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Predicting Thai stock index trend using deep neural network based on technical indicators

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Abstract

In this study, we aimed to find a suitable model for predicting the direction of the Stock Exchange of Thailand index (SET50 index) by developing a deep neural network model that builds upon the advancements of a hybrid model of an artificial neural network and genetic algorithm. Due to the complexity of stock data and the challenging predictability, a single hidden layer may not be sufficient. Therefore, we proposed a deep neural network model with three hidden layers, optimizing the number of nodes in each layer to achieve accurate predictions of the movement of the index. The input data consists of technical indicators widely used by technical stock analysts. These indicators are calculated over four different lookback periods of 3, 5, 10, and 15 days. The data was collected from the SETSMART system, which can retrieve historical data and real-time data via an API. We focused on data from the period of 2015–2019, comprising 1,220 records. Our test results showed that the proposed model achieved the highest average accuracy at 82.94%, outperforming the previous model.

Keywords: Artificial neural networks, Deep neural networks, SET50 index, Stock market prediction.

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1. Introduction

Predicting stock indices or stock prices is challenging due to the high complexity of the data, wherein multiple factors influence whether stocks rise or fall. There are two types of stock analysis. The first is fundamental analysis, which involves analyzing various economic and financial factors that influence the market or a company's business, such as its business operations, profitability, growth prospects, and the overall economic situation both domestically and internationally. The second type is technical analysis, which involves analyzing historical statistical data, such as closing prices, trading volumes, and daily trading data. Such data is used to calculate technical indicators, which are then analyzed to predict future stock movements. Accurate analysis can lead to profitable outcomes in the stock market, prompting significant interest among researchers in predicting stock prices and stock indices.

In the past, various techniques have been employed for predicting stock prices, including machine learning models and statistical models. Support Vector Machine (SVM) and Artificial Neural Network (ANN) are two machine learning models that have been successful in predicting stock indices [1, 2]. In 1990, Kimoto, et al. [3] discussed a stock buying and selling timing prediction system for the Tokyo Stock Exchange, based on a modular neural network. It achieved accurate predictions and demonstrated excellent profitability in stock trading simulations. Since that time, machine learning has become widely employed for forecasting stock indices in both developed and emerging markets. For example, Manish and Thenmozhi [4] used several machine learning methods, including Random Forest, SVM, Linear Discriminant Analysis, Logit, and ANN, to predict the direction of the S&P CNX NIFTY market index movement. They found that SVM outperformed other models. Cao, et al. [5] compared the predictive performance of the Shanghai Stock Exchange's stock price between four models: the Capital Asset Pricing Model (CAPM), the Fama–French three-factor model, the univariate neural network model, and the multivariate neural network model. Their results demonstrated the superior efficiency of ANNs over linear models. Bollen, et al. [6] utilized Twitter posts to forecast the Dow Jones index. Guresen, et al. [7] employed four models: Dynamic Architecture for Artificial Neural Networks (DAN2), GARCH-DAN2, GARCH-MLP, and ANN Multilayer Perceptron (ANN-MLP) to predict the NASDAQ index and discovered that ANN-MLP provided the highest accuracy. Kara, et al. [8] developed and compared two models based on ANN and SVM to predict the direction of the Istanbul stock index. Using ten technical indicators as inputs, they conducted comprehensive parameter tuning for both models. Their results showed that the ANN model outperformed the SVM model, obtaining an average accuracy of 75.74%. Liu and Wang [9] investigated and forecasted price fluctuations with the use of an optimized Legendre neural network. Patel, et al. [10] utilized SVM, ANN, Naïve Bayes, and Random Forest to predict the direction of the S&P Bombay Stock Exchange and CNX Nifty indices. They proposed an idea of transforming the technical indicators input data into trend deterministic data. Inthachot, et al. [11] utilized SVM and ANN machine learning models to predict the direction of the Thailand stock index (SET50 index). Using technical indicators as input data, they found that the ANN model was able to provide a more accurate prediction. Subsequently, Inthachot, et al. [12] proposed a hybrid model of GA and ANN. GA selects variables as input data. Experimental results for the SET50 index showed an average accuracy of 63.60%. Hu, et al. [13] employed an ISCA-BPNN machine learning model, a back-propagation learning model enhanced with a sine-cosine algorithm, to forecast the movements of the DJI index and the S&P 500 index from Google Trends data. Experimental results demonstrated a maximum accuracy of 89.98%.

