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Exploring the Effectiveness of Deep Neural Networks with Technical Analysis Applied to Stock Market Prediction

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Abstract. The sustainable development of the national economy depends on the continuous growth and growth of the capital market, and the stock market is an important factor of the capital market. The growth of the stock market can generate a huge positive force for the country's economic strength, and the steady growth of the stock market also plays a pivotal role in the overall economic pulsation and is very helpful to the country's high economic development. There are different views on whether the technical analysis of the stock market is efficient. This study aims to explore the feasibility and efficiency of using deep network and technical analysis indicators to estimate short-term price movements of stocks. The subject of this study is TWSE 0050, which is the most traded ETF in Taiwan's stock exchange, and the experimental transaction range is 2017/01 ~ 2019 Q3. A four layer Long Short-Term Memory (LSTM) model was constructed. This research uses well-known technical indicators such as the KD, RSI, BIAS, Williams% R, and MACD, combined with the opening price, closing price, daily high and low prices, etc., to predict the trend of stock prices. The results show that the combination of technical indicators and the LSTM deep network model can achieve 83.6% accuracy in the three categories of rise, fall, and flatness.

Keywords: deep neural network, long short-term memory, technical analysis, fintech.

1. Introduction

How to make good use of the funds at hand for investment and financial management and financial planning is often the most concerned topic for modern people. Common investment and financial management methods include the purchase and sale of derivative financial commodities such as stock trading, funds, futures, and options, foreign currency investment, fund investment, and insurance planning. The variety of

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financial commodities in the market has different characteristics, and investment returns and risks also vary. In recent years, the popularity of financial digitization and the vigorous development of artificial intelligence have also driven the future trend of mobile finance and new types of Financial Technology (FinTech). The development of the stock market has been under the influence of liberalization and internationalization. With the advancement of Internet technology and the growing popularity of financial knowledge, stock investment has become a part of investment and management in life [1], [2]. Investors' funds will not be confined to this class of stocks, and the spread of buying and selling stocks to earn changes in stock prices is also one of the favorite operations of retail investors [3]. Investment and financial management are closely related to the pulse of social development, and it is also the topic of most concern for young people entering the society. However, investors who do not have professional financial background or knowledge may be vulnerable to losses due to opaque market information [4], [5]. At the same time, due to the huge market information, the variety of financial products and the diversity of technical analysis indicators, novice investment and financial management faced with a wealth of information and could not absorb and judge [6], [7].

In recent years, Deep Neural Network [8] and various Deep Learning algorithms have shined in the major competitions of Pattern Recognition and Machine Learning. The rapid development of deep neural networks has not only opened up new areas of machine learning research, but also various applications have gradually appeared around people's lives, such as speech recognition, emotion recognition, natural language processing and image recognition [9], [10], [11]. In the field of deep learning, Recurrent Neural Network (RNN) [12], Long Short Term Memory (LSTM) [13] are particularly suitable for processing time-series data, such as natural language processing, machine translation, speech recognition, and financial index prediction. At present, the mainstream financial commodity analysis and decision tools are mainly based on fundamental analysis, chip analysis and technical index analysis. The main purpose of this research is to explore the feasibility and effectiveness of the application of technical analysis indicators in deep networks. The remainder of this paper is as follows: section 2 is the literature and techniques review; section 3 is the methodology of this research; section 4 is the experimental design, results and discussion, and the last section is conclusion and future research.

2. Literature Review

Stock analysis tools can be divided into 'Fundamental Analysis' and 'Technical Indicator Analysis' in essence. Fundamental analysis is a method of valuation of securities or stocks, which uses financial analysis and economics research to evaluate corporate value or predict securities (such as stocks or bonds) [14], [15].

