Chaos, Solitons and Fractals 132 (2020) 109559

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Frontiers

A new LSTM based reversal point prediction method using upward/downward reversal point feature sets

JuHyok U[a,b], PengYu Lu[a,*], ChungSong Kim[b], UnSok Ryu[c], KyongSok Pak[c]

[a] School of Management, Harbin Institute of Technology, Harbin 150001, China
[b] Kim Chaek University of Technology, Pyongyang 950003, Democratic People's Republic of Korea
[c] Kim Il Sung University, Pyongyang 999093, Democratic People's Republic of Korea

ARTICLE INFO

Article history:
Received 11 July 2019
Revised 1 November 2019
Accepted 4 December 2019
Available online 13 December 2019

Keywords:
Reversal point
Stock Market
Candlestick
LSTM

ABSTRACT

A novel Long-Short Term Memory (LSTM)-based prediction model of stock price reversal point was proposed by using upward/downward reversal point feature sets. (1) Based on the combinations of candlestick indicators and technical indicators, 27 sets of feature candidates were constructed, and then the feature sets suitable to each stock in terms of URP/DRP prediction were respectively extracted. (2) LSTM-based URP/DRP predictors were constructed, the results of which are combined to improve the prediction accuracy. Using this model, reversal point prediction has been conducted for 10 Chinese stocks and 10 American stocks. In results, the mean prediction accuracy (F1) was 68.6% and 55.2% for the Chinese and the American stock markets, respectively. Results show that the average prediction accuracy has been evaluated to be higher for Chinese market by 13.4% compared to American one. Comparing with Support Vector Machine (SVM), Multilayer Perceptron (MLP) and Convolutional Neural Networks (CNN) model, F1 of proposed model has been increased by 5.9%, 11.7% and 5.3%, respectively.

1. Introduction

Financial market is considered as a complex system with nonlinear characteristics affected by many interrelated economic, political and psychological factors. Therefore, in such a financial market, an accurate prediction of stock fluctuation is very important as well as regarded as a difficult problem [1]. According to the efficient market hypothesis, as all the available information are reflected in the stock prices, it is impossible to predict the stock prices using historical information [2,3]. Many studies provide evidence agreeing to this hypothesis [4-7], while some studies have been conducted showing that the efficient market hypothesis is not established. Lo et al. [8] proposed a systematic method to recognize technical patterns such as head-and-shoulders using nonparametric kernel regression, showing that some technical patterns can provide incremental information for American stock markets. Brock [9] analyzed the data of American stock prices for historical 90 years, and found that the investment returns are higher when investors use technical analysis compared to using a buy-and-hold strategy.

As providing a lot of evidence does not conform to the efficient market hypothesis, researches on stock price prediction based on statistical analysis or machine learning have actively being conducted. Most typical research methods contain time series based prediction and text mining based prediction. Text mining based prediction method extracts features, such as sentiment, from news data, and predicts the stock price using these features [10–12]. Time series based prediction method predicts stock price by constructing a prediction model by using stock time series data, while it contains statistical model based method and artificial intelligence based method. Statistical model based method predicts stock price by applying time series model, such as ARIMA (Autoregressive Integrated Moving Average) [13,14], to historical stock price data, while artificial intelligence based method predicts stock price by applying Support Vector Machine (SVM) [15–17], Artificial Neural Network (ANN) [18–20], etc.

Recently, deep learning technology has been attracted great interest in the artificial intelligence research area. Being a species of multilayer ANN based machine learning, deep learning can solve a series of problems in traditional ANN, and can improve the performance of the algorithm. For these advantages, it has shown better performance in most artificial intelligence, including speech recognition, computer vision, etc., and has been widely applied in stock price prediction.

Li et al. [21] compared six prediction models, i.e., SVM, Naive Bayes, Decision Tree, Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), and Long-Short Term Memory (LSTM) in the

* Corresponding author.
E-mail address: lupengyu@hit.edu.cn (P. Lu).

https://doi.org/10.1016/j.chaos.2019.109559

prediction of next day stock trend. Results showed that the performance of deep learning models MLP, RNN, LSTM is better than other models with respect to accuracy. For the prediction of future stock price fluctuation, Tsantekidis et al [22] proposed CNN model and conducted a comparison with SVM and MLP model. In result, CNN model has been evaluated to have the best performance. [23,24] proposed deep learning models for stock price prediction, including MLP, RNN, LSTM and CNN, and compared their performance with ARIMA model. In this experiment, all the deep learning models outperformed ARIMA. Especially, CNN has been observed to have better performance than others. Maknickiene et al. [25] used the LSTM networks to predict the exchange rate and forex trading and thus improved the prediction accuracy compared to feedforward neural networks. Chen et al. [26] have used the LSTM model to estimate the rate of return of the Chinese stock market and have verified that the LSTM model performs better than the random prediction method. To evaluate the performance of LSTM in financial time series prediction, Fischer et al. [27] compared it with deep networks, random forests and logistic regression. For the prediction of stock price volatility, Kim et al. [28] proposed a new hybrid model that combined the LSTM model with various generalized autoregressive conditional heteroscedasticity (GARCH)-type models. For the prediction of next day stock price, Pang et al. [29] proposed LSTM model with an embedded layer (ELSTM) and LSTM model with an automatic encoder (AELSTM). Embedded layer and automatic encoder have been used to reduce the dimension of data, and ELSTM model has been observed to be more stable. Bao et al. [30] have obtained higher prediction accuracy of stock price by combining wavelet transforms (WT), stacked autoencoders (SAEs) and LSTM, where WT has been used to eliminate noise, while SAEs has been used to generate deep high-level features. Recently, many research works tried to use cloud computing to solve the constraints of the desktop in the analysis of stock market and prediction of stock price [31,32].

Although there have been conducted a lot of studies on stock market as mentioned above, their mainstream is the prediction of future stock price. However, the prediction of the ever-changing stock price is very difficult to be accurately conducted and therefore has no so much contribution to the decision-making of investors. Moreover, investors actually pay more attention to the reversal point (RP) of stock price change trend instead of the ever-changing stock price itself. In other words, when the change of stock price is suddenly stopped or reversed after sustaining a constant rising or falling trend for a certain period, whether it is a temporary fluctuation of stock price or a reverse of its trend has a crucial impact on the decision-making of investors. Therefore, the main objective of this study is to propose a novel prediction model of trend reversal point, actually contributable to the decision-making of investors.

Recently, many technical analysis methods are widely used in the prediction of RP by using a series of technical indicators. The technical indicator analysis is a method of predicting the stock price by selecting certain indicator and setting some evaluation criteria. New technical indicators such as Moving Average Convergence and Divergence (MACD), Relative Strength Index (RSI), Commodity Channel Index (CCI), etc. are created by secondary processing of basic data such as price and trading volume by using a time series analysis and statistical methodology. Evaluation of overbought or oversold is used to predict the RP and the trading point. Many research works on prediction of RP have previously been conducted by selecting these technical indicators as input and by using different machine learning tools such as SVM, ANN, etc. [33–38]. Chang et al. [33] used MACD, RSI and trading volume as input variables, and constructed a prediction model by using backpropagation neural network (BPN). Luo and Chen [34] proposed a prediction model(PLR-WSVM) by combining of piecewise linear representation (PLR) and weighted support vector machine (WSVM), and empirically used 15 technical indicators as input variables. Luo et al. [35] considered that the relative indicators are more useful than the absolute indicators in the prediction of RP. Absolute indicators are removed from the existing system, and relative indicators such as the turnover rate (TR), changing rate of turnover rate (CTR) and accumulated turnover rate (ATR), are added in. Zhang et al. [36] proposed a new status box method for the prediction of stock price trends. 12 trend tracking indicators and 7 trend reversal indicators were used to construct the status box. Chang et al. [37] proposed a new method for predicting RP of trends by using the Takagi-Sugeno fuzzy rule-based model (TS model). A support vector regression (SVR) classifier has been used for training of trading signal by using 28 technical indicators. Wu et al. [38] improved the accuracy in the prediction of RP by using the sentiment indicators extracted from the news together with technical indicators.

On the other hand, many studies have used Japanese candlestick patterns for the prediction of future stock prices and trends. The Japanese candlestick chart was firstly developed by a Munehisa Homma in the 18th century and has been applied to the rice market in Osaka, Japan [39,40]. For its strong stereoscopic and intuitiveness and sufficient amount of information, Japanese candlestick chart makes it possible to fully understand the basic trends of the stock market. Therefore, many research works have been conducted to understand the movements of stock prices by using candlestick chart analysis. Particularly, researches for establishing a trading strategy using the candlestick reversal pattern and studies proving its effectiveness have been conducted. Zhu et al. [41] verified the usefulness of the five candlestick reversal patterns, such as engulfing and harami, to the Chinese market. According to their research, bearish harami and cross patterns are effective in predicting downward trends, while bullish piercing, engulfing and harami are beneficial for upward trend prediction. Lu [42] investigated the profitability of twelve one-day candlestick patterns in the Taiwanese stock market. The results show that four patterns are profitable and candlestick approach is more appropriate for small firms and lower priced stocks. Chen et al. [43] studied the prediction accuracy of four pairs of two-day candlestick patterns in the Chinese stock market. For all of four pairs, the prediction accuracy declines as the increment of predicting time, and the prediction accuracy is stronger for stocks of medium market value rather than those of large market value. On the base of fuzzy theory, Naranjo et al. [44] proposed a method of modeling trading rules based on candlestick patterns. They used three fuzzied patterns including bullish kicking, Hammer and Piercing and tested in two markets: Nasdaq-100 and Eurostoxx. do Prado et al. [45] verified its validation to the Brazilian stock market for 16 candlestick patterns. Results showed that no patterns can uniformly be applied to the Brazilian stock market and some patterns such as Harami-Bullish have a local prediction accuracy.