Additionally, owing to the complexity and nonlinearity of stock data, a single-hidden-layer ANN may not be sufficient for accurate predictions. Therefore, many researchers have utilized deep learning for stock prediction [14-16]. For example, in recent years, Yoshihara, et al. [17] utilized a recurrent deep neural network model to forecast the movement of the Nikkei stock market. Gao, et al. [18] compared the predictive performance of four models: convolutional neural network model (CNN), MLP model, attention-based neural network model, and long short-term memory (LSTM) model on the S&P 500 index, CSI 300 index, and Nikkei 225 index. Their results showed that the attention-based neural network model outperformed the other models. Livieris, et al. [19] applied a deep neural network model to forecast the movement of stock exchange indices. Nabipour, et al. [20] applied deep learning algorithms and machine learning models on continuous data and binary data to predict movements of stock market indices. They compared the performances of several algorithms and learning models. The results showed that LSTM and RNN models outperformed other prediction models when using continuous data. Bhandari, et al. [21] applied the LSTM model on past data to predict the closing price of the S&P 500 index in the future. Their results indicated that the single-layer LSTM model outperformed the multilayer LSTM model in terms of fit and prediction accuracy.

The SET stock exchange has attracted global investor interest, being ranked as one of the world's leading emerging markets. It stands out in the ASEAN region, particularly in Thailand, Indonesia, and Vietnam. SET was established in 1975 with 16 companies, and as of 2024, it has over 700 registered companies. The SET50 index is derived from the data of the 50 largest companies in Thailand based on their market capitalization and strong liquidity. The data pertaining to the SET50 index can be retrieved from the SETSMART system, which is a comprehensive information service platform of SET, offering a wide range of financial and investment information. This includes real-time trading data and historical data. The SETSMART system also provides various tools and APIs that enable users to analyze data. In recent years, numerous studies have focused on forecasting the Thai stock market [11, 12, 22-25]. Forecasting the movement of the SET50 index is essential for investors, as it can assist in decision-making for trading. SET50 index futures and options are available for trading in the TFEX Futures Market. If there is a model that can accurately predict stock market directions, investors can use it to support their investment decisions, potentially increasing profits or reducing investment risks.

In this study, we developed a model to predict the direction of the SET50 index using a deep neural network, with technical indicators serving as input data. The process for selecting input data employed the ANN-GA hybrid intelligence model (Inthachot, et al. [12]) to determine the most suitable input variables. The model has three hidden layers and determines the suitable parameters for obtaining an accurate prediction model.

In the following sections, we provide a detailed overview of the components of this study. First, we present the details of the dataset, including the preprocessing steps undertaken to prepare the data for use in this research, as well as the selection of technical indicators used as input features. Additionally, we explain the structure of the deep neural network model applied for predicting stock index direction. Furthermore, we describe the methods used to evaluate the model's prediction performance. In Section 3, we provide the experimental results of this study and discuss the findings. Finally, Section 4 provides a summary of the main findings from the research and offers suggestions for potential avenues of exploration in future studies.

2. Data, Materials, and Methods

The research methodology for this study can be divided into six steps. In the first step, the SET50 index data is collected from the SETSMART system over a period of five years. In the second step, the collected data is used to calculate 11 technical indicators across four different historical time periods. The third step involves normalizing the entire dataset to a uniform range as described by Atsalakis and Valavanis [1] using the min-max normalization method. In the fourth step, appropriate input variables are selected using the genetic algorithm approach to reduce the number of input variables while retaining key features. In the fifth step, the proposed DNN model is applied to the entire dataset to identify three optimal parameter sets. Finally, in the last step, the DNN model is tested using the selected parameter sets from step four by evaluating its predictive performance on each year's data separately. The workflow of the research process is illustrated in Figure 1.