The fundamental analysis is to study the reasons for price changes, including economic factors, non-economic factors, internal market factors, current industrial conditions, domestic and foreign economic conditions, etc [16], [17], [18]. The data to be collected for the fundamental analysis is huge, and not every relationship with the stock price is equally important. There are many parts that need to be judged by individuals. In addition, some information may be hidden by the company. If investors do not have strong financial and economic analysis capabilities and internal information, they may suffer losses [19]. Technical analysis, also known as trend analysis or market analysis, is to analyze the data of past prices and trading volumes and convert them into graphs or indicators. It uses statistical methods to analyze historical data to predict future prices [18], [20]. From the perspective of technical analysis, changes in stock prices and trading volume will affect the behavioral decision-making patterns of investors [21]. As long as the changes in stock prices and trading volumes are used to predict trends, excess returns will be obtained. Technical analysis mostly shows the behavior of investors in the past with graphics, and analyzes the past behavior of investors to predict the future trend of the market [22], [23], [24]. The basic theory of technical analysis is that stock price fluctuations and trends change mainly from market supply and demand, and are determined by the transaction behavior of all investors after integrating all relevant economic factors and information, resulting in stocks rising or falling to form a trend [25]. Based on past experience, the stock market or stock price usually leads the economic fundamentals by half a year to nine months, that is, the stock market or stock will rise or fall first, and then economic data will appear [26]. Based on this, researchers believe that technical analysis not only has the function of leading indicators, but also reflects the future trend of stock prices. Investment stocks can select individual stocks that have the potential to rise as long as the technical indicators are used properly, and sell at a high point of the swing to increase capital returns [27].

Technical analysis originated from "Dow Theory" published by Dow in 1930 [28]. Dow Theory assumes that all information will be reflected in stock prices. The main method of Dow theory is to divide market fluctuations into three trends according to the time period-long-term trends that last for 1 to several years, secondary movements that last for weeks to months, and short-term fluctuations at the intraday level. Based on the characteristics of "high point refresh, low point rise", it is judged as a bull market (or a bear market on the contrary) as a basis for buying and selling to capture the long-term trend of the market [29]. Then Elliott 1871 [30] proposed the "Elliott wave principle" to further improve the entire technical analysis system. The theory believes that the stock market behaves like the waves of the sea will rise and fall. There should be five upward waves in a complete cycle and three downward waves.

Subsequently Malkiel [31] proposed the efficient market hypothesis, assuming that the stock market is an efficient market, all the stock market information is immediately and completely reflected on the stock price, and it is concluded that the technical analysis of the stock market is invalid. Malkiel's [32] empirical research indicates that the return on the use of technical analysis is inferior to the buy and hold trading strategy. Hudson et al. [33] used empirical models to study the UK stock price from 1935 to 1994, and the results showed that there was no excess return. However, in subsequent research, Bohan used the S&P 500 weekly data to apply RSI stock market technical indicators to prove the validity of technical analysis [34]. Hinich and Peterson pointing out that the stock price series exhibits a non-linear change, and empirical evidence shows that the Moving Average (MA) technical indicator has a significant performance in predicting the US Dow Jones Industrial Average Index (DJIA) [35]. Pruitt [36] combined three technical indicators: cumulative trading volume, relative strength and weakness, and moving averages to develop an investment strategy called CRISMA (Cumulative Volume Relative Strength Moving 10 Average). The research period and objects were 1976 to 1985. For 204 stocks of the years, empirical results found that its trading strategy is better than the buy and hold strategy. Lo, Mamaysky, and Wang [37] automatically identify patterns in technical analysis using non-major kernel regression methods. During the study period and objects were the stock prices of NYSE / AMEX and NASDAQ in the United States from 1962 to 1996. Empirical evidence shows that according to the technical analysis, the proposed pattern-based approach can get excess returns and beat buy-and-hold strategies. In addition, recent studies have shown that technical analysis indicators can obtain excess returns compared to the broader market in investment trading strategies [38], [39], [40], [41], [42].

