IMPROVING STOCK INVESTMENT DECISION WITH ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Artificial neural network (ANN) is used for providing investment decisions to investors but are not yet widespread in the Thai stock market because of doubts about the effectiveness of such techniques and the market efficiency level, which makes trading data unable to be used to predict the future direction of stock prices. Thus, this study aims to explore the effectiveness of using artificial neural networks to improve investment decisions and to prove the efficiency of the Stock Exchange of Thailand by testing the accuracy of investment decision recommendations from such techniques. The independent variables of this research are from data from the previous day, which are typically used in technical analysis, including price, trading value, returns, the existence of holiday after trading, and returns of the Dow Jones Index, which represents foreign investment. The reason for using these data is that they reflect the information on demand and supply in stock trading, and the domestic stock exchange and foreign stock exchanges publicly disclose them. The results of the study support the feasibility of using ANN to provide decision advice to investors. The recommendations were correct up to 70% and showed that the Stock Exchange of Thailand was not able to meet the assumption of low pricing efficiency.

Keywords: Artificial Neural Network (ANN); the Stock Exchange of Thailand; market efficiency

1. INTRODUCTION

Though modern finance theory has introduced the concept of an efficient market where no one can beat the market and get high abnormal returns from their investment, many investors do not believe in it and keep trying to overperform the market with their techniques (Fama, 1970). The supported evidence is

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those investors who continuously show their marvelous investment performance above the market average return. The well-known examples of these investors are Warren Buffet, Benjamin Graham, and Peter Lynch (Wirawan and Sumirat, 2021).

For Thailand, the stock exchange was found in 1975 and has been developed for better information distribution. However, there are controversies about the stock market efficiency.

In many stock markets, Artificial Intelligence (AI) is introduced as a substitute for traditional technical analysis which applies statistical techniques on historical price and trade value to find out the change in demand and supply of a stock. The ability to learn from the given information of AI makes it a high-potential tool that would help investors improve their investment performance from both risk and return perspectives. One of the popular AI investment tools is the Artificial Neural Network (ANN).

The ANN is constructed to imitate a human being's brain (Devadoss and Ligori, 2013). Accordingly, the ANN can learn from the given data and improve its performance when more data is available. However, it may have fewer limitations, compared to a human being's brain. The ANN could deal with big data and process data analysis efficiently with better computer performance (Hassani and Silva 2015). If the patterns from historical market data exist, the ANN could easily find them. Hence, investors could take advantage of applying the ANN to predict market trends and make better investment decisions. The profitable stocks could be discovered through the deployment of the ANN techniques. Several studies have shown the possibility of improving investment using ANN techniques with the price and trading volume data (Picasso et al., 2019; Khan et al., 2011). However, if the market efficiency in pricing exists or the current market price of a stock has ultimately reflected the old price and trade volume pattern, the ANN could be a useless tool.

For most investors' benefit, this study emphasizes the ANN's investment decision making based on the price movement prediction by using the popular public information of historical price and trade volume in the form of historical returns, high price, low price, open price, and close price of the day, trade value of different groups of investors, including retail investor group, institutional investor group, foreign investor group, and proprietary trade group. The Stock Exchange of Thailand Index (SET Index) is the proxy for the overall price of Thai stocks.

There are several benefits from this research. The findings not only pave the way to use the ANN techniques to improve investors' investment performance by focusing on technical analysis data but also prove the existence of the weak-form market efficiency. Additionally, the findings disclose the technical analysis's public data which is important determinants of the market movement and worth using by investors to determine their investment timing.

2. RESEARCH OBJECTIVE

1. to investigate the effectiveness of using ANN to analyze trading data to improve investor investment decisions.

2. to verify the existence of the weak-form efficiency in the Thailand stock market.

3. LITERATURE REVIEW

Market Efficiency

Market efficiency is introduced in the literature of Fama (1970) and becomes well known in modern finance theory. Under market efficiency, stock prices reflect all relevant information, and no one could reap abnormal returns from his investment. There are different levels of market efficiency under three forms of hypotheses: weak-form hypothesis, semi-strong form hypothesis, and strong-form hypothesis. If the market is in the weak-form efficiency, all past price and trading data have been reflected in the current price. Accordingly, a technical analysis could not be used to beat the market. If the market is in the semi-strong form hypothesis, no one can use public information to grab abnormal returns. Both technical and fundamental analysis could not be used to improve investors' returns. If the market reaches the strong-form hypothesis level, all data are reflected in the stock's current price. No one can get abnormal returns.