As shown above, many studies on prediction of RP have been conducted by using technical indicators. However, it is still not clear which combination of indicators is most appropriate. In addition, there have been a number of studies to predict the reversal of trends and to establish a trading strategy by using the candlestick reversal pattern. However, as mentioned above, no pattern can be uniformly applied to all stocks and it is necessary to find individual patterns that can be effectively applied to each stock. According to [25–29], it has been verified that LSTM is superior to other learning methods for the effective extracting of significant information from complex financial time series data. As one type of Recurrent Neural Networks (RNN), LSTM networks have feedback connections inside the neural network for the training of sequence data. Therefore, it can be effectively used for sequential data modeling and time series analysis.

Although many researchers have used candlestick patterns or technical indicators for the prediction of trend reversal points, no one has ever used both of them together. Moreover, there is no any combination of candlestick patterns and technical indicators uniformly applicable to URP and DRP predictions of all stocks. Therefore, we have proposed a new LSTM-based prediction model of trend reversal point. (1) Based on the combinations of candlestick indicators and technical indicators, 27 sets of feature candidates were constructed, and then the feature sets suitable to each stock in terms of URP/DRP prediction were respectively extracted. (2) LSTM-based URP/DRP predictors were constructed, the results of which are combined to improve the prediction accuracy. URP/DRP predictors are constructed by using the LSTM networks which consist of input and output layers and a hidden layer, and the structural parameters of both predictors are all determined through training process. The hidden layer is exploited to capture the nonlinear relationships between variables.

The latter part of the paper consists of the followings. Section 2 introduces LSTM and Japanese candlestick patterns. The proposed model is described in Section 3. Section 4 illustrates the experimental results and analysis. The discussions and objects of lateral research works will be given in Section 5.

2. Background

2.1. Japanese candlestick chart

Japanese candlestick chart has been developed in the 18th century by Munehisa Homma, and has been introduced to the Western world by Steve Nison [39] in his book published in 1991. Candlesticks are composed of open, high, low and close prices of each time unit. The color of candlestick can be decided by comparing open and close prices. A white candlestick means that close price is higher than open price, while a black candlestick means that close price is lower than open price. Schematic diagram of Japanese candlestick has been shown in Fig. 1.

The thick part of the candlestick is called the real body that shows the interval between open and close prices. Lines going up and down from the real body are called shadows or tails. Although it is made of only four data, there are dozens of kinds of candlesticks which can be made from the combinations of these four data. Each candlestick pattern can represent different market status and price movement. Fig. 2 shows typical candlestick reversal patterns that are well-known [39,40].

Long white candlestick reflects a bullish period, while long black one reflects a bearish period. The hammer pattern at the bottom section predicts an upward reversal, while a shooting star at the head predicts a downward reversal. As shown above, the candlestick chart can make the current price status and imbalance between demand and supply to be easily grasped. For its convenience of using with other different assistant parameters, candlestick chart has a superiority of more elaborate and accurate analysis in prediction of ascension and decline of stock price versus to line chart or bar chart [39].

Many research works have been conducted to predict stock price movement and confirm a trading strategy by using candlestick patterns [41–45]. However, the exact numerical expression of all candlestick patterns is not so easy to be obtained and it is impossible to get a candlestick pattern that can be uniformly applied in all of the markets and stocks [41]. The current study will propose a method to predict the RPs by making new indicators that can generally express candlestick patterns.

2.2. Long Short Term Memory (LSTM)

As having a loop structure that past data can affect to the future, a recurrent neural network (RNN) has been recognized as the most appropriate algorithm for resolving problems associated with sequence data [46,47].

Long short term memory (LSTM) networks were invented by Hochreiter and Schmidhuberm [48]. LSTM networks are constructed to resolve the problem of long-term dependencies, and can deal with the vanishing and exploding gradient problem in traditional RNNs. As shown in Fig. 3, in LSTM, each of the cells has a complicated recurrent structure and they are chronologically connected to each other in time. The LSTM has two property values including the hidden state h_t and the cell state C_t. Here, h_t represents the value of the cell that changes with time, and C_t is used to maintain the memory for a long term. Information related to inner state and input can be arbitrarily added or removed in LSTM. LSTM has a complex recurrent structure consisted of several gates in its cell. The forget gate f_t makes the cell to remember or forget the input x_t and the previous hidden state h_{t-1}. Thus, the connection of x_t and h_{t-1} to the cell state C_t can be adjusted by f_t.

The input gate i_t^1 and i_t^2 will determine whether or not to feed the input x_t and the previous hidden state h_{t-1} to the cell state C_t. And output is determined by output gate o_t based on the cell state C_t. All of these relations can be represented by following equations.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t^1 = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

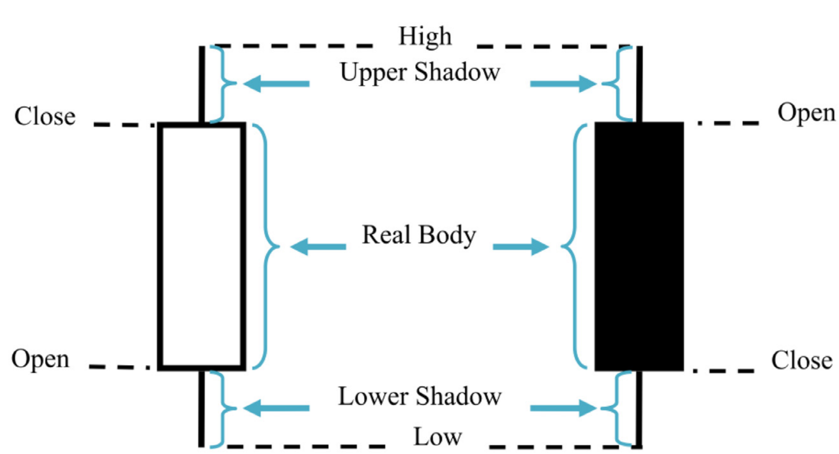

Fig. 1. Schematic diagram of Japanese Candlestick. Open, High, Low and Close indicate the opening price, the highest price, the lowest price and the closing price, respectively.

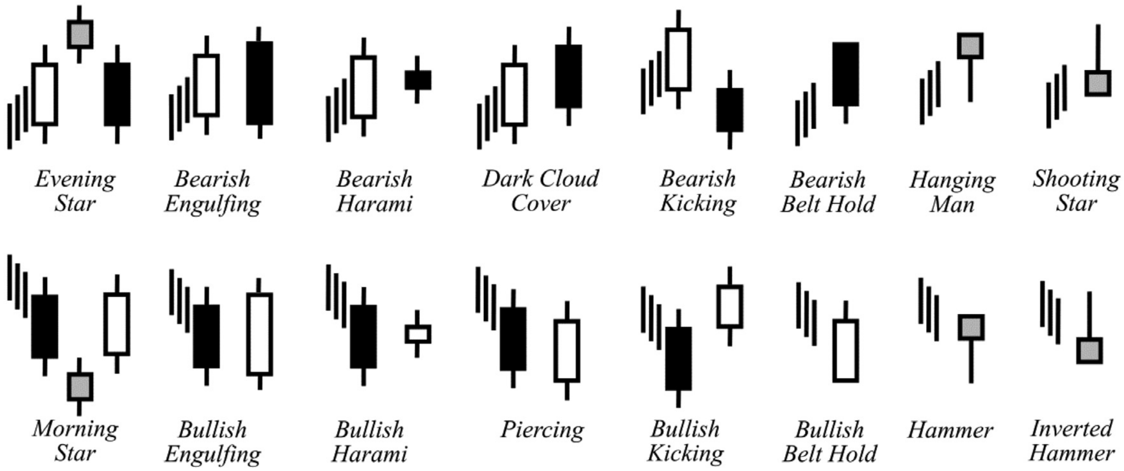

Fig. 2. Candlestick Reversal Patterns

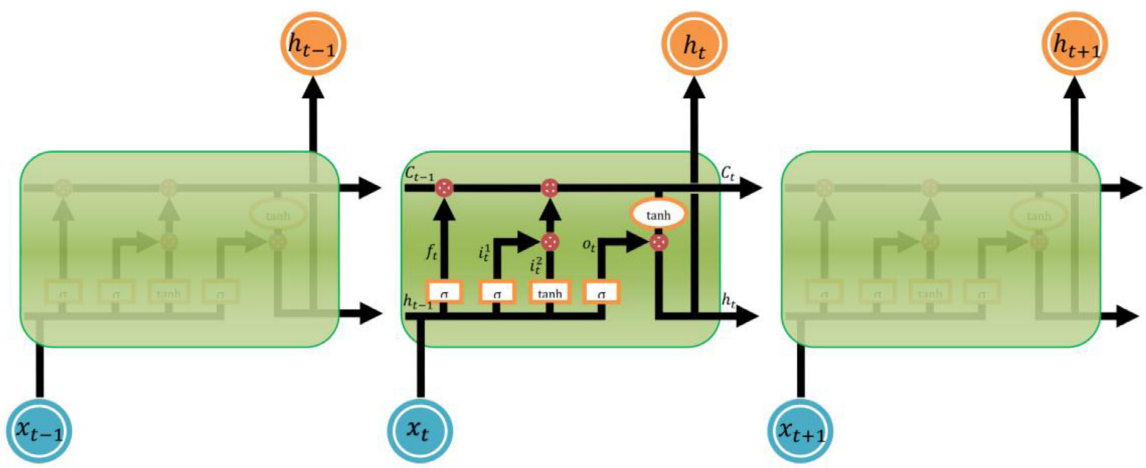

Fig. 3. Structure of LSTM memory cell [47]

$$i_t^2 = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t^1 * i_t^2 \tag{4}$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{6}$$

where W is weight matrix, b refers to bias vector, $\sigma(\ \cdot\ )$ refers to the sigmoid function, and $tanh(\bullet)$ is the hyperbolic tangent function. Using Eqs. (1) to (6), we can make precise adjustments to the input data and internal state that will be reflected in the cell state.

3. Methodology

3.1. Reversal point definition

The main purpose of the current study is to predict the reversal point of stock prices. The most important problem of the current study is to determine whether the time point when the stock prices in upward or downward trend alternate the direction is a real reversal point or a temporary fluctuation. Therefore, it is very important how to define the trend, candidate reversal point and reversal point.