In recent years, due to improvements in deep learning algorithms, computing efficiency, and excellent fault tolerance, deep neural networks have been widely used in the fields of stock price prediction and many derivative financial commodities such as futures, options and even house prices. Yu et al. [43] used a hybrid AI neural model combined with WTM text exploration technology to predict monthly WTI crude oil prices from 2000 to 2002 by collecting specific vocabulary and monthly WTI crude oil closing prices in monthly news from 1970 to 1999. The result confirms that the prediction accuracy in the case of ANN alone is 61%, while the accuracy of the hybrid AI neural model can reach 80%. Zhuge et al. [44] used semantic analysis to substitute the data of the community's opinions and comments on the Internet into the LSTM model for prediction. Compared with the traditional time series model and ANN model, the prediction of the Shanghai Stock Exchange's comprehensive stock price index has better accuracy. Nelson et al. [45] used the LSTM model to predict stock prices on the Brazilian Stock Exchange. The study period was from 2008 to 2015, and compared with traditional models and strategies, and found that the LSTM model has higher returns and lower risks. Soon [46] compared the performance of Feed-forward Neural Network (FFNN) and RNN when predicting the closing price of Commerce International Merchant Bank (CIMB) Kuala Lumpur Stock Exchange (KLSE), and its model used opening price, closing price and exchange rate information. The results show that both FFNN and RNN models can reach 90% prediction accuracy. Chen and Wei [47] proposed a Convolutional Neural Network (CNN) prediction model based on a company relationship graph. The experimental data uses the CSI 300 Index (CSI 300), which is close to 3,000 companies, traded between April 29, 2017 and December 31, 2017, with an average accuracy of approximately 60%. Many subsequent studies have also shown that machine learning and deep neural networks have superior performance when applied to the trend of time series data such as stock market trends [48], [49], [50], [51], [52], [53], [54], [55].

3. Methodology

3.1. Recurrent Neural Network, Long Short-Term Memory and System Model

General neural networks, such as Deep Convolutional Neural Network (DCNN) [56], processed samples are Independent and Identically Distributed (IID), and the problem solved is also a classification problem, a regression problem or a feature expression problem. However, more real problems are not satisfying IID, such as language translation, automatic text generation. They are a sequence of problems, including time series and spatial sequences. Compared to DCNN, sequence data or time series data is more suitable for processing with Recurrent Neural Network (RNN) [57]. The reason that RNN is recurrent is that it performs the same operation on every element of a sequence, and the subsequent output depends on the previous calculation.

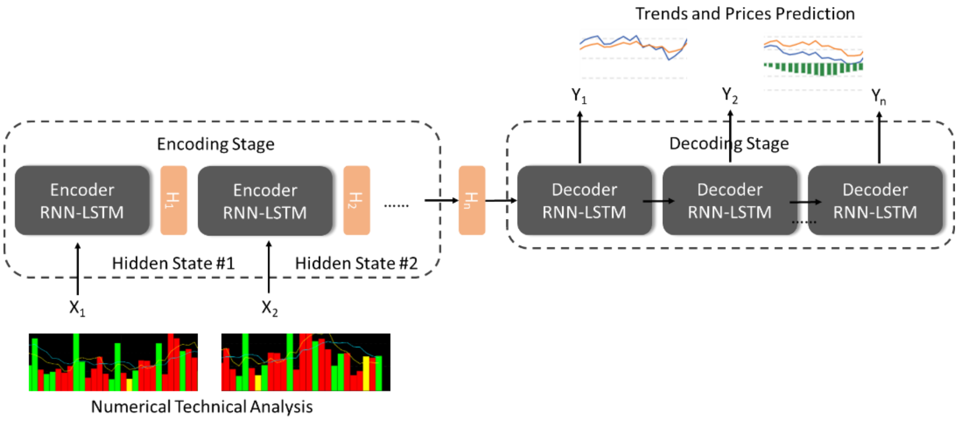


Fig. 1. Technical analysis and the proposed RNN-LSTM model

Another way to look at RNN is to think that it has some "Memory" that captures some of the previously calculated information. Long Short-Term Memory (LSTM) [58] is a special RNN, mainly to solve the gradient disappearance and gradient explosion problems in long sequence training. Because LSTM has the characteristics of remembering long-term trends and forgetting short-term fluctuations and errors, and can handle non-linear function problems, it is quite suitable for forecasting non-linear events that are easily affected by investors' mentality. This research uses LSTM neural network as the target stock price prediction model, the proposed model is shown as Fig. 1.