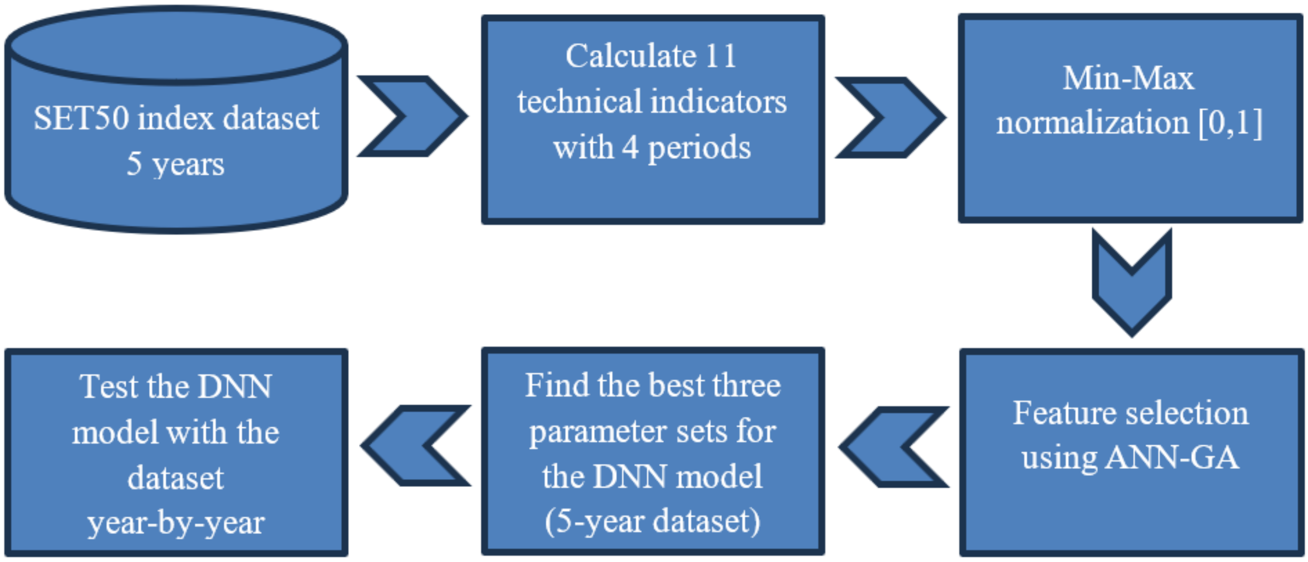

Figure 1.
The workflow of the research process.

2.1. Data and Technical Indicators

We used a SET50 index dataset consisting of daily closing prices obtained from the SETSMART system. The dataset spans from January 2015 to the end of December 2019, totalling 1,220 records. During this period, there were 660 instances of upward trends, representing 50.25%, and 607 instances of downward trends, representing 49.75%, as shown in Table 1. Overall, over the past five years, the upward and downward trends have been quite similar, indicating that the market has remained balanced in the long term, making it relatively difficult to predict the direction.

Table 1.
Descriptive statistics of the SET50 index data from 2015 to 2019.

Year	Uptrend		Downtrend		Total
	Times	Percentage	Times	Percentage	
2015	104	42.80	139	50.20	243
2016	138	56.56	106	43.44	244
2017	132	54.10	112	45.90	244
2018	122	49.80	123	50.20	245
2019	117	47.95	127	52.05	244
Total	660	50.25	607	49.72	1,220

The data is used to compute values for 11 technical indicators widely recognized for their effectiveness in predicting the direction of stock prices and stock indices [8, 10, 12]. These technical indicators are selected based on their proven ability to capture key market trends, momentum, and volatility, making them suitable inputs for predictive models in financial markets. Each technical indicator is calculated over four different lookback periods: 3, 5, 10, and 15 days. These periods were chosen to capture both short-term and medium-term trends in the market, ensuring that the model incorporates a range of time horizons for more accurate predictions. As a result, a total of 44 variables are generated, with 11 technical indicators computed for each of the four-time frames. The types of technical indicators used as input are listed in Table 2, and the equations used to calculate these indicators are shown in Table 3.

Table 2.
Types of technical indicator inputs.