3.1.1. Trend

Since the candlestick reversal pattern is known to be valid only when the stock price in upward or downward trends, thus many studies have defined the upward trend and downward trend as Eqs. (7) and (8), respectively [40].

$$MA_3(t-6) < MA_3(t-5) < \cdots < MA_3(t-1) < MA_3(t) \tag{7}$$

$$MA_3(t-6) > MA_3(t-5) > \cdots > MA_3(t-1) > MA_3(t) \tag{8}$$

where $MA_3(t)$ represents the 3-day moving average on day t .

$$MA_3(t) = \frac{1}{3}\sum_{i=0}^{3} Close(t-i) \tag{9}$$

This method was firstly proposed by Caginalp and Laurent [40], and has since been used in many studies that used the candlestick reversal pattern [42,43]. Depending on investor expectations, the five-day moving average may be used or the past period may be adjusted. In this study, the upward trend and downward trend were defined by using the 5-day moving average of the past five days as shown in Eqs. (10) and (11).

$$MA_5(t-5) < MA_5(t-4) < \cdots < MA_5(t-1) < MA_5(t) \tag{10}$$

$$MA_5(t-5) > MA_5(t-4) > \cdots > MA_5(t-1) > MA_5(t) \tag{11}$$

where MA_5 represents the 5-day moving average on day t. According to the trend of time t, Trend(t) can be valued as follows.

$$Trend(t) = \begin{cases} 1, & if\ upward\ trend\ at\ time\ t \\ -1, & if\ downward\ trend\ at\ time\ t \\ 0, & otherwise \end{cases} \quad (12)$$

3.1.2. Candidate reversal point (CRP)

In this study, when the close price of stock in upward trend (or downward trend) is lower (or higher) than the close price on the day before or same with it, we regard that time point as candidate reversal point (CRP) which can be expressed as follows.

$$CRP(t) = \begin{cases} 1, & if\ Trend(t) = 1\ and\ Close(t) \le Close(t-1) \\ -1, & if\ Trend(t) = -1\ and\ Close(t) \ge Close(t-1) \\ 0, & otherwise \end{cases} \quad (13)$$

3.1.3. Reversal point (RP)

On the base of Trend and CRP, the RP can be defined as follows.

$$RP(t) = \begin{cases} 2, & if\ CRP(t) = 1\ and\ \dfrac{MA_5(t) - \min\limits_{i=1,a} MA_5(t+i)}{MA5(t)} > \theta \\ 1, & if\ CRP(t) = -1\ and\ \dfrac{\max\limits_{i=1,a} MA_5(t+i) - MA_5(t)}{MA_5(t)} > \theta \\ 0, & in\ other\ case \end{cases} \quad (14)$$

where $RP(t) = 2$ represents the DRP, $RP(t) = -1$ the URP, $RP(t) = 0$ not RP, a the time period, and θ the threshold value to guarantee a return. That is, if the fluctuation magnitude of the 5-day moving average value within 10 days from the time point of the CRP exceeds 3%, that time point is regarded as a RP. And values of a and θ are set according to investor expectations. For example, if a stock trader trades once a week (5 business days) and regards a 5% gain or loss as significant, then the RP will be identified by using $\theta = 0.05$ and $a = 5$. As candlestick charts are generally used to grasp short-term price fluctuations [39–41,43], we set a as to be 10 and θ as to be 0.03.

3.2. Feature set (Input Variables)

Though many technical indicators have been used in RP prediction, however, it is still not fully certificated that how to combine these indicators will most appropriate. Many studies tried to predict trend fluctuation using candlestick pattern [39-45], however, no study has reported the investigation on the combination of technical indicators and candlestick patterns. Current study creates new candlestick indicators that can represent one-day candlestick pattern and combine them with technical indicators. Using them as the input data of the prediction model, we can improve the prediction accuracy. Both of the candlestick indicators and technical indicators are calculated from the basic data of the stock price data including open price, high price, low price, close price, and trading volume explained below.

Open(t): the open price at time t.
High(t): the high price at time t.
Low(t): the low price at time t.
Close(t): the close price at time t.
Volume(t): the trading volume at time t.

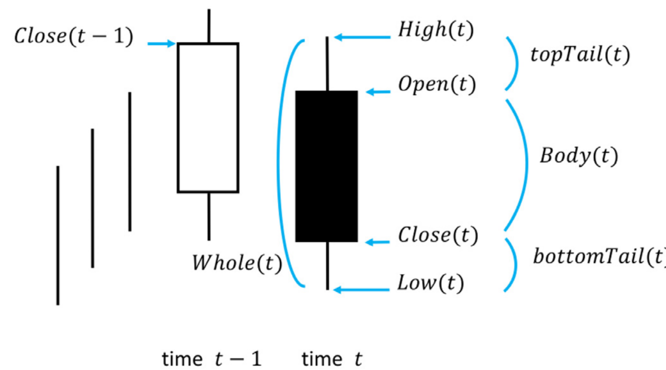

Fig. 4. Interrelation of Candlestick Indicators. *Open*(t), *High*(t), *Low*(t) and *Close*(t) indicate the opening price, the highest price, the lowest price and the closing price at a time t, respectively.

3.2.1. The candlestick indicators

We newly defined five candlestick indicators that can fully represent the one-day candlestick pattern. Calculation formulas of these five candlestick indicators have been given in Eqs. (15)~(19).

$$Candle(t) = \begin{cases} 1, & if\ Close(t) > Open(t) \\ -1, & if\ Close(t) < Open(t) \\ 0, & if\ Close(t) = Open(t) \end{cases} \quad (15)$$

where $Candle(t) = 1$ represents the white candlestick, $Candle(t) =$ -1 the black candlestick, $Candle(t) = 0$ doji candlestick.

$$Body(t) = \frac{abs(Open(t) - Close(t))}{Close(t-1)} \quad (16)$$

$$topTail(t) = \frac{High(t) - max(Open(t),\ \ Close(t))}{Close(t-1)} \quad (17)$$

$$bottomTail(t) = \frac{min(Open(t),\ \ Close(t)) - Low(t)}{Close(t-1)} \quad (18)$$

$$Whole(t) = \frac{High(t) - Low(t)}{Close(t-1)} \quad (19)$$

where $Body(t)$ is the real body of the candlestick, $topTail(t)$ is the upper shadow, $bottomTail(t)$ is the lower shadow and $Whole(t)$ is the total length of the candlestick. The relationship between candlestick indicators has been shown in Fig. 4.

3.2.2. The technical indicators

In this study, the most widely used technical indicators have also been used together with five candlestick indicators introduced above. The technical indicators used in the current study are as follows.

3.2.2.1. Moving average convergence and divergence (MACD)

Moving average convergence divergence (MACD) is a trend-following momentum indicator that shows the relationship between two moving averages. It is calculated by subtracting long-period exponential moving average (EMA) from the short-period moving average. It can be calculated as Eq. (20).

$$MACD(t) = EMA_5(t) - EMA_{10}(t) \quad (20)$$

where EMA_5 represents 5-day EMA. EMA_{10} 10-day EMA.

3.2.2.2. Rate-of-change (ROC)

The price rate of change (ROC) is a momentum indicator that represents the rate of price fluctuation between the current price and the price of n days before. It is calculated as follows.

$$ROC_n(t) = \frac{Close(t) - Close(t-n+1)}{Close(t-n+1)} \times 100, \qquad n = 5 \tag{21}$$

$$ROCMA_n(t) = \frac{MA_n(t) - MA_n(t-n+1)}{MA_n(t-n+1)} \times 100, \qquad n = 5 \tag{22}$$

$ROCMA_n(t)$ represents the rate of change of movement average price.

3.2.2.3. Stochastic oscillator

The Stochastic Oscillator is a momentum indicator that represents the relationship between the current price and the price range over a period of time.

$$StoK_n(t) = \frac{Close(t) - L_n(t)}{H_n(t) - L_n(t)} \times 100, \qquad n = 5 \tag{23}$$

$$StoD_n(t) = \frac{1}{3}\sum_{i=1}^{3} StoK_n(t-i+1), \qquad n = 5 \tag{24}$$

$$StoR_n(t) = \frac{H_n(t) - Close(t)}{H_n(t) - L_n(t)} \times 100, \qquad n = 5 \tag{25}$$

where H_n represents the highest price over last n days, L_n the lowest price over last n days.

3.2.2.4. Commodity channel index (CCI)

The Commodity Channel Index (CCI) is an indicator that represents the strength and direction of the price trend by the difference between recent price and the moving average of the average price.

$$CCI_n(t) = \frac{M(t) - m_n(t)}{0.015 \times d_n(t)}, \qquad n = 14 \tag{26}$$

where

$$M(t) = \frac{High(t) + Low(t) + Close(t)}{3} \tag{27}$$

$m_n(t)$ represents the moving average of $M(t)$ over last n days, $d_n(t)$ the moving standard deviation of $M(t)$ over last n days.

$$CCIS_n(t) = \frac{1}{9}\sum_{i=1}^{9} CCI_n(t) \tag{28}$$

3.2.2.5. Relative strength index (RSI)

The relative strength index (RSI) is a momentum indicator that can identify overbought or oversold conditions by comparing the magnitude of gains and losses over a certain time period.

$$RSI = 100 - \frac{100}{1 + RS} \tag{29}$$

where $RS = Average\ Gain\ /\ Average\ Loss$.