In our architecture, the LSTM is composed of two sets of RNNs, Encoder and Decoder. The input of the network is the filtered technical indicator features and basic information of individual stocks, and the output is the trend category, future trends and regression values. The LSTM model uses the gradient descent method to continuously transfer the training error to the neuron training and minimize the error. During the training process, the weights of each time will be continuously modified according to the errors found during the training. The weight update and error minimization are as follows:

$$E = \sum_{j} \frac{1}{2} (t_j - y_j)^2 \tag{1}$$

In equation (1), E is the error function of the network, t_j is the target output, and y_j is the prediction. Then find the partial derivatives for each weight ω_{ji}:

$$\frac{\partial E}{\partial \omega_{ji}} = \frac{\partial \left(\frac{1}{2}(t_j - y_j)^2\right)}{\partial y_j} \frac{\partial y_j}{\partial \omega_{ji}} \tag{2}$$

$$\frac{\partial E}{\partial \omega_{ji}} = -(t_j - y_j)\frac{\partial y_j}{\partial \omega_{ji}} \quad \textbf{(3)}$$

Then use Chain Rule to expand the activation function of each neuron:

$$\frac{\partial E}{\partial \omega_{ji}} = -(t_j - y_j)g'(h_j)\frac{\partial h_j}{\partial \omega_{ji}} \quad \textbf{(4)}$$

$$\Delta\omega_{ji} = \alpha\left(t_j - y_j\right)\frac{\partial g}{\partial h_j} \cdot x_i \quad \textbf{(5)}$$

α is the learning rate, g is the activation function of each neuron, and g' is the corresponding first derivative.

RNN-LSTM is a network in which nodes are connected along a sequence to form a directed graph, showing temporal dynamic behavior of time series. The feedforward calculation is as follows:

$$\begin{gathered} h(t) = Vx(t) + Uh(t-1) \\ O(t) = W\big(Vx(t) + Uh(t-1)\big), \forall t \end{gathered} \quad \textbf{(6)}$$

where $x(t)$ is the input of time t, $h(t)$ is the output of the hidden layer at time t, and $O(t)$ is the output at time t. U, V, W are the weight matrices for input layer to hidden layer, hidden layer to output layer, and hidden layer to the next time point hidden layer, respectively. In a time series recursive network, the gradient error will be passed back and forth along the time series layer by layer (back-propagation through time):

$$\Delta W = \frac{\partial E(t)}{\partial W}, \Delta V = \frac{\partial E(t)}{\partial V}, \Delta U = \frac{\partial E(t)}{\partial U} \quad \textbf{(7)}$$

3.2. Technical Analysis and Strategy

Technical analysis is a quantitative analysis of the price of a commodity based on statistics, and the signals of buying and selling are obtained through changes in technical indicators. There are many related discussions on the validity of technical analysis. From the past literature, the technical indicators, calculation methods, sample data or sample period used will affect the research results. This paper aims to explore the effectiveness of the Simple Moving Average (SMA), Stochastic Oscillator (KD), relative strength index (RSI), and Moving Average Convergence/Divergence (MACD) indicators as the effectiveness of deep learning training attributes, and test whether the technical analysis method is feasible in deep network architecture. According to the characteristics of individual financial indicators, this study converts them into appropriate normalized input values. The meaning of each indicator is as follows:

Simple Moving Average (SAM)

The concept of a moving average (MA) can be said to be the earliest and most basic method in technical analysis tools. Its theoretical basis is to average prices over a period of time according to the concept of "Average Cost" by Dow Jones. When the bulls are moving, the moving average is showing an upward trend due to higher and higher prices. Conversely, when the market is showing a short pattern, the moving average is showing a downward trend due to lower and lower prices. Most people in the market are profitable and easy to get out of the “long” trend. In turn, the long-term moving average is driven upwards, which makes the trend of the trend upward. The equation of SAM is shown below:

$$SAM = \frac{p_1 + p_2 + p_3 + \cdots + p_n}{n} \quad \textbf{(8)}$$

when calculating continuous values, one can directly use the original SAM increment:

$$SAM_{t1,n} = SAM_{t0,n} - \frac{p_1}{n} + \frac{p_{n+1}}{n} \quad \textbf{(9)}$$