No.	Indicator Type	Short Description
1	SMA (Simple Moving Average)	A fundamental trend indicator.
2	WMA (Weighted Moving Average)	A trend indicator that places more emphasis on recent prices.
3	MACD (Moving Average Convergence Divergence)	An indicator that tracks trends using moving averages.
4	ADX (Average Directional Index)	Measures the strength of the stock market trend.
5	MOM (Momentum)	Measures the speed of price movement.
6	ROC (Rate of Change)	Measures the momentum of price swings.
7	RSI (Relative Strength Index)	Measures the strength of the price trend.
8	LWR (Larry William's R%)	Measures the strength of price movement.
9	Stock (Stochastic K%)	Measures the change in price levels relative to a given period.
10	StocD (Stochastic D%)	A constant used to measure the speed and strength of price movement.
11	CCI (Commodity Channel Index)	An indicator that reflects price levels in relation to the average.

Table 3.
Technical indicators used in this study and their equations [8], [12].

Indicator name	Equation	Level (n)	Total
Simple n-day moving average (MA)	$\frac{C_t + C_{t-1} + \cdots + C_{t-n-1}}{n}$	3, 5, 10, 15	4
Weighted n-day moving average (WMA)	$\frac{(n)C_t + (n-1)C_{t-1} + \cdots + C_{t-(n-1)}}{n + (n-1) + \cdots + 1}$	3, 5, 10, 15	4
Momentum (MOM)	$C_t - C_{t-n}$	3, 5, 10, 15	4
Stochastic K% (StocK)	$\frac{C_t - LL_{t-(n-1)}}{HH_{t-(n-1)} - LL_{t-(n-1)}} \times 100$	3, 5, 10, 15	4
Stochastic D% (StocD)	$\frac{\sum_{i=0}^{n-1} K_{t-i}\%}{n}$	3, 5, 10, 15	4
Relative Strength Index (RSI)	$100 - \frac{100}{1 + (\sum_{i=0}^{n-1} \frac{UP_{t-i}}{n}) / (\sum_{i=0}^{n-1} \frac{DW_{t-i}}{n})}$	3, 5, 10, 15	4
Moving Average Convergence Divergence (MACD)	$MACD(n)_{t-1} + \frac{2}{n+1} \times (DIFF_t - MACD(n)_{t-1})$	3, 5, 10, 15	4
Larry William's R% (William)	$\frac{H_n - C_t}{H_n - L_n} \times -100$	3, 5, 10, 15	4
Commodity Channel Index (CCI)	$\frac{M_t - SM_t}{0.015 D_t}$	3, 5, 10, 15	4
Rate of Change (ROC)	$\frac{C_t - C_{t-n}}{C_{t-n}} \times 100$	3, 5, 10, 15	4
Average Directional Index (ADX)	$SMA\left(\frac{+DI_n - (-DI_n)}{+DI_n + (-DI_n)}\right)$	3, 5, 10, 15	4
Total			44

Note: n is n-day period times ago; C_t is closing price; L_t is low price at time t; H_t is high price at time t; $DIFF = EMA(12)_t - EMA(26)_t$; EMA is exponential moving average; $EMA(k)_t = EMA(k)_{t-1} + \propto (C_t - EMA(k)_{t-1})$; $\propto$ is smoothing factor = $\frac{2}{1+k}$; k = 10 in k −day exponential moving average; LL_t and HH_t are the lowest low and highest high in the last t days, respectively; $M_t = \frac{H_t + L_t + C_t}{3}$; $SM_t = \frac{\sum_{t=1}^{n} M_{t-i+1}}{n}$; $D_t = \frac{\sum_{i=1}^{n} \lvert M_{t-i+1} - SM_t \rvert}{n}$; UP_t is upward index change at time t, DW_t is downward index change at time t; $+DI_n$ is plus directional indicator and $-DI_n$ is minus directional indicator.

2.2. Feature Selection

Because of the large number of input variables, totaling 44, the selection process becomes increasingly complex. Specifically, the consideration of whether to include or exclude each variable results in a total of 2^{44} possible combinations, amounting to an enormous number of potential cases. To address this issue, Inthachot, et al. [12] employed a genetic algorithm (GA), an optimization method that mimics the principles of evolutionary biology. The GA is particularly well-suited for solving complex optimization problems with large search spaces, such as variable selection in machine learning models. The outcomes of Inthachot, et al. [12] research led to the selection of 12 input variables: SMA3, SMA5, SMA10, Stock5, StocD10, MACD3, MACD15, LWR3, LWR10, LWR15, ROC10, and ADX10 (the number following a technical indicator variable type is the time frame used in the calculation). This selection was made after applying the genetic algorithm to systematically evaluate and prioritize variables from the original set of 44. These 12 variables are subsequently used as input data for the study's prediction model.