3.2.2.6. Volume ratio(VR)

The volume ratio (VR) is the ratio of the trading volume in ascending days to the one in declining days over a certain period of time.

$$VR = \frac{A + U/2}{D + U/2} \times 100 \tag{30}$$

where A denotes the total volume of the periods when the price ascend, D denotes the total volume of the periods when the price declined, U is the total volume of the periods when the price unchanged

3.2.2.7. Psychological line(PL)

PL is the ratio of the days of ascending in stock price to total days over a certain period of time.

$$PL = \frac{A}{n} \times 100 \tag{31}$$

3.2.2.8. Volume moving average (VMA)

Similar to the price moving average, VMA is the average trading volume of stock over a certain period.

$$VMA_n(t) = \frac{1}{n}\sum_{i=1}^{n} Volume(t-i+1), \qquad n = 20 \tag{32}$$

$$pctMV_n(t) = \frac{Volumn(t)}{VMA_n(t-1)} \tag{33}$$

$pctMV_n$ is the ratio of current trade volume versus to VMA on the day before.

3.2.2.9. AB ratio

The AB Ratio is an indicator that can be used to determine whether the trend is bullish or bearish by comparing high and low prices based on open price and closing price for a certain period of time.

$$ARatio_n(t) = \frac{\sum_{i=1}^{n} (High(t-i+1) - Open(t-i+1))}{\sum_{i=1}^{n} (Open(t-i+1) - Low(t-i+1))} \times 100 \tag{34}$$

$$BRatio_n(t) = \frac{\sum_{i=1}^{n} (High(t-i+1) - Close(t-i))}{\sum_{i=1}^{n} (Close(t-i) - Low(t-i+1))} \times 100 \tag{35}$$

$$ABRaio_n = \frac{ARatio_n(t)}{BRatio_n(t)} \tag{36}$$

3.2.2.10. Percentage change of the close price(pctChange)

$$pctChange(t) = \frac{Close(t) - Close(t-1)}{Close(t-1)} \tag{37}$$

3.2.3. Feature candidate set

As mentioned in the Introduction section, it is not so clear which combination of indicators will be most appropriate for RP prediction, and there is no feature set uniformly appropriate for all stocks. In order to improve the prediction accuracy, we constructed 27 feature candidate sets by different combinations of previously introduced technical indicators and candlestick indicators, and chose the most appropriate feature set for each stock by real experiments. The 27 feature candidates are shown in Table 1. In this table, S_0 ~ S_5 are feature candidate sets that combine only technical indicators, and S_6 is a feature candidate set consisting of five candlestick indicators proposed in this study. In addition, S_7 ~ S_{26} are feature candidate sets that combine technical indicators and candlestick indicators.

3.3. The LSTM based predict model using upward/downward reversal point feature set

As will be seen in Experiment result and analysis section, experiment results show that there is no feature set that will uniformly appropriate for the prediction of URP and DRP. In order to improve the accuracy of prediction system, we proposed a new prediction model consisting of LSTM-based URP and DRP predictors. The block diagram of the proposed model for the prediction of trend reversal point was shown in Fig. 5.

Table 1
The feature candidate sets.

Kind	Set	Input variables	Output
Technical Indicators	S_0	*CRP, Trend, Candle,* $pctMV_{20}$, VR_{20}, PL_{20}, CCI_{14}, $CCIS_{14}$, RSI_{20}, $StoK_5$, $StoD_5$, $StoR_5$, *MACDR,* $ROCMA_5$, ROC_5, *pctChange*	*RP*
	S_1	*CRP, Trend, Candle,* $pctMV_{20}$, VR_{20}, PL_{20}, *pctChange*	*RP*
	S_2	*CRP, Trend, Candle,* CCI_{14}, $CCIS_{14}$, RSI_{20}, *pctChange*	*RP*
	S_3	*CRP, Trend, Candle,* $StoK_5$, $StoD_5$, $StoR_5$, *pctChange*	*RP*
	S_4	*CRP, Trend, Candle, MACD,* $ROCMA_5$, ROC_5, *pctChange*	*RP*
	S_5	*CRP, Trend, Candle,* $ARatio_{26}$, $BRatio_{26}$, $ABRatio_{26}$, *pctChange*	*RP*
Candlestick Indicators	S_6	*CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
Technical Indicators and Candlestick Indicators	S_7	*CRP, Trend, Candle,* $pctMV_{20}$, VR_{20}, PL_{20}, *Body, topTail, bottomTail, Whole*	*RP*
	S_8	*CRP, Trend, Candle,* CCI_{14}, $CCIS_{14}$, RSI_{20} *Body, topTail, bottomTail, Whole*	*RP*
	S_9	*CRP, Trend, Candle,* $StoK_5$, $StoD_5$, $StoR_5$, *Body, topTail, bottomTail, Whole*	*RP*
	S_{10}	*CRP, Trend, Candle, MACD,* $ROCMA_5$, ROC_5 *Body, topTail, bottomTail, Whole*	*RP*
	S_{11}	*CRP, Trend, Candle,* $ARatio_{26}$, $BRatio_{26}$, $ABRatio_{26}$, *Body, topTail, bottomTail, Whole*	*RP*
	S_{12}	$pctMV_{20}$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{13}	VR_{20}, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{14}	PL_{20}, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{15}	CCI_{14}, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{16}	$CCIS_{14}$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{17}	RSI_{20}, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{18}	$StoK_5$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{19}	$StoD_5$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{20}	$StoR_5$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{21}	*MACD, CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{22}	$ROCMA_5$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{23}	ROC_5, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{24}	$ARatio_{26}$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{25}	$BRatio_{26}$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*
	S_{26}	$ABRatio_{26}$, *CRP, Trend, Candle, Body, topTail, bottomTail, Whole*	*RP*

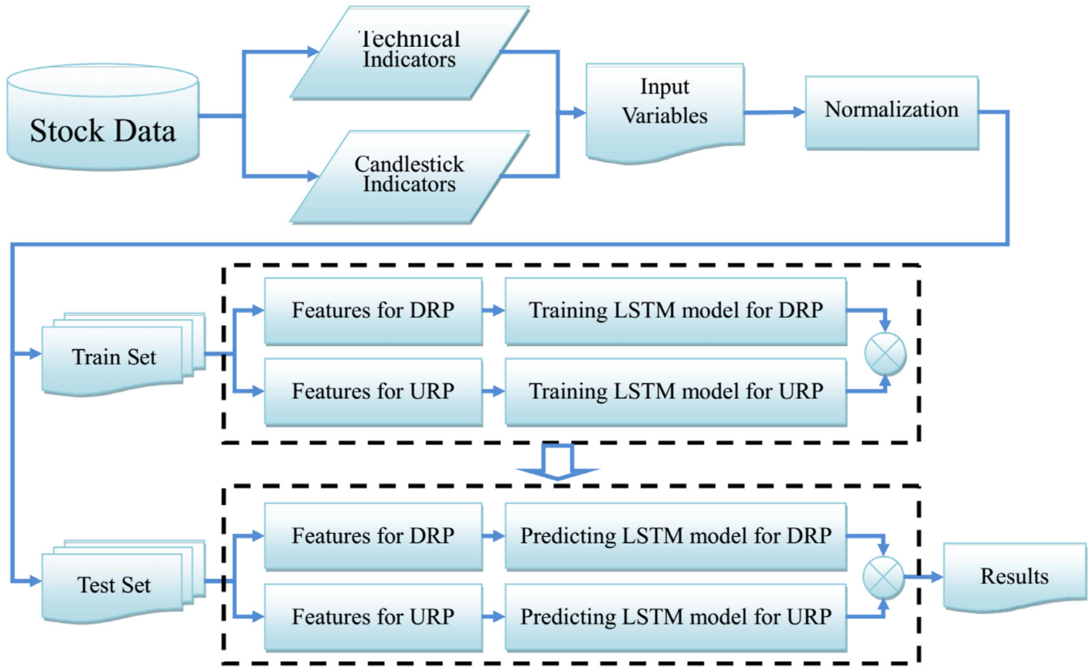

Fig. 5. Block diagram of the proposed model

The system mainly consists of the input data pre-processing part and the training and testing part. In the input data pre-processing part, the input variables for RP predictors are constructed by calculating a series of technical and candlestick indicators from the basic data on stock. Then, these input variables are normalized according to Eq. (38).

$$X' = \frac{X - X_{mean}}{X_{std}} \tag{38}$$

where X he vector data that should be normalized, X_{mean} denotes the mean value of the data and X_{std} denotes the standard deviation of the data. The normalized input variables are divided into 90% and 10%, which are respectively used as training and testing data of RP predictor. Among 27 feature candidate sets, through the training process, the feature sets (upward and downward feature sets) suitable for URP-prediction and DRP-prediction are respectively selected, and then the structural parameters of URP and DRP prediction models were determined according to the corresponding feature sets. Both URP and DRP prediction models exploit the LSTM networks constituted of input and output layers and a hidden layer, and the number of neurons in the hidden layer is chosen as a value providing the best prediction accuracy among 7 values (10, 20, 30, 60, 100, 120, and 200), respectively in both models. The proposed prediction model is designed to predict the future-10-days trend by using the past-10-days data as input data (time step = 10).

4. Experimental results and discussion

Stock data that has been used in the current study have been downloaded from Yahoo Finance. Since deep learning requires as much training data as possible, 10 stocks with more than 2500 trading days have been randomly selected in Chinese and American markets, respectively. 90% of the stock data of each corporation has been used as training data, while 10% has been used as testing data. Stock data of Chinese and American markets have been shown in Table 2 and Table 3, respectively.

Precision, Recall and F1 have been used as the measurement units for analysis of experimental results. They can be represented as follows, respectively.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{39}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{40}$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{41}$$

Table 2
Stock data of Chinese corporations.

Ticker	Name	Period	Trading days
600019.SS	Baoshan Iron & Steel Co., Ltd.	2000/12/12 ~ 2018/3/29	4028
600029.SS	China Southern Airlines Co., Ltd.	2003/7/25 ~ 2018/4/11	3473
600036.SS	China Merchants Bank Co., Ltd.	2002/4/09 ~ 2018/4/11	3814
600048.SS	Poly Real Estate Group Co.,Ltd.	2006/7/31 ~ 2018/3/29	2805
600111.SS	China Northern Rare Earth (Group) High-Tech Co.,Ltd.	1997/9/24 ~ 2018/3/29	4914
600340.SS	China Fortune Land Development Co., Ltd.	2003/12/30 ~ 2018/3/29	3125
600519.SS	Kweichow Moutai Co., Ltd.	2001/8/27 ~ 2018/3/29	3950
600606.SS	Greenland Holdings Co., Ltd.	1996/5/06 ~ 2018/3/29	4909
601001.SS	DaTong Coal Industry Co.,Ltd.	2006/6/23 ~ 2018/4/11	2677
601002.SS	Gem-Year Industrial Co., Ltd.	2007/1/26 ~ 2018/4/10	2684

Table 3
Stock data of American corporations.