KD Line

The stochastic index, also known as the KD line [59], measures the position of the closing price at the highest and lowest price ranges to determine trends and entry and exit points. The random exponential coordinates are in the range of 0-100. The K line represents the closing price and the highest price within a certain period of time, the percentage of the lowest price. When the K line is higher than the D line, but the D line is broken in the overbought area, it is a sell signal (dead cross). When the K line is lower than the D line, but breaks through the D line in the oversold area, it is a buy signal (golden cross). To calculate the KD value, one must first obtain the RSV indicator:

$$RSV = \frac{C_n - L_n}{H_n - L_n} \times 100\% \quad \textbf{(10)}$$

where *n* is the ttransaction date interval, C_n is the closing price of the n-th day, H_n is the highest price in the past *n* days and L_n is the lowest price in the past *n* days, and

$$K_n = \alpha \times RSV_n + (1 - \alpha) \times K_{n-1} \quad \textbf{(11)}$$

$$D_n = \alpha \times RSV_n + (1 - \alpha) \times D_{n-1} \quad \textbf{(12)}$$

If there is no K value or D value of the previous day, 50% can be substituted. In total, The K value is the 3-day smoothing moving average of the RSV value, and the D-value is the 3-day smoothing moving average of the K value.

Relative Strength Index (RSI).

The Relative Strength Index (RSI) [60] is a relative strength index, an indicator of the strength of the market's rise and fall. RSI is a technical indicator based on the strength of market fluctuations. This indicator can indicate the change in the strength of bullish and bearish forces. When the RSI value rises, it means that the bullishness of the market is greater than the bearish force. Conversely when RSI falling, it means that the market is more bearish than bullish. Then, the average value of the uptrend during the period is used as a percentage of the sum of the rise and the average of the downtrend to represent the RSI of the relative strength of the buyer and the seller. The equation is shown below:

$$RSI = \frac{EMA_{(U,n)}}{EMA_{(U,n)} + EMA_{(D,n)}} \quad \textbf{(13)}$$

suppose the price changes upwards is U and downward is D. In the day when prices rise, U = Today's closing price minus yesterday's closing price and D = 0. In the days when prices fell, U = 0 and D = yesterday's closing price minus today's closing price. EMA$_{(U,n)}$ is the U average in n days, and EMA$_{(D,n)}$ is the D average in *n* days.

Bias Ratio (BIAS)

BIAS [61] represents the gap between the stock closing price and the moving average of the day to analyze the degree of stock price deviation. Its function is mainly to measure the degree of deviation of the stock price from the moving average during the fluctuation process. When the stock price fluctuates sharply, it deviates from the moving average trend. As a result, possible retracements or rebounds, as well as the movement of stock prices within the normal fluctuation range, form the credibility of continuing the original trend.

$$BIAS_n = \frac{Close - MA_n}{MA_n} \times 100\% \quad \textbf{(14)}$$

$BIAS_n$ indicates the deviation rate of the past n days, *Close* is the closing price of the nth day, and MA_n is the moving average of the past n days. Positive BIAS implied price may fall, otherwise it may rise.

William’s Oscillator (Williams%R)

The William indicator [62] is an oscillator that measures the ratio of the peak (highest price) created by both long and short sides to the daily closing price and the ratio of stock price fluctuations within a certain period of time, providing a signal that the stock market trend is reversed. The William%R uses the pendulum principle to discern overbought or oversold stocks, discriminates highs and lows, and proposes effective investment signals.

$$Williams\%R = \frac{H_n - C_n}{H_n - L_n} \times 100\% \quad \textbf{(15)}$$

where C_n is the closing price on the n*th* day, and H_n and L_n are the highest and lowest prices for the past *n* days.

Moving Average Convergence / Divergence (MACD)

The MACD [63] was proposed by Gerald Appel in the 1970s to study the strength, direction, energy, and trend cycle of stock price changes in order to capture the timing of stock buy and sell. The MACD uses the difference between the 12-days EMA and the 26-days EMA as a signal to determine the operation.

$$DIF_t = EMA_{t(close,12)} - EMA_{t(close,26)}$$
$$9MACD_t = MACD_{t-1} \times \frac{8}{10} + DIF_t \times \frac{2}{10} \quad \textbf{(16)}$$

where $EMA_{t(close,12/26)}$ is the exponential moving average of the closing price on day t (12/26), and$9MACD_t$ is a 9-day exponentially smooth moving average