Subsequently, the data will be normalized using the min-max normalization method, ensuring that all data points fall within the range [1]. This normalization is applied to achieve equal weighting for each variable. For the output variable, which represents the prediction target, there is only one variable with two possible values: 0 or 1. A value of 0 in the output indicates a prediction that the SET50 index for the next day will be less than or equal to the SET50 index on the day of prediction, signifying a downtrend. In other words, a value of 1 in the output signifies a prediction that the SET50 index for the next day will be higher than the SET50 index on the day of prediction, indicating an uptrend. This binary classification simplifies the prediction task, focusing on whether the market will move upward or downward rather than predicting the exact future value of the index.

2.3. Deep Neural Network

DNN is a specific subset of artificial neural networks, a type of machine learning characterized by a structure similar to artificial neural networks but with a deeper architecture consisting of many layers. The unique characteristic of a DNN is that it has many nodes in the hidden layers, unlike traditional neural networks, which have fewer nodes. Each layer in a DNN is made up of interconnected nodes, or neurons. Neurons in one layer are connected to neurons in the next layer, whereby each connection is assigned a weight. During training, a DNN changes the values of these weights as it learns the patterns in the input data. Throughout the training process, the network adjusts these weights to capture the intricate patterns in the input data. The research and application of DNN in stock market prediction are highly diverse. This involves selecting different types of DNN to compare prediction results across various stock markets. The selection of appropriate input variables includes fundamental data, public sentiment from social media, and technical indicators. DNN Thakkar and Chaudhari [14] and Liu, et al. [15] have been extensively utilized for predicting movements in the stock market, thanks to its exceptional ability to identify complex patterns or relationships within a large dataset.

We employed a DNN model with three hidden layers to predict the next day's movement of the SET50 index. The model had five layers: one input layer, three hidden layers, and one output layer. A set of 12 technical indicator variables served as the input data. The three hidden layers, denoted as *h1, h2, and h3*, were essential in capturing the complex, non-linear relationships between the input variables and the output. To determine the optimal number of nodes, we experimented with five different configurations for each hidden layer, as shown in Table 4.

Table 4.
All possible parameters for trying to find a suitable DNN model.

Parameter	Value
Number of nodes, first hidden layer (*h1*)	20, 40, 60, 80, 100
Number of nodes, second hidden layer (*h2*)	20, 40, 60, 80, 100
Number of nodes, third hidden layer (*h3*)	20, 40, 60, 80, 100
Epoch (*ep*)	2000, 4000, 6000, 8000, 10000
Momentum constant (*mc*)	0.9
Learning rate (*lr*)	0.1

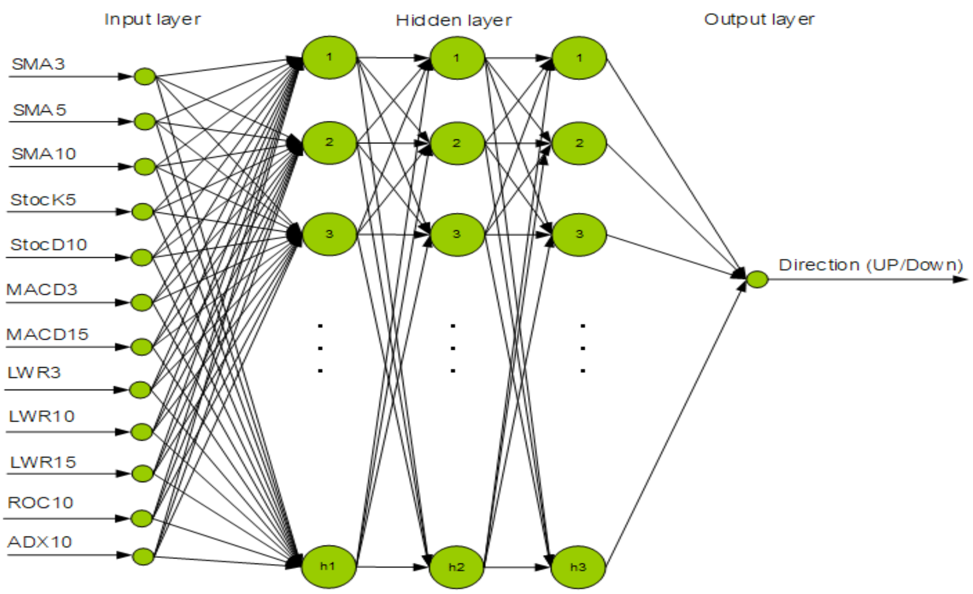

Figure 2.
Our proposed DNN model.

