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Research on analysis and application of quantitative investment strategies based on deep learning

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Abstract: *Due to the dynamics and complexity of the stock market, stock prediction models may encounter some challenges in predicting future stock movements, resulting in their poor generalisation ability. This paper discusses the application and effectiveness of deep learning technology in the financial field by studying the quantitative investment strategy based on deep learning. First, theoretical foundations of deep learning are introduced. Then, the methods for constructing quantitative investment strategies based on Long Short-Term Memory Network (LSTM) are elaborated, including data preprocessing, model selection and training, and strategy execution. Next, the performance and stability of the strategy are evaluated through backtesting and empirical analysis of historical data. Finally, the research results are summarized, and the direction of further research and application is prospected.*

Keywords: *Quantitative investment, Deep learning, Strategy analysis, Performance evaluation*

1. Introduction

The stock market is a high-risk and high-return market, and its stock prices have a direct impact on the stock market as a whole. Accurate stock price forecasting is crucial for investors and traders as they can make informed investment decisions based on the forecast results and maximise their return on investment. However, stock price belongs to a kind of time series data in financial data, which has some special properties, including non-linearity and high noise, making it challenging to analyse and forecast stock price [1], which is not only affected by national policies and related public opinion, but also related to uncontrollable factors such as investor sentiment and blindness, making the stock market show a large random volatility based on the Based on the above factors, the results of stock price prediction often fail to achieve the expected results. At the same time, with the rapid development of artificial intelligence and big data, as well as the increasingly obvious trend of the deep integration of financial theory and computers, stock price prediction is gradually transformed from a research problem in the field of finance to a hot research problem in the field of computers [2].

Long Short-Term Memory Network (LSTM), as an improved version of Simple Recurrent Neural Network (Simple RNN), effectively overcomes problems such as gradient vanishing that occurs in Recurrent Neural Networks (RNN). This improvement makes LSTM better able to handle longer time series, and it has been widely used in time series prediction research in recent years. By combining the characteristics of the stock market and using wavelet noise reduction and normalisation to preprocess the data, Peng Yan et al. built an LSTM network prediction model with less computational complexity and more accuracy[3].Abdul et al. proposed a stock prediction model based on the Multilayer Sequential Long and Short-Term Memory (MLS LSTM) with the Adam Optimizer, which has a higher accuracy compared to other machine learning and deep learning algorithms with higher accuracy [4] .

However, the complexity and uncertainty of the stock market make the LSTM model may perform poorly in some cases and have low predictive generalisation ability for other stock data, so further research is needed to improve the predictive generalisation ability. Deep learning has