4. Experiments

4.1. Experimental Setup

This study uses the FTSE TWSE Taiwan 50 (TWSE 0050) Index as the research sample [64]. Most mutual funds are stock funds. These funds use stocks as the main investment target and can also be traded according to the professional judgment of the fund manager. ETFs are mutual funds that passively track the performance of an index and are listed in a centralized market. ETFs combine the trading characteristics of closed-end funds and open-end funds in trading methods. They can be traded on exchanges, and can also be purchased and redeemed. The main difference between ETFs and stocks is that buying an ETF is equivalent to buying securities that are tracked during the purchase period, effectively dispersing the risk of a single target and avoiding the price of a single target. The ETF operation aims to replicate the performance of the index, the investment portfolio is also consistent with the index constituent stocks, and the shareholding is also quite transparent. The TWSE0050 selected in this study has both the characteristics of stocks and ETFs. Investors can buy this stock at the market value in the stock exchange market, or they can invest in a fixed amount through banks. TWSE 0050 constituents include the top 50 listed companies on the Taiwan Stock Exchange, accounting for more than 70% of the total market capitalization of the Taiwan Stock Exchange. The data required for this study was obtained through the Taiwan Stock Exchange, and the transaction date used was 2017/1/4 ~ 2019/10/15 Q3, a total of 684 records. The first 2/3 of the data is set as training data, and the last 1/3 is test data. Each experiment features include daily opening price, closing price, highest price, lowest price, ups and downs, volume and turnover, and the normalized indicators.

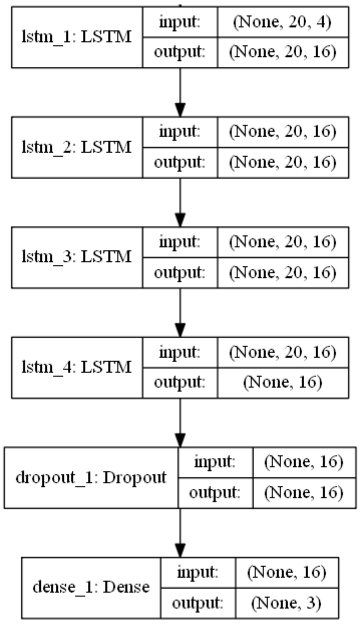


Fig. 2. The proposed LSTM layered architecture

The proposed LSTM layered architecture is set as Fig. 2. The model contains 4 LSTM layers and a full-connected layer. The experiments in this study were trained by ASUS ESC8000 G3, with Intel Xeon processor E5-2600 v3, NVIDIA GeForce GTX 1080ti GPU×8, and 64GB RAM. In the classification case, the data label is adjusted as follows:

1. Trend up: $Close_{t+1}$-$Close_t$ > $Close_t$ × α
2. Flat trend: $Close_t$ × α > $Close_{t+1}$-$Close_t$ >$-Close_t$ × α
3. Trend down: $Close_{t+1}$-$Close_t$ < $-Close_t$ × α

where $Close_t$ is the closing price of day *t*, $Close_{t+1}$ is the closing price of day t+1, and α is an adjustable parameter. In subsequent experiments, α is set to 1.0%. Deep network model uses four layers of LSTM with cross-entropy loss function, and the LSTM input timestamp is 20 days. The dropout rate was set to 0.5. The learning model is trained with a batch size 16 for 30~100 epochs using the inverse decay learning rate policy, which de-fined as follows:

$$\ell = \frac{\ell_0}{1 + (r \times t)} \tag{17}$$

where ℓ_0 is the initial learning rate at epoch 0, *t* is the number of current epochs, *r* is a hyperparameters to be tuned. The learning rate started at 0.01 and reduced every epoch with *r* = 0.1.

4.2. Technical Index Attribute Setting

As mentioned in the previous section, the technical analysis indicators used in this research are KD, RSI, BIAS, William%R and MACD. The financial range given by each indicator has different financial significance. In this study, each value of technical indicators is classified into three categories A, B, and C according to their financial significance, indicating that the future stock price may rise, stay flat, and fall.

KD Normalization

The cross breakthrough of the K line and the D line is more accurate when it is above 80 or below 20. When the cross is around 50, it means that the market trend is caught in the market. At this time, the trading signals provided by the cross breakthrough are invalid. When the K line is higher than the D line but the next day K falls below the D value, it is a sell signal (death cross); when the K line is lower than the D line but the next day K breaks the D value upward, it is a buy signal (gold cross). In this experiment, the KD indicator is converted into the following attributes and input into the model:

$$\begin{cases} A: K_{t-1} < D_{t-1}, D_t < K_t, \text{and } (20 < K_{t-2} < 80 \text{ or } 20 < K_{t-1} < 80 \text{ or } 20 < K_t < 80) \\ B: K_{t-1} > D_{t-1}, D_t > K_t \text{ and } (20 < K_{t-2} < 80 \text{ or } 20 < K_{t-1} < 80 \text{ or } 20 < K_t < 80) \\ C: \text{Otherwise} \end{cases} \quad \textbf{(18)}$$