This trial-and-error process involved testing various combinations of node counts to identify the setup that yielded the best predictive performance. By fine-tuning the number of nodes, our goal was to achieve a balance between model complexity and computational efficiency, ensuring that the DNN could accurately predict the direction of the SET50 index without overfitting to the training data.

The model employed a rectified linear unit (ReLU) function as the activation function for each node. ReLU is commonly adopted in deep learning because of its straightforward implementation and effectiveness. In the output layer, the model can output two possible values: 0 or 1, where 0 indicates a predicted downward movement of the SET50 index, and 1 indicates an upward movement. Our proposed DNN model is shown in Figure 2.

In the model above, there are many parameters that require adjustment. Adjusting these parameters to fit the data appropriately will help improve the prediction accuracy. The model's parameters that need adjustment include the number of nodes in the first hidden layer *(h1),* the second hidden layer *(h2),* and the third hidden layer *(h3),* the learning rate *(lr),* the momentum constant (mc), and the number of epochs *(ep).*

To find good values for various parameters, five values for h1, h2, h3, and ep were explored. The values for mc and lr were fixed at 0.9 and 0.1, respectively. In total, the parameter tuning process involved five different values for each of the four parameters, leading to a total of 5 × 5 × 5 × 5 = 625 different combinations to be evaluated. All runs were executed using the Anaconda programming environment.

2.4. Performance Evaluation

A common method for measuring the success of a stock direction prediction model is to compare its predictive performance against a simple prediction model (Naïve model). The Naïve model assumes that the stock index direction on the following day will be the same as the direction on the previous day, as shown in Equation 1.

$$y'_t = \begin{cases} Up, & I_t - I_{t-n} > 0 \\ Down, & I_t - I_{t-n} \le 0 \end{cases} \qquad (1)$$

Where y'_t is the predicted stock index direction.
I_t is the stock index at time t,
and n is the period for prediction.

The performance measure of a machine learning model in predicting stock index movement is generally its accuracy. This study uses accuracy and F-measure as performance measures. Accuracy is calculated from the prediction results of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as shown in Equation 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

F-measure is calculated by Equations 5 from precision and recall defined by Equations 3 and 4 respectively.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$F-measure = \frac{2 \times Precision \times Recall}{Precision+Recall} \qquad (5)$$

3. Results and Discussion

In the first phase, we aimed to find the tentatively best parameters for the DNN model running on a 5-year dataset to predict the direction of the SET50 index most accurately. The goal was to identify the best-performing parameters that would deliver the highest prediction accuracy. The best three combinations of parameters from the first phase were used in the second phase, where the model ran on 5 separate 1-year datasets. The results for the entire dataset in the first phase revealed the top three combinations of parameters, as shown in Table 5. Notably, the parameter set with the highest performance consists of *h1 = 40, h2 = 40, h3 = 20, ep = 4000, mc = 0.9, and lr = 0.1.* This set achieved a remarkable accuracy rate of 89.86% on the training dataset while also maintaining strong performance on the testing dataset, with an accuracy of 89.75%, resulting in an overall average accuracy of 89.81%.

In the second phase, the three sets of parameters obtained from the first phase were tested with data separated for each year over a period of five years (2015–2019). The testing results and overall performance metrics are shown in Table 6. From the data in the table, it is observed that the year with the lowest accuracy rate (76.33%) is 2015, while the year with the highest accuracy rate (87.35%) is 2017. When calculating the average over the five-year period, it is found that the parameter set h1 = 80, h2 = 80, h3 = 80, and ep = 6000 has the lowest average accuracy rate of 81.63%. Conversely, the parameter set h1 = 40, h2 = 40, h3 = 20, and ep = 4000 has the highest average accuracy rate of 82.94% and an F-measure of 0.8282 over the five-year period.