Technical analysis

Technical analysis is the technique that analyzes the pattern of historical data of price and trade volume from the market to predict future stock prices (Blume et al., 1994). Investors and stock analysts widely use technical analysis techniques with the belief in market inefficiency. The basis of the belief is based on the simple idea of economics. The price of a stock is determined by the demand and supply of stocks in the market. The techniques attempt to find the change in demand and supply to predict the new price. The trade value and old price patterns could provide information on a stock's demand and supply (Sun et al., 2016). Securities companies hire many technical analysts to find the right timing for their customers and their investment. There are many popular technical analyses, for example, the support and resistance level, moving average, head and shoulder, Fibonacci, Bollinger band, and Elliot wave. However, many researchers do not agree with the effectiveness of technical analysis. The research of Hsu and Kuan (2005) concludes that these techniques are successful only for a particular period of time or by luck. Lo et al (2000) reports that technical analysis is subjective by nature. Altarawneh et al. (2022) confirms that different predictors may choose different optimal time range of the simple moving average, weighted moving average, etc., used in their forecast.

Technical Analysis and Weak-Form Market Efficiency

If technical analysis could beat the market, historical data could be used to generate abnormal returns. Accordingly, the weak-form market does not exist. However, the results of past studies on the weak-from market efficiency are inconclusive. There is evidence that supports and does not support weak-form market efficiency. For example, Konak and Şeker (2014) reports the existence of weak form efficiency in the developed stock market. Erdaş and Yağcilar (2020) discovers evidence of weak-form efficiency in their investigation of exchange rates. Yousaf, et al (2021) finds the validity of weak form market efficiency in STOXX. Several articles exhibit evidence that the weak-form level might not be reached. Many research results exhibit successful investment performance by using technical analysis techniques. The studies of Brock et al. (1992) and Sullivan et al. (1999) show the fat return from technical analysis techniques of

9.4% per year and 17.2%, respectively. A recent study by Shil and Kotha (2021) confirms that the stock market is not in weak form efficiency.

In Thailand, the evidence for weak-form efficiency is inconclusive. Ratner and Leal (1999) reports the possibility of using technical trading strategies to gain excess return. Oppositely, there are evidences showing that the use of technical analysis could not generate an abnormal return (Ling and Ruzita, 2017; Yu, Nartea, Gan, and Yao, 2013). Accordingly, it is doubtful for the use of trading data to gain abnormal returns.

Artificial Neural Network (ANN)

The ANN's algorithm is non-linear programming which could learn the newly added data to improve its prediction results. Subsequently, the ANN could overcome the limitations of the traditional statistical methodology which relies on linear analysis (Lam, 2004). Additionally, the ANN's flexible algorithm and machine-learning capability should bring advantages over typical technical analysis techniques. With the improvement of computer technology, the Artificial Neural Network (ANN) has become more widely introduced to improve investors' returns (Vui et al., 2013).

Artificial Neural Network (ANN) and Weak-Form Market Efficiency

Technical analysis input data are often used in ANN for improving investment performance and proving the weak-form market efficiency as these data are easily accessible to most investors. The commonly used data include the previous return of local and foreign indices, trade value, fund flows from different types of investors, close price, open price, high price, and low price. Most ANN studies show the predictive ability of ANN by using these data; for example, previous returns are used for the study of Thenmozhi (2006). Close price, open price, high price, and low price are examined on their prediction ability (Vijh et al., 2020) and fund flows are tested in Kong et al. (2019)'s prediction model. Trade value is used in the study of Dinh and Kwon (2018). Thus, most ANN studies support the inefficient market from the level of the weak-form hypothesis.

However, there are rare studies concerning using technical analysis data under the ANN in Thailand. Therefore, this study should be useful for those interested in using ANN to improve investment performance and prove weak-form market efficiency.

4. RESEARCH METHODOLOGY

1. Population and Sample

The historical data of the Stock Exchange of Thailand (SET) are examined in this research. The samples are the daily dataset from Thomson Reuters Datastream data from 11 March 2020, when COVID-19 was announced by the World Health Organization (WHO) to avoid the structure change in the market to 30 May 2023. The data contain the SET's total return index, high price, low price, trade value, close price, and open price, retail investors' buy value and sell value, foreign investors' buy value and sell value, institutional invesotrs' buy value and sell value, proprietary traders' buy value and sell value and sell value, and Dow Jones Composite index, and holiday.

The data are converted into logarithm format to be used as input factors. The return is computed as Ln(It/It-1), where It is the total return index at time t and It-1 is the total return index at time t-1. 10% of the highest return day and 10% of the lowest return day were removed from the sample to avoid the impact of the highly unusual circumstances. The data of 755 days are left for the study examination.