RSI Normalization

RSI defines the value of relative strength between 0 and 100. When the indicator rises to 80, it indicates that the stock market has been overbought. If it continues to rise, if it exceeds 90, it means that it has reached the warning zone of severe overbought. The stock price has formed a head. Conversely, if it is lower than 20, it indicates that the market is oversold, and the stock price may enter the bottom. Therefore, the RSI numerical threshold for this study is set to 20 and 80:

$$\begin{cases} A: RSI_t \leq 20 \\ B: 20 < RSI_t < 80 \\ C: RSI_t \geq 80 \end{cases} \quad \textbf{(19)}$$

BIAS Normalization

A positive BIAS is called a positive deviation, and a value of more than 3.5% may have a price drop correction, and the stock price may fall; a negative BIAS is called a negative deviation, and a value of -3% or less may have a price increase correction. In order to make the value of the attribute more concise and easy to understand, we convert the BIAS value into the following value, where *t* is a trading day:

$$\begin{cases} A\!: \ BIAS_t \leq -0.03 \\ B\!: \ -0.03 < BIAS_t < 0.035 \\ C\!: BIAS_t \geq 0.035 \end{cases} \quad \textbf{(20)}$$

W%R Normalization

When the value of the W%R is greater than 80, it is oversold, and the stock price trend will bottom out; when the value of the W%R is less than 20, it is overbought and will recommend selling. This study converts W%R into the following categories, where t is a trading day:

$$\begin{cases} A\!: W\%R_t \geq 80 \\ B\!: 20 < W\%R_t < 80 \\ C\!: W\%R_t \leq 20 \end{cases} \quad \textbf{(21)}$$

MACD Normalization

When DIF is higher than MACD but the next day DIF falls below the MACD value, it is a sell signal and indicating that the stock price may fall in the future; While DIF is lower than MACD but the next day DIF breaks the MACD value, a buy signal indicating that the future stock price may rise. We convert the MACD value into the following categories, where *t* is a trading day:

$$\begin{cases} A\!: DIF_{t-1} < 9MACD_{t-1} \ and \ 9MACD_t < DIF_t \\ B\!: DIF_{t-1} > 9MACD_{t-1} \ and \ 9MACD_t > DIF_t \\ C\!: \text{Otherwise} \end{cases} \quad \textbf{(22)}$$

4.3. Experimental Results

In this experiment, the number of epoch ranges from 30 to 100 until convergence. The test uses basic features plus technical analysis indicators, including normalized KD, RSI, BIAS, Williams%R and MACD. The experimental results are shown in Figs. 3-5.

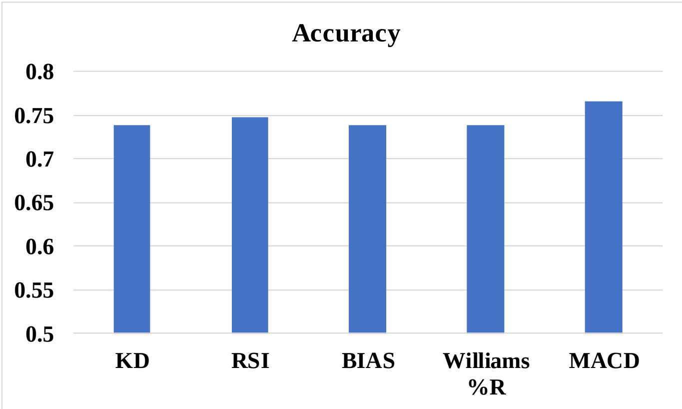
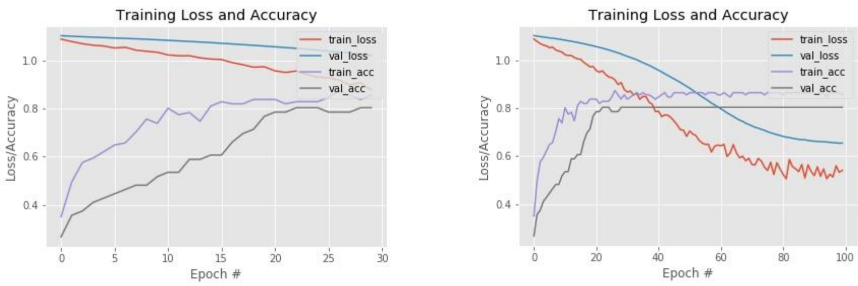