Overall, parameter set 1 (40; 40; 20; 4000) demonstrated the best overall performance, yielding the highest accuracy and F-measure over multiple years and having the highest overall average compared to other parameter sets. Parameter set 2 (80; 20; 100; 6000) performed the worst across all metrics. Parameter set 3 (80; 80; 80; 6000), although performing well in certain years, had an overall average similar to parameter set 2, which was lower than set 1.

Table 5.
The best three sets of parameters for the DNN model.

No.	*h1*	*h2*	*h3*	*ep*	Accuracy (%)		
					Training	Testing	Average
1	40	40	20	4000	89.86	89.75	89.81
2	80	20	100	6000	90.16	89.34	89.75
3	80	80	80	6000	89.75	89.75	89.75

Table 6.
The prediction performance for each year of the DNN model with the best three parameter sets.

Year	Parameter combination (*h1*; *h2*; *h3*; *ep*)					
	(40; 40; 20; 4000)		(80; 20; 100; 6000)		(80; 80; 80; 6000)	
	Accuracy (%)	F-measure	Accuracy (%)	F-measure	Accuracy (%)	F-measure
2015	78.37	0.8068	76.33	0.7883	77.14	0.7929
2016	84.49	0.8066	83.67	0.7975	84.49	0.8151
2017	87.35	0.8659	84.90	0.8396	84.49	0.8357
2018	81.22	0.8233	82.45	0.8354	81.63	0.8245
2019	83.27	0.8382	81.22	0.8188	80.41	0.8074
Average	82.94	0.8282	81.71	0.8159	81.63	0.8151

Therefore, the parameter configuration of set 1 (40; 40; 20; 4000) should be considered the primary option for use, as it provides the best results in both accuracy and F-measure, indicating the most accurate and precise performance throughout all experimental periods. This parameter set shows consistent performance across different years, suggesting that it offers an optimal balance of nodes in the hidden layers and training epochs, which enhances its ability to generalize well to unseen data while avoiding overfitting.

Because of the difficulty of directly comparing models since they are evaluated on different datasets, there is a widely accepted method for performance comparison. This involves assessing the predictive performance against a Naïve model using the same dataset. The Naïve model is a simple prediction model that forecasts tomorrow's index based on today's index. The accuracy rate of the Naïve model with the dataset used in this study was 50.25%, as shown in Table 7.

Table 7.
The best prediction performances of Naïve model, ANN-GA model and our DNN model.

	Naïve	ANN-GA	DNN
Average accuracy	50.25%	63.60%	82.94%

Source: Inthachot, et al. [12]

Table 7 shows a comparison of the best performance of three stock direction prediction models: Naïve, ANN-GA Inthachot, et al. [12], and our DNN models. The DNN model achieved the highest average accuracy at 82.94%, compared to the ANN-GA model, which had an average accuracy of 63.60%, and the Naïve model, which had the lowest average accuracy at 50.25%. These results indicate that the DNN model proposed in this study outperforms the other models in predicting the SET50 index direction.

4. Conclusion

We have developed a good model for predicting the movement of the index of SET50 (Thailand's stock market exchange) over a five-year period (2015–2019). The SET50 index was retrieved from the SETSMART system, the stock exchange's information service platform. Learning from historical data, the DNN model capable of handling the difficulty and complexity of predicting stock index movement was introduced. The proposed DNN model consists of five layers: one input layer, three hidden layers, and one output layer. The input data comprises 11 technical indicators commonly used by technical analysts, calculated over four different time frames, resulting in a total of 44 input variables. To obtain a smaller set of input variables, a genetic algorithm was employed. To optimize the model further, experiments were conducted to determine an appropriate number of nodes in each hidden layer and a set of near-optimal parameter values. The results of the experiments show that the proposed model achieved an accuracy of up to 82.94%, outperforming existing models reported in the literature. Because the stock index is highly volatile, investors can apply this predictive model to speculate on the movement of the stock index to guide their investment decisions, reducing risk and gaining profit. However, this model is only suitable for short-term investment. For future research directions, several approaches can be explored. One of these involves experimenting with other advanced deep learning techniques or increasing the number of hidden layers to further improve the accuracy of stock index direction predictions. Additionally, incorporating the analysis of fundamental factors or other economic indicators, such as economic news, commodity price indices, or social media data, could enhance the predictive capabilities of the model, leading to more accurate forecasts.

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