Ticker	Name	Period	Trading days
AAPL	Apple Inc.	1996/5/6 ~ 2018/4/19	5527
BAC	Bank of America Corporation	1996/5/6 ~ 2018/4/13	5523
AMZN	Amazon.com, Inc.	1997/5/15 ~ 2018/4/16	5264
AA	Alcoa Corporation	1996/5/6 ~ 2018/4/18	5525
AXP	American Express Company	1996/5/6 ~ 2018/4/27	5533
T	AT&T Inc.	1987/12/31 ~ 2018/5/11	7653
MO	Altria Group, Inc.	1996/5/6 ~ 2018/4/30	5533
ABT	Abbott Laboratories	1996/5/6 ~ 2018/5/3	5537
AMAT	Applied Materials, Inc.	1996/5/6 ~ 2018/5/4	5538
AMGN	Amgen Inc.	1996/5/6 ~ 2018/5/9	5541

Table 4
Predictive power of feature candidate sets including candlestick, technical and combined indicators. The bold characters show the highest F1 value in each class.

Kind	Set	URP			DRP		
		Precision	Recall	F1	Precision	Recall	F1
Technical Indicators	S_0	86.7	86.7	**86.7**	78.6	78.6	78.6
	S_1	57.9	91.7	71	78.6	78.6	78.6
	S_2	66.7	80	72.7	58.3	100	73.7
	S_3	58.8	83.3	69	100	57.1	72.7
	S_4	83.3	66.7	74.1	70	100	82.4
	S_5	56.5	86.7	68.4	62.5	71.4	66.7
Candlestick Indicators	S_6	52.9	81.8	64.3	84.6	73.3	**78.6**
Technical Indicators and Candlestick Indicators	S_7	81.8	60	69.2	80	85.7	82.8
	S_8	50	91.7	64.7	81.3	86.7	83.9
	S_9	64.3	81.8	72	85.7	85.7	85.7
	S_{10}	92.3	80	85.7	63.6	100	77.8
	S_{11}	83.3	55.6	66.7	90	64.3	75
	S_{12}	45.8	100	62.9	78.6	73.3	75.9
	S_{13}	56.3	81.8	66.7	100	64.3	78.3
	S_{14}	100	50	66.7	81.8	64.3	72
	S_{15}	52.6	83.3	64.5	75	80	77.4
	S_{16}	50	90.9	64.5	100	50	66.7
	S_{17}	55	73.3	62.9	63.6	100	77.8
	S_{18}	64.3	69.2	66.7	78.6	78.6	78.6
	S_{19}	58.8	90.9	71.4	84.6	78.6	81.5
	S_{20}	71.4	76.9	74.1	100	71.4	83.3
	S_{21}	91.7	73.3	81.5	75	85.7	80
	S_{22}	69.2	64.3	66.7	90	60	72
	S_{23}	59.1	76.5	66.7	68.8	78.6	73.3
	S_{24}	57.9	100	73.3	77.8	100	**87.5**
	S_{25}	90	60	72	90.9	71.4	80
	S_{26}	72.7	61.5	66.7	80	80	80

where True Positives (TP) is the correctly predicted positive values, False Positives (FP) is wrongly predicted positive values, and False Negatives (FN) is wrongly predicted negative values. Precision and recall are both important indexes in the prediction, but it can not be said that performance is high if only one of them is high. As being an aggregate index of both, F1 is used as the main measurement unit.

Experiments have been conducted in followed stages. First, the prediction accuracy of 27 feature candidate sets consisted of a combination of candlesticks and technical indicators are evaluated and the effectiveness of the proposed candlestick indicators is verified. Next, URP-prediction and DRP-prediction are conducted for 20 Chinese and American stocks and the performance of the proposed model are evaluated by analyzing two results. Then the performance of the proposed model on Chinese and American markets is compared. Lastly, experiments have been conducted compared with SVM, MLP, and CNN, which have been widely using in the prediction of the stock price.

4.1. Performance evaluation of feature candidate sets

We have conducted experiments with 27 feature candidate sets for all stocks, and the highest experiment values have been given in Table 4 and Fig. 6.

Table 5
Prediction accuracy of feature candidate sets for 600019.SS.

Set	F1		Set	F1		Set	F1	
	URP	DRP		URP	DRP		URP	DRP
S_0	42.9	78.6	S_9	26.7	85.7	S_{18}	28.6	78.6
S_1	15.4	78.6	S_{10}	33.3	62.1	S_{19}	16.7	81.5
S_2	30.8	68.8	S_{11}	44.4	75	S_{20}	26.7	83.3
S_3	16.7	64	S_{12}	16.7	75.9	S_{21}	40	62.1
S_4	28.6	51.9	S_{13}	26.7	78.3	S_{22}	16.7	69.2
S_5	16.7	61.5	S_{14}	40	72	S_{23}	30.8	73.3
S_6	16.7	74.1	S_{15}	26.7	75	S_{24}	35.3	66.7
S_7	30.8	82.8	S_{16}	35.3	66.7	S_{25}	25	80
S_8	22.2	78.6	S_{17}	21.1	72	S_{26}	50	66.7

As shown in Table 4, the prediction results (F1) for URP and DRP of S_6 which is only consisted of candlestick indicators are 64.3 and 78.6, respectively. Results show that candlestick indicators can be said to have certain predictive power, and F1 of S_{24}, which is constructed by combining candlestick indicators and technical indicators, is 87.5 that is the highest among the 27 feature candidate sets. Therefore, we can know that combining the technical indicators and candlestick indicators can allow us to get a better result.

Table 5 and Fig. 7 shows the prediction result (F1) of 27 feature candidate sets for stock 600019.SS. As can be seen above, using the

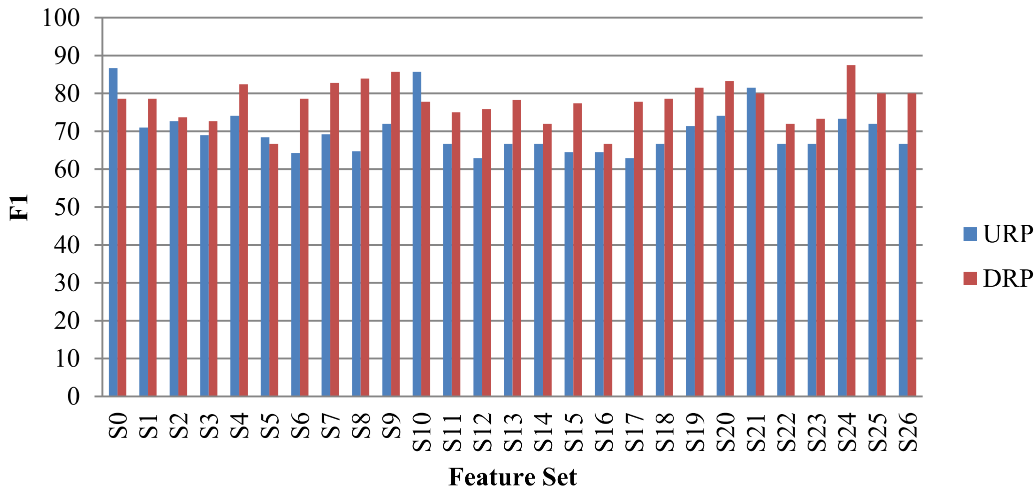

Fig. 6. F1 value of 27 Feature sets

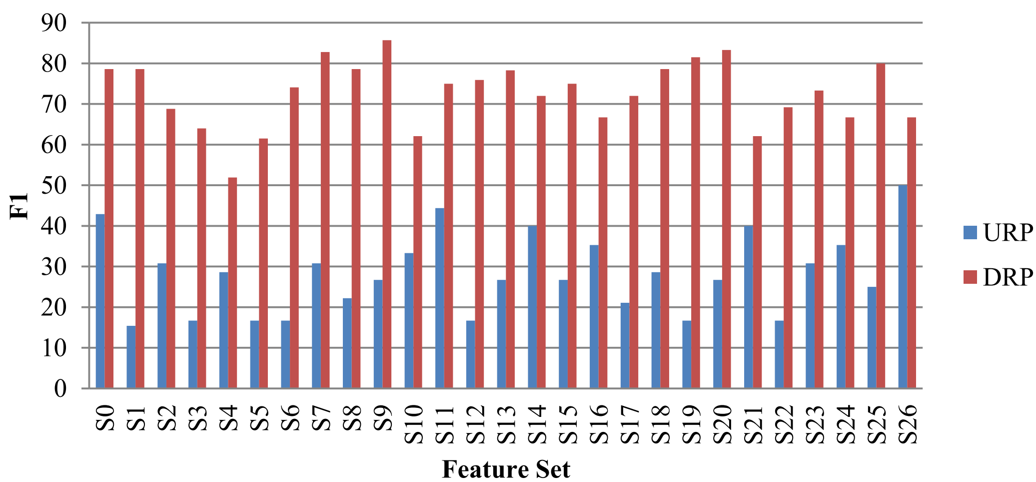

Fig. 7. F1 value of 27 Feature sets for 600019.SS.

feature candidate sets only consisted of technical indicators, the highest values of prediction accuracy for URP/DRP were 42.9 (S_0) and 78.6 (S_0), while they are 16.7 and 74.1 for using feature candidate sets (S_6) only consisted of candlestick indicators, which are rather less than those for using technical indicators. However, using the feature candidate sets constructed by combining of technical indicators and candlestick indicators, the highest values of prediction accuracy were 50(S_{26}), 85.7(S_9) for URP and DRP, respectively, which were 7.1% and 7.1% higher than those for only using technical indicators, respectively. It can be seen that if we flexibly combine technical indicators and candlestick indicators, we can effectively improve the prediction accuracy.

