CloseMA2 is a lagging indicator. Second, the models with this label generate trading signals too frequently, which in turn results in poor trading performance due to the effects of processing fees and the securities transaction tax.

After backtesting the aforesaid machine learning models, this study discovers that label selection is relatively important when it comes to developing trading strategies. When predicting stock price movements for the next day using the Adj Close1 label, there is a high probability that the machine learning models with this label are unable to generate profits despite having an accuracy of greater than 0.5. This is because the empirical test in this study takes into account the existence of processing fees and the securities transaction tax in real-world scenarios. In fact, it is not possible to execute only a long or short-position strategy every day based on trading signals, except when trading signals change from long to short or short to long. Daily stock price movements cannot be converted into actual returns when only a long or short-position strategy is taken. Only returns generated from the moment when only a long or short-position strategy is taken until the end of the strategy can reflect the real scenario. Therefore, it is found that these trading strategies can be ranked by trading performance in descending order as follows: Trading strategies with optimal parameters in technical analysis > Buy-and-hold strategy > Machine learning-based trading strategies > Trading strategies adopted in previous studies. However, it is not suitable to directly apply trading strategies with optimal parameters in technical analysis in practice. Therefore, we can continue to explore the direction of optimizing machine learning-based trading strategies in hopes of beating the buy-and-hold strategy in the near future.

On the whole, the empirical results of this study show that combining the sentiment index machine learning model with the technical analysis of previous literature and the technical analysis of optimized parameters can analyze the long-term stock price trend to a certain extent, thereby improving investment returns.

5.2 Research Limitations and Recommendations

1. This study directly converts news into SR news sentiment indicators, and only uses the optimism and pessimism of the vocabulary to interpret the news. The information obtained may not be sufficient. The news content is often accompanied by other information related to the overall industry, which needs further interpretation and analysis, in order to know the real hidden information of the news.

2. The specific parameters of technical indicators mentioned in the above conclusions are of high importance. This study proposes to use the technical indicators MA, MACD, RSI and KD in the characteristic variables of the machine learning model to expand the parameter range, not only based on previous literature and market common parameters, but also including more parameters for training, which may improve the overall effectiveness of the machine learning model.

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