Fig. 3. Technical analysis indicator accuracy



(a) (b)

Fig. 4. Training Loss and Accuracy (a) with epochs 30 and (b) with epochs 100

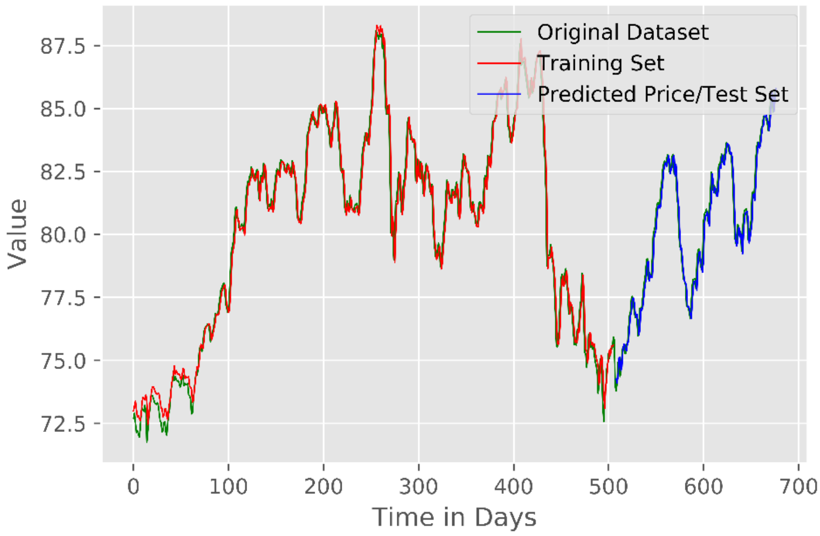


Fig. 5. Regression Results

The experimental results show that the accuracy of individual KD, RSI, BIAS, Williams%R, and MACD are 0.74, 0.75, 0.74, 0.74, and 0.76, respectively. The average accuracy of all indicators is 0.75. Among all the indicators, MACD obtained the highest estimation accuracy. Observation shows that the MACD indicator smoothes the closing price of the stock price according to the moving average and calculates the arithmetic average before integrating. The indicator uses the signs of the short-term and long-term moving average trends and performs double smoothing. Compared to other basic moving average-based indicators, MACD can provide more learnable information on the time series deep neural network. Further observations show that the current mainstream financial technology indicators are highly correlated with the moving average, therefore the network may automatically smooth out the differences in its deep structure. In addition, if all technical indicators are combined, the accuracy can reach 83.6%, and reach convergence in about 50 epochs. Fig. 5 is the regression results. The green line is the original data, the red line is the regression prediction result of the training data, and the blue line is the prediction result of the test data. The results show that our proposed model can accurately predict the trend and turn of the stock price in most cases.

5. Conclusions

Differs from previous studies [65], [66], this research constructs a four-layer LSTM deep neural network and explores the effectiveness of technical indicators in the deep network. The experimental data uses TWSE0050 transaction data from 2017 to 2019 Q3. The research results show the prediction accuracy combined with comprehensive technical indicators can up to 83%. The use of individual indicators can also achieve an average accuracy of 75%. The results of this study demonstrate that the use of technical analysis to the prediction of stock prices in the deep network is indeed feasible and effective. The indicators used in this research are general-purpose technical analysis indicators. The nature and calculation methods are applicable to all daily volatile financial commodities, such as exchange rate indexes, crude oil prices, futures and other derivative financial commodities. Therefore, the effectiveness of this study can be applied to different financial commodity transactions.

The focus of future research is to improve the accuracy of model estimates. In addition to technical analysis indicators, the fundamentals of individual stocks, chip analysis, financing/securities lending, etc., are also important reference indicators and this study will further examine how these important business factors can be added to the deep model.

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