4.2. Evaluation of performance on each stock or market

There is no feature set appropriate for both URP/DRP predictions of a certain stock. For example, for stock 600019.SS, the most appropriate feature set for URP-prediction is S_{26}, while that one for DRP-prediction is S_9. From this, we construct feature sets and prediction models for URP and DRP-prediction, respectively, and maximize the prediction accuracy by predicting the RP in the method of combining individual prediction results. Fig. 8 shows the result of applying feature set S_9 (for DRP) to stock 600019.SS, while Fig. 9 shows the result of applying feature set S_{26} (for URP). Fig. 10 shows the prediction results of applying both of two feature sets. In the figures, blue circles show the accurately-predicted RPs, while pink squares show the wrongly-predicted RPs.

In the prediction model based on feature set S_9 (Fig. 8), most DRPs were accurately predicted, while only one URP was accurately predicted. In the prediction model using the feature set S_{26} (Fig. 9), the URPs were relatively well predicted compared with the prediction model using S_9, while the DRPs were not predicted well. However, in the proposed prediction system (Fig. 10), prediction accuracy has been significantly improved by combining the results of two predictors.

Similarly, we have conducted experiments for all stocks of two markets and provided a comprehensive analysis with them. Table 6 and Fig. 11 show the experimental results for 10 stocks in the Chinese market, while Table 7 and Fig. 12 show that one for 10 stocks in the American market. Comprehensive analyses of two markets have been illustrated in Table 8 and Fig. 13, respectively.

As can be seen in Table 6 and Table 7, in the Chinese market, the average values of F1 for URP-prediction and DRP-prediction are 66.2 and 71, respectively, and shown to be more appropriate for DRP-prediction. For the American market, the prediction performance for URP was better than for DRP. The average value of F1 for URP was 66.4, while the one for DRP was 46. Especially, the prediction for DRP of 7 stocks was not successful, their prediction accuracies were all less than 40%. However, DRP-prediction value for the BAC, AA, and AMGN stocks were relatively well predicted to be 70, 62.5, and 60, respectively. As shown in Table 8, the aver-

Fig. 8. The predicted RPs for 600019.SS using feature set S_9

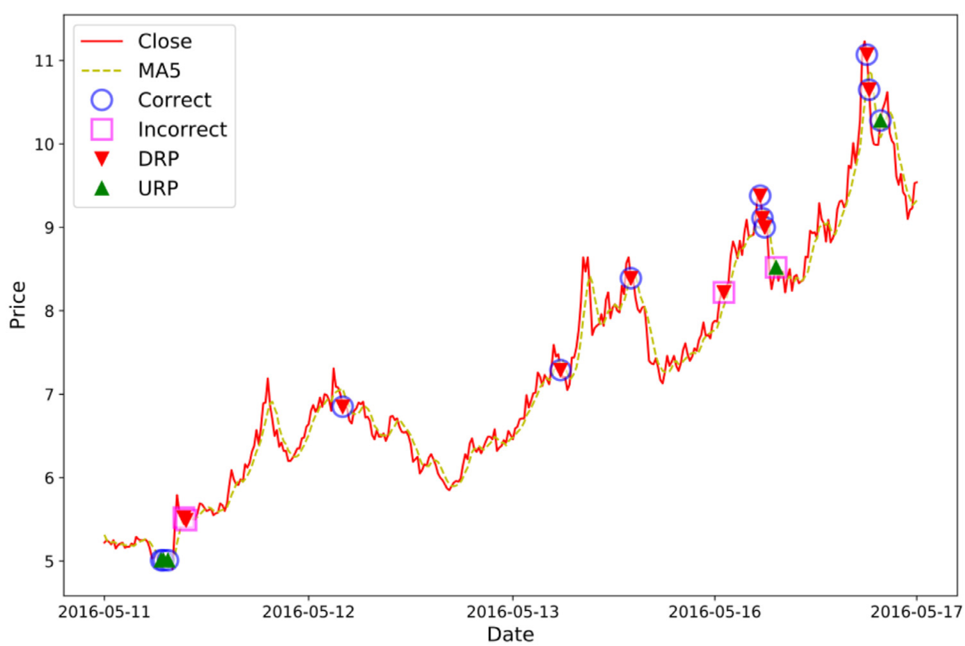

Fig. 9. The predicted RPs for 600019.SS using feature set S_{26}

Table 6
Predictive power of RP for Chinese market.

Ticker	URP				DRP			
	Precision	Recall	F1	Feature set	Precision	Recall	F1	Feature set
600019.SS	80	36.4	50	S_{26}	85.7	85.7	85.7	S_9
600029.SS	55.6	71.4	62.5	S_7	100	60	75	S_{19}
600036.SS	66.7	66.7	66.7	S_{10}	57.1	57.1	57.1	S_{21}
600048.SS	57.9	91.7	71	S_1	66.7	50	57.1	S_{24}
600111.SS	54.5	60	57.1	S_{18}	55.6	93.8	69.8	S_8
600340.SS	43.8	100	60.9	S_6	77.8	100	87.5	S_{24}
600519.SS	86.7	86.7	86.7	S_0	66.7	40	50	S_0
600606.SS	100	50	66.7	S_{14}	84.6	73.3	78.6	S_6
601001.SS	100	50	66.7	S_{10}	70	100	82.4	S_4
601002.SS	77.8	70	73.7	S_{10}	60	75	66.7	S_5
Average	72.3	68.3	66.2		72.4	73.5	71	

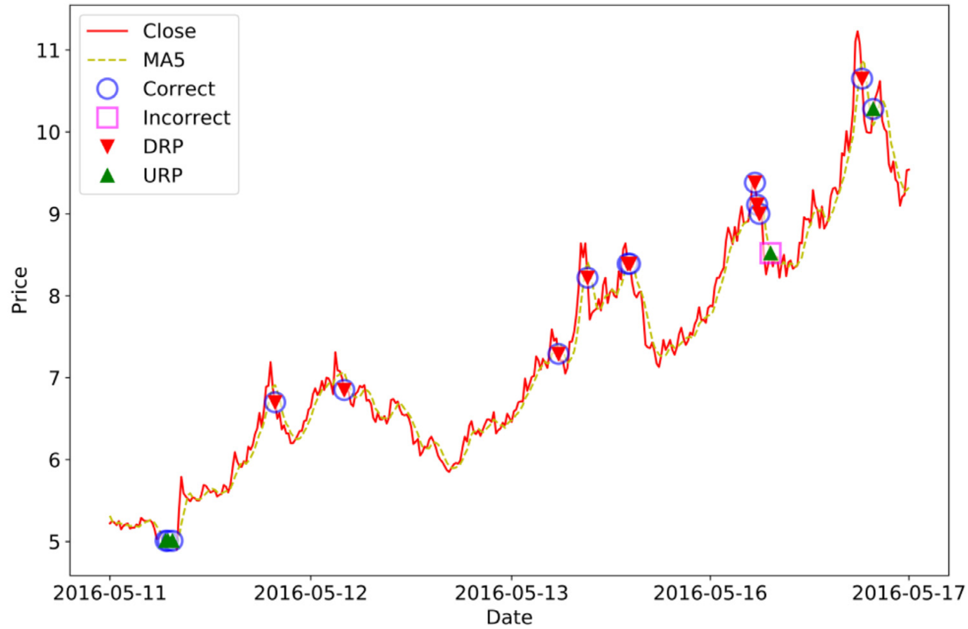

Fig. 10. The predicted RPs for 600019.SS using feature set S_{26} and S_9

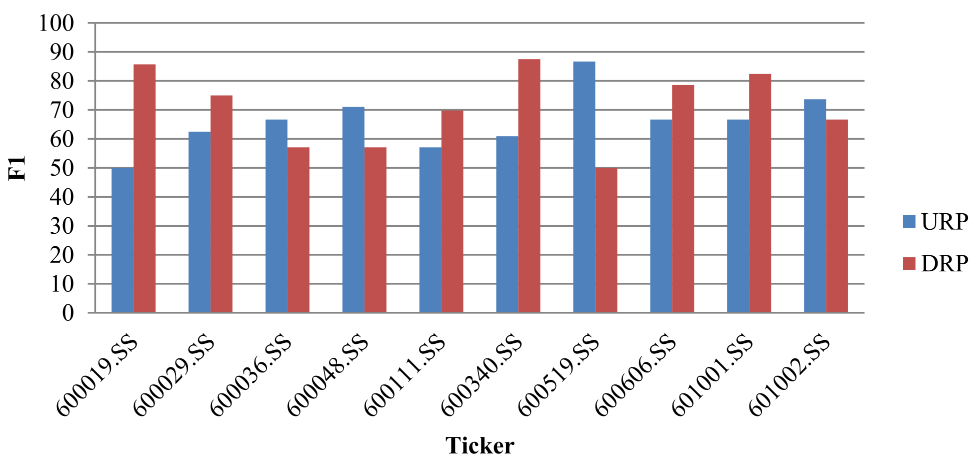

Fig. 11. Evaluation of F1 for stocks in Chinese market.

Table 7
Predictive power of RP for American market.

Ticker	URP				DRP			
	Precision	Recall	F1	Feature set	Precision	Recall	F1	Feature set
AAPL	71.4	76.9	74.1	S_{20}	100	25	40	S_{20}
BAC	66.7	80	72.7	S_2	100	53.8	70	S_7
AMZN	52.6	90.9	66.7	S_{11}	100	25	40	S_{25}
AA	59.1	76.5	66.7	S_{23}	76.9	52.6	62.5	S_{15}
AXP	71.4	62.5	66.7	S_0	100	25	40	S_2
T	80	44.4	57.1	S_{19}	50	28.6	36.4	S_7
MO	62.5	50	55.6	S_7	100	20	33.3	S_{10}
ABT	54.5	60	57.1	S_{10}	100	25	40	S_{17}
AMAT	88.9	57.1	69.6	S_{20}	42.9	33.3	37.5	S_{11}
AMGN	44	84.6	57.9	S_{15}	75	50	60	S_7
Average	65.1	68.3	64.4		84.5	33.8	46	

Table 8
Predictive power for two markets.