The input data includes the 1-day lag log return of the SET Index (RETURN-1), 1-day lag log return of the Dow Jones Composite Index (LN_DJR-1), 1-day lag of log value of high price to low price (LN_H/L-1), 1-day lag of log of the ratio of a day to its previous day trade values (LN_VAL-1), 1-day lag of log of the ratio of close price to open price (LN_C/O-1), 1-day lag of log of the ratio of buy value to sell value of institutional investor (LN_BSI-1), 1-day lag of log of the ratio of buy value to sell value of proprietary trade group (LN_BSP-1), and 1-day lag of log of the ratio of buy value to sell value of retail investor group (LN_BSR-1), and 1-day lag of log of the ratio of buy value to sell value of foreign investor (LN_BSF-1). The dummy variable are used for the last independent variable, HOLIDAY (equals to 1 if there is a holiday or more after the trading day and otherwise is 0), and for the dependent variable, DECISION, (equal to 1 if SET Index return increase by 0.25% or more, otherwise equals to 0). The reason for using 0.25% for the cut-off is to ensure that investors can cover the cost brokerage fee and make a profit.

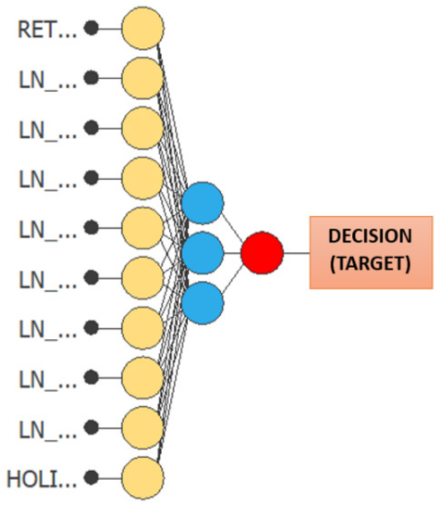
2. Research Methodology

For this study, the input data from the technical analysis are carefully selected based on two criteria: their availability for ordinary investors and the researchers' reviews. Next, the correlation analysis is used to exhibit the association between the input data and the decision result. The high association implies the relevant input variables to the output variable: the essential determinants of the investment decision in the ANN analysis. Then, the Neural Designer Application, the Artificial Neural Network (ANN), is applied to investigate the data to help investors make the right investment decision to improve their investment performance.

Initially, the Neural Designer Application splits the data into three groups to find the best model with ANN techniques. The first group (60 % of the data) is for training to learn and form a trained model. The second group (20% of data) is the selection dataset which is used as the validation set. The third group (20% of data) is for adjusting parameters and selecting the best model, and the last data set is the testing dataset, which validates for the last model. In same way as the human learning process, the input, hidden and output layers are designed as shown in Figure 1 and the Neural Designer Application determines the number of the hidden layers and trains the process with the algorithms to minimize the error.

Figure 1

The Artificial Neural Network Model



For the calculation of ANN, all input will be multiplied by their weights, wi, and added by b to form a weighted sum, Z, as follows:

$$Z = b + \sum_{i=1}^{n} x_i w_i \qquad (1)$$

Then, the weighted sum, Z, is transformed with the non-linear function to get output y as follows:

$$y = f(z) \qquad (2)$$

$$y = f(b + \sum_{i=1}^{n} x_i w_i) \qquad (3)$$

The weights and model will be adjusted until the overall errors are lowest. The effectiveness of the ANN is measured by the accuracy of the investment decision recommendation percentage: buy suggestion is followed by the next day's positive return, hold suggestion is followed by the next day's no return, and sell suggestion is followed by the next day's negative return.

5. RESULTS

1. Descriptive Analysis

The descriptive data in Table 1 reveals some essential characteristics of the tested data. The returns of the SET Index and Dow Jones Composite are very close at 0.005% and 0.006%, respectively. SET Index's returns, Dow Jones Composite's return, trading value, and the institutional investors' trading value are skewed to the left, while other data are skewed to the right. The log of the ratio of close price to open price is the only leptokurtic variable with a kurtosis value of 38.3585. The other variables are platykurtic.

Table 1

Descriptive Analysis

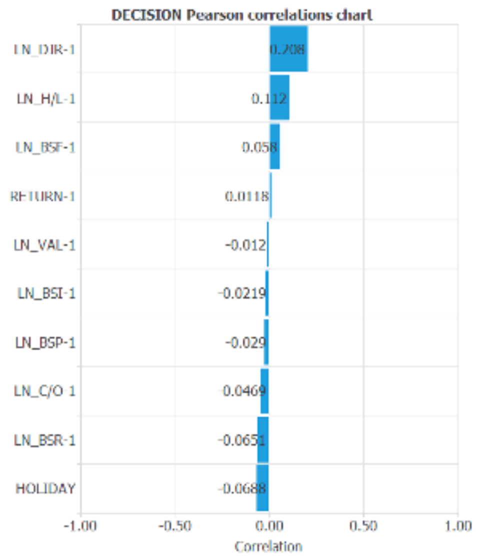
	RETURN-1	LN_DJR-1	LN_H/L-1	LN_VAL-1	LN_C/O-1	LN_BSI-1	LN_BSP-1	LN_BSR-1	LN_BSF-1	HOLIDAY	DECISION
Mean	0.0005	0.0006	0.0107	18.0905	-0.0008	-0.0412	0.0079	0.0132	-0.0107	0.2397	0.4026
Median	0.0004	0.0003	0.0094	18.0921	-0.0009	-0.0315	0.0082	0.0135	-0.0143	0.0000	0.0000
Maximum	0.0151	0.0324	0.0408	18.4465	0.1132	0.3549	0.4038	0.1445	0.0926	1.0000	1.0000
Minimum	-0.0143	-0.0190	0.0033	17.7316	-0.0603	-0.7257	-0.2054	-0.1178	-0.1135	0.0000	0.0000
Std. Dev.	0.0075	0.0101	0.0051	0.2277	0.0089	0.2537	0.0823	0.0822	0.0643	0.4272	0.4908
Skewness	-0.0480	-0.0329	1.3172	-0.0347	2.4737	-0.0775	0.0335	0.0294	0.0451	1.2217	0.3978
Kurtosis	-0.4440	-0.3476	1.9332	-1.2220	38.3585	-1.1015	-0.1316	-1.0992	-1.0800	-0.5088	-1.8467
Observation	755	755	755	755	755	755	755	755	755	755	755

2. Correlation Analysis

According to correlation analysis results in Figure 2, the study discovers that the determinants are not strongly associated with the decision. The top 3 independent variables which strongly positive associate with the decision are 1-day lag log return of the Dow Jones Composite Index (LN_DJR-1), the 1-day lag of the log value of high price to low price (LN_H/L-1), and 1-day lag of log of the ratio of buy value to sell value of foreign investor (LN_BSF-1) at 0.208, 0.112, and 0.058, respectively. The top 3 independent variables which strongly positive associate with the decision are the existence of holiday(s) after trading day (HOLIDAY), 1-day lag of the log of the ratio of buy value to sell value of the retail investor group (LN_BSR-1), and the 1-day lag of log of the ratio of close price to open price (LN_C/O-1), at -0.0686, -0.0651, and -0.0469 respectively. These six most essential determinants might be worth using in the prediction model.

Figure 2

The Correlation Analysis on the Input Data and Investors' Decision Making



3. The ANN Analysis

As shown in Table 2, the Neural Designer suggests the optimal number of input are seven variables after removing the redundant variables, and the optimal selection error has dropped to 0.0779367 when compared to the optimal training error of 0.56318.

Table 2

The Optimal Inputs Selection Result

	Value
Optimal number of inputs	7
Optimal training error	0.563181
Optimum selection error	0.0779367

According to ANN analysis, the suggested variables for the prediction of the investment decision are the 1-day lag of log value of high price to low price (LN_H/L-1), 1-day lag of log of the ratio of close price to open price (LN_C/O-1), 1-day lag of log of the ratio of buy value to sell value of foreign investor (LN_BSF-1), 1-day lag of log of the ratio of buy value to sell value of retail investor group (LN_BSR-1), 1-day lag of log of the ratio of buy value to sell value of proprietary trade group (LN_BSP-1), 1-day lag log return of the Dow Jones Composite Index (LN_DJR-1), and the existence of holiday after trading day (HOLIDAY). All top-ranking seven variables in the correlation analysis are selected in the ANN. The algorithm from the software discovers a set of equations for deriving the decision probability as follows:

scaled_LN_H_div_L_res__one_ = (LN_H_div_L_res__one_-0.01071999967)/0.005102809984;
scaled_LN_C_div_O_res__one_ = (LN_C_div_O_res__one_-9.805930313e-05)/0.008970749564;
scaled_LN_BSF_res__one_ = (LN_BSF_res__one_+0.003283000086)/0.06463319808;
scaled_LN_BSR_res__one_ = (LN_BSR_res__one_-0.005629709922)/0.08250950277;
scaled_LN_DJR_res__one_ = (LN_DJR_res__one_-0.0009855709504)/0.01018460002;
scaled_HOLIDAY = HOLIDAY*(1+1)/(1-(0))-0*(1+1)/(1-0)-1;
perceptron_layer_1_output_0 = tanh(-0.997498 + (scaled_LN_H_div_L_res__one_*0.127136) + (scaled_LN_C_div_O_res__one_*-0.613403) + (scaled_LN_BSF_res__one_*0.617432) + (scaled_LN_BSR_res__one_*0.169983) + (scaled_LN_DJR_res__one_*-0.0402832) + (scaled_HOLIDAY*-0.299438));
probabilistic_layer_combinations_0 = 0.79187 +0.64563*perceptron_layer_1_output_0
DECISION = 1.0/(1.0 + exp(-probabilistic_layer_combinations_0))

The probability value from the last equation would be compared with each selected threshold as a cutoff for the suggested decisions. Table 3 shows the prediction accuracy and error mismatch when different probability thresholds are applied as the cutoff for buying decisions for a profit. The ANN analysis of Neural Designer suggests that thresholds of 0.7 and 0.8 are best for the buy recommendation. At this threshold, the prediction accuracy is up to the highest at 70.89%, and the error mismatch is the lowest at 29.10%. The results suggest that ANN could be used to improve investment performance as other examinations of ANN in literature reviews.

Table 3

The Summary of the ANN's Prediction Accuracy at Different Thresholds

	Prediction Accuracy			Error Mismatch		
Threshold	Real Positive	Real Negative	Total	Real Positive	Real Negative	Total
0.1	30.50%	4.00%	34.50%	0.00%	65.60%	65.60%
0.2	30.50%	12.60%	43.10%	0.00%	57.00%	57.00%
0.3	25.80%	28.50%	54.30%	4.60%	41.10%	45.70%
0.4	18.50%	40.40%	58.90%	11.90%	29.10%	41.00%
0.5	13.20%	51.70%	64.90%	17.20%	17.90%	35.10%
0.6	6.60%	60.30%	66.90%	23.80%	9.30%	33.10%
0.7	4.60%	66.20%	70.89%	25.80%	3.30%	29.10%
0.8	1.30%	69.50%	70.89%	29.10%	0.00%	29.10%
0.9	0.00%	69.50%	69.50%	30.50%	0.00%	30.50%

6. DISCUSSION

1. The ANN can help investors improve their decision for investment in the Stock Exchange of Thailand like in many countries' stock exchanges. However, several studies also suggest that accuracy could be improved further if ANN is used together with other techniques. The study of Taiwan Market has the accuracy is around 60% (Tsai and Wang, 2009). However, when they improve their prediction by combining the ANN and Decision Tree model, the level of accuracy increases to 77%. The historical trading data are still helpful for investors in improving their investment performance. Several studies confirm the better use of the ANN for enhancing technical analysis, for example, the study of Vanstone and Finnie (2010), Ayala (2021), etc.

2. The research's empirical results indicate that Thailand's stock market does not reach weak form pricing efficiency. The ANN examination finds the useful data for effective predicting the investment decision are 1-day lag of log value of high price to low price, 1-day lag of log of the ratio of close price to open price, the 1-day lag of log of the ratio of buy value to sell value of foreign investor, the 1-day lag of log of the ratio of buy value to sell value of retail investor group, the 1-day lag of log of the ratio of buy value to sell value of proprietary trade group, 1-day lag log return of the Dow Jones Composite Index, and the existence of holiday after trading day. The conclusion of the weak-form inefficiency is like the conclusion of most researchers who use ANN in the investigation (Rahman and Hossain, 2006; Sezer et al., 2017; Nti, 2020). Investors should not ignore trading price and volume when they make decision to invest or not to invest.

7. RECOMMENDATION

1. Implication of the study

1. The historical data of price and trade volume from the stock market are valuable and should be considered when the investment decision is made.

2. Investors should consider using the ANN technique to improve their investment performance since the ANN technique can learn the data with a non-linear algorithm and has no subjective bias. The study exhibits ANN's ability to recognize the pattern of the data and ability to predict the investment decision as high as 70%.

2. Recommendation for further research

1. Other technical analysis data should be included for the future ANN analysis because there are different trading data used in technical analysis that are not included in this study, such as different price averages.

2. Further study should be done on combining the ANN with other technical analysis techniques to explore better ways to utilize ANN for improving investment performance.

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