Market	F1		
	URP	DRP	Average
China	66.2	71	68.6
America	64.4	46	55.2

age values of F1s of URP and DRP were 68.6 and 55.2 for Chinese and American markets, respectively. Results show that the average prediction accuracy is 13.4% higher for Chinese market compared to American market. More specifically, the prediction accuracies for URP of Chinese and American market were similar, respectively are 66.2 and 64.4. However the prediction accuracy for DRP of Chinese market was significantly higher than that for American one,

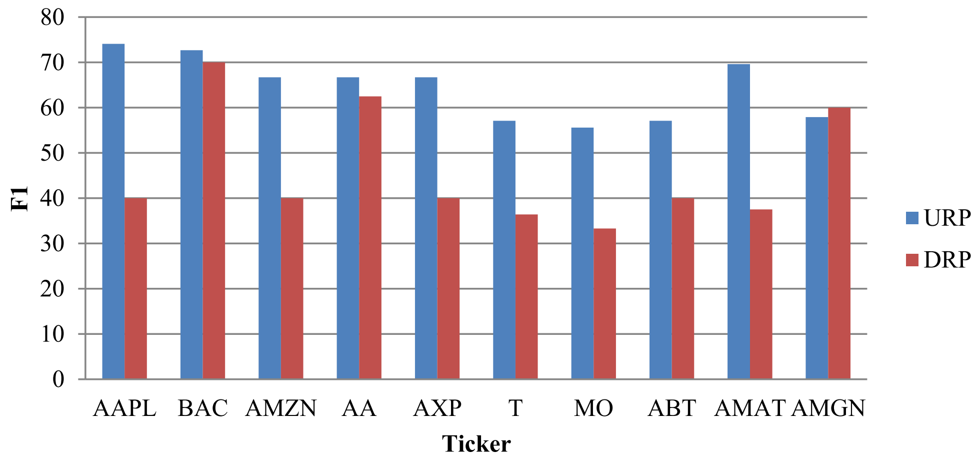

Fig. 12. Evaluation of F1 for stocks in American market.

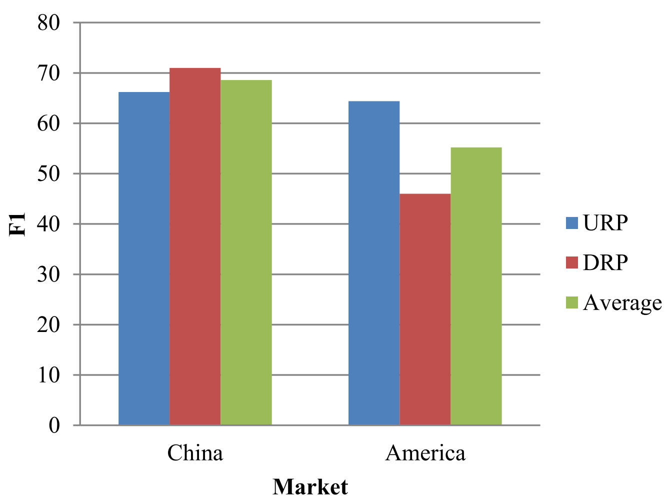

Fig. 13. Evaluation of F1 for two markets.

Table 9
Predictive accuracy of each model for Chinese market.

Model	F1		
	URP	DRP	Average
LSTM	66.2	71	68.6
SVM	61.7	57.9	59.8
MLP	54.1	59.1	56.6
CNN	58.5	65	61.8

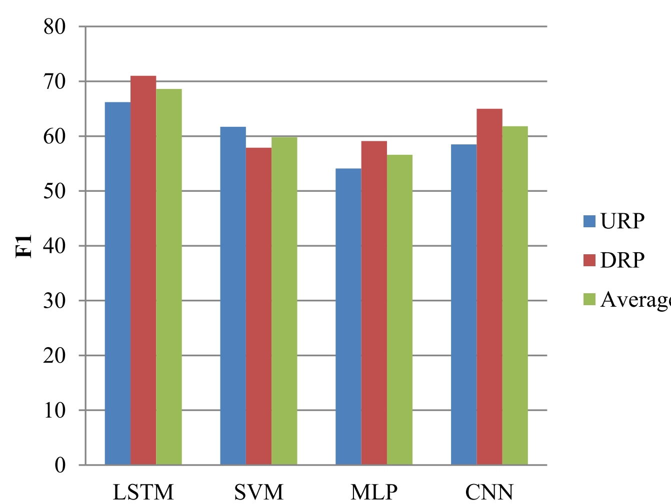

Fig. 14. Evaluation of F1 for each model in Chinese market.

they are respectively 71 and 46. In result, the prediction accuracies for URP/DRP of all stocks differ from each other. It is due to the fact that each market or stock has its own inherent characteristics, and same criterions have been set for URP and DRP. Therefore, if we set flexible criterions appropriate for URP/DRP with considering the movement characteristics of each stock, a better prediction accuracy can be expected.

4.3. Benchmark

For the prediction of stock price, several kinds of models have been suggested, including SVM, MLP, CNN, LSTM, etc. Some research works have compared the prediction models. [21] showed that MLP and LSTM outperformed SVM, while [22–24] showed that CNN outperformed MLP or LSTM. Therefore, in order to confirm the superiority of our proposed LSTM model, we have conducted a comparative analysis with SVM, MLP, and CNN, which has been widely using in the prediction of the stock price. Experiments for each model and proposed model used the same data and applied the same method. SVM used Radial Basis Function as the kernel function. Different sets of gamma and cost have been used for experiments to obtain the highest prediction accuracy, where gamma has been chosen from (1e-10, 1e-9, 1e-8, 1e-7, 1e-6, 1e-5, 0.0001, 0.001, 0.01, 0.1, 1) and cost has been chosen from (10, 100, 1000, 10000, 1e+5, 1e+6, 1e+7). MLP has been constructed with 3 kinds of structures, respectively single layer, two layers and three layers, and the neuron numbers of each layer were 200, 100 and 100, respectively. CNN has been constructed with a single layer, and the neuron numbers have been chosen from 7 values (10, 20, 30, 60, 100, 120 and 200) to provide the best prediction accuracy for each stock. Comparison results of all models for Chinese markets have been shown in Table 9 and Fig. 14, while comparison results of all models for American markets have been shown in Table 10 and Fig. 15.

As can be seen in Table 9 and Fig. 14, URP/DRP prediction accuracy (F1) of LSTM model for Chinese markets were 66.3% and 71%, respectively, which outperformed other models. URP prediction accuracy of SVM was 61.7%, while CNN 58.5%, MLP 54.1%, which was 2nd, 3rd and 4th, respectively. DRP prediction accuracy of CNN was 65%, while MLP 59.1%, SVM 57.9%, which participated 2nd, 3rd and 4th, respectively. The total prediction accuracies for the two RPs

Table 10
Prediction accuracy for each model in American market.

Model	F1		
	URP	DRP	Average
LSTM	64.4	46	55.2
SVM	59.9	44.5	52.2
MLP	54.4	32.9	43.7
CNN	58.5	44.1	51.3

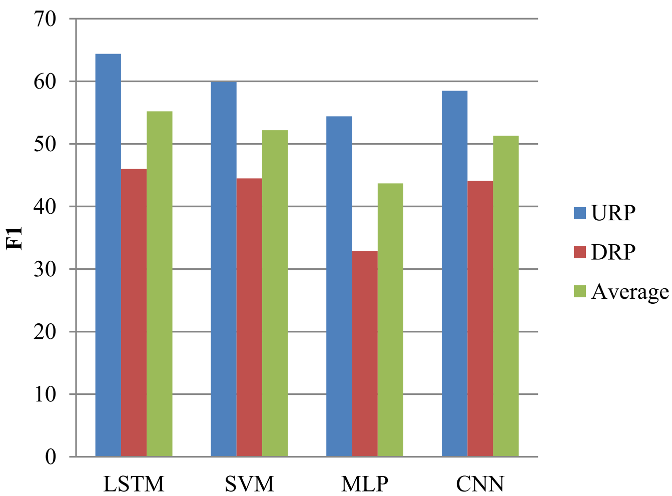

Fig. 15. Evaluation of F1 for each model in American market.

Table 11
Prediction accuracy of each model.

Model	F1		
	URP	DRP	Average
LSTM	65.3	58.5	61.9
SVM	60.8	51.2	56
MLP	54.3	46	50.2
CNN	58.5	54.6	56.6

were 61.8% for the CNN, 59.8% for the SVM and 56.6% for the MLP, which ranked 2nd, 3rd and 4th, respectively.

As shown in Table 10 and Fig. 15, URP/DRP prediction accuracy of LSTM were 64.4% and 46% for American markets, which outperformed other models. SVM, CNN, MLP participated 2nd, 3rd and 4th, respectively. Considering DRP prediction results, LSTM is 46%, MLP is 32.9% and CNN is 44.1%. Prediction accuracies of all of four models were not so considerable.

Evaluations of the total performance of each model have been shown in Table 11 and Fig. 16. As shown in Table 11, the prediction accuracy of the proposed LSTM based model was 61.9% was highest, which was higher than SVM, MLP and CNN by 5.9%, 11.7% and 5.3%, respectively. As shown in Table 11, the prediction accuracy of the proposed LSTM based model was 61.9% was highest, which was higher than SVM, MLP and CNN by 5.9%, 11.7% and 5.3%, respectively.

5. Conclusion

A novel LSTM based stock price reversal point prediction model has been proposed. The proposed model consists of URP and DRP predictors, and the results of both predictors have been combined to improve the prediction accuracy. Current study tried to improve the prediction accuracy for each stock by choosing URP/DRP feature sets appropriate them among 27 feature candidate sets constructed by combining of candlestick indicators and technical indicators, not by uniformly using a certain feature set for all stocks.

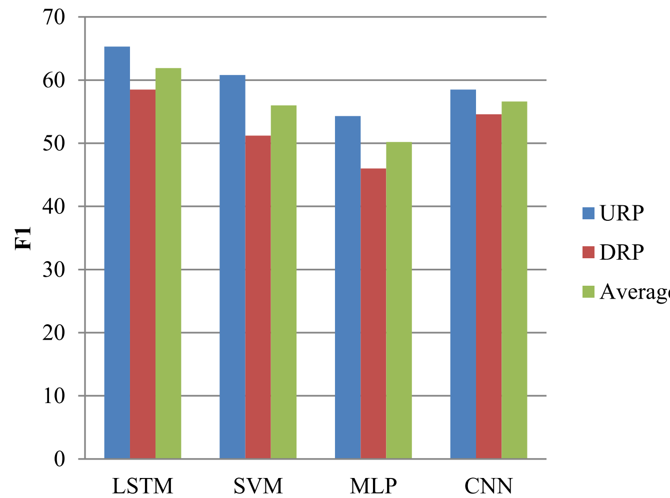

Fig. 16. Evaluation of F1 for each model.

The proposed model has been used to the reversal point prediction for 20 stocks in Chinese and American markets, and the results have been compared with those of SNM, MLP and CNN. Results show that average prediction accuracy (F1) for Chinese markets and American ones were 68.6% and 55.2%, respectively. The average prediction accuracy for Chinese markets was 13.4% higher than American ones. The prediction accuracies for URP of Chinese and American markets were 66.2 and 64.4, respectively, which can be said to be relatively well predicted. However, DRP predictions showed a remarkable dominance in the Chinese market compared to the American one, their prediction accuracies were 71 and 46, respectively. Especially for the American market, except 3 companies, the prediction accuracies for DRP of 7 companies were all less than 40%, which can represent unsuccessful prediction. Proposed LSTM based model provided the improvement of 5.9%, 11.7% and 5.3%, respectively compared to SVM, MLP and CNN.

Declaration of Competing Interest

None.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] Enke D, Thawornwong S. The use of data mining and neural networks for forecasting stock market returns. Expert Syst Appl 2005;29:927–40.
[2] Fama EF. Efficient capital markets: a review of theory and empirical work. J Finance 1970;25:383–417.
[3] Jensen MC. Some anomalous evidence regarding market efficiency. J Financ Econ 1978;6:95–101.
[4] Fama EF, Marshall EB. Filter rules and stock-market trading. J Bus 1966;39:226–41.
[5] Van HJC, Parke GGC. The random-walk theory: an empirical test. Financ Anal J 1967;23:87–92.
[6] Malkiel B. A Random Walk Down Wall Street: Including a Life-cycle Guide to Personal Investing. W.W. Norton & Company; 1999.
[7] Bessembinder H, Chan K. Market efficiency and the returns to technical analysis. Financ Manag 1998;27:5–17.
[8] Lo AW, Mamaysky H, Wang J. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. J Finance 2000;55:1705–65.
[9] Brock W, Lebaron LB. Simple technical trading rules and the stochastic properties of stock returns. J Finance 1992;47:1731–64.

[10] Cakra Y, Trisedya BD. Stock price prediction using linear regression based on sentiment analysis. In: International Conference on Advanced Computer Science and Information Systems; 2015. p. 147–53.
[11] Sun A, Lachanski M, Fabozzi FJ. Trade the tweet: social media text mining and sparse matrix factorization for stock market prediction. Int Rev Financ Anal 2016;48:272–81.
[12] Peng Y, Jiang H. Leverage Financial News to Predict Stock Price Movements Using Word Embeddings and Deep Neural Networks. In: Proceedings of NAACL-HLT; 2016. p. 374–9.
[13] Ariyo AA, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. In: 2014 UKSim-AMSS 16th International Conference on Computer Modeling and Simulation; 2014. p. 106–12.
[14] Stoean R, Stoean C, Sandita A. Evolutionary regressor selection in ARIMA model for stock price time series forecasting. Intell Dec Technol 2017:117–26.
[15] Nayak RK, Mishra D, Rath AK. A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices. Appl Soft Comput 2015;35:670–80.
[16] Pan YC, Xiao Z, Wang XN, Yang DL. A multiple support vector machine approach to stock index forecasting with mixed frequency sampling. Knowl--Based Syst 2017;122:90–102.
[17] Nahil A, Lyhyaoui A. Short-term stock price forecasting using kernel principal component analysis and support vector machines: the case of Casablanca stock exchange. Procedia Comput Sci 2018;127:161–9.
[18] Zahedi J, Rounaghi MM. Application of artificial neural network models and principal component analysis method in predicting stock prices on Tehran Stock Exchange. Phys A 2015;438:178–87.
[19] Qiu M, Song Y, Akagi F. Application of artificial neural network for the prediction of stock market returns: the case of the Japanese stock market. Chaos Soliton Fract 2016;85:1–7.
[20] Jeon S, Hong B, Chang V. Pattern graph tracking-based stock price prediction using big data. Future Gener Comp Sy 2017;80:171–87.
[21] Li W, Liao J. A comparative study on trend forecasting approach for stock price time series. In: IEEE International Conference on Anti-counterfeiting, Security, and Identification; 2017. p. 74–8.
[22] Tsantekidis A, Passalis N, Tefas A, Kanniainen J, Gabbouj M, Iosifidis A. Forecasting stock prices from the limit order book using convolutional neural networks. In: IEEE Conference on Business Informatics (CBI); 2017. p. 7–12.
[23] Selvin S, Vinayakumar R, Gopalakrishnan EA, Menon VK, Soman KP. Stock price prediction using LSTM, RNN and CNN-sliding window model. In: Advances in Computing, Communications and Informatics (ICACCI), 2017 International Conference on IEEE; 2017. p. 1643–7.
[24] Hiransha M, Gopalakrishnan EA, Menon VK, Soman KP. NSE stock market prediction using deep-learning models. Procedia Comput Sci 2018;132:1351–62.
[25] Maknickienė N, Maknickas A. Application of neural network for forecasting of exchange rates and forex trading. In: Proceedings of the 7th international scientific conference on business and management; 2012. p. 10–11.
[26] Chen K, Zhou Y, Dai F. A LSTM-based method for stock returns prediction: a case study of China stock market. In: Proceedings of the 2015 IEEE international conference on big data (Big Data). IEEE; 2015. p. 2823–4.
[27] Fischer T, Krauss C. Deep learning with long-term memory networks for financial market predictions. Eur J Oper Res 2018;270:654–69.
[28] Kim HY, Won CH. Forecasting the volatility of stock price index: a hybrid model integrating LSTM with multiple GARCH-type models Expert. Syst Appl 2018;103:25–37.
[29] Pang XW, Zhou YQ, Wang P, Lin WW, Chang V. An innovative neural network approach for stock market prediction. J Supercomput 2017:1–21.
[30] Bao W, Yue J, Rao Y. A deep learning framework for financial time series using stacked autoencoders and long-short term memory. PLOS ONE 2017;12(7):e0180944.
[31] Chang V. The Business intelligence as a service in the cloud. Future Generat Compu Syst 2014;37:512–34.
[32] Chang V, Li C, De Roure D, Wills G, Walters RJ, Chee C. The financial clouds review. In Grid and Cloud Computing: concepts. Methodol Tool Appl 2012:1062–83.
[33] Chang PC, Fan CY, Liu CH. Integrating a piecewise linear representation method and a neural network model for stock trading points prediction. In: IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews, 39; 2009. p. 80–92.
[34] Luo LK, Chen X. Integrating piecewise linear representation and weighted support vector machine for stock trading signal prediction. Appl Soft Comput 2013;13(2):806–16.
[35] Luo LK, You SY, Xu YR, Peng H. Improving the integration of piece wise linear representation and weighted support vector machine for stock trading signal prediction. Appl Soft Comput 2017;56:199–216.
[36] Zhang XD, Li A, Ran R. Stock trend prediction based on a new status box method and AdaBoost probabilistic support vector machine. Appl Soft Comput 2016;49:385–98.
[37] Chang PC, Wu JL, Lin JJ. A Takagi–Sugeno fuzzy model combined with a support vector regression for stock trading forecasting. Appl Soft Comput 2016;38:831–42.
[38] Wu JL, Yu LC, Chang PC. An intelligent stock trading system using comprehensive features. Appl Soft Comput 2014;24:39–50.
[39] Nison S. Japanese Candlestick Charting Techniques. New York: New York Institute of Finance; 1991.
[40] Caginalp G, Laurent H. The predictive power of price patterns. Appl Math Finance 1998;5:181–205.
[41] Zhu M, Atri S, Yegen E. Are candlestick trading strategies effective in certain stocks with distinct features? Pac Basin Financ J 2016;37:116–27.
[42] Lu TH. The profitability of candlestick charting in the Taiwan stock market. Pac Basin Financ J 2014;26:65–78.
[43] Chen S, Bao S, Zhou Y. The predictive power of Japanese candlestick charting in Chinese stock market. Phys A 2016;457:148–65.
[44] Naranjo R, Arroyo J, Santos M. Fuzzy modeling of stock trading with fuzzy candlesticks. Expert Syst Appl 2018;93:15–27.
[45] do Prado HA, Ferneda E, Morais LC, Luiz AJ, Matsura E. On the effectiveness of candlestick chart analysis for the Brazilian stock market. Procedia Comput Sci 2013;22:1136–45.
[46] Graves A. Generating sequences with recurrent neural networks. Comput Sci 2013 arXiv preprint arXiv:1308.0850.
[47] Olah C. Understanding LSTM Networks 2015;http://colah.github.io/posts/2015-08-Understanding-LSTMs/.
[48] Hochreiter S, Schmidhuber J. Long short-term memory. Neural computation 1997;9(8):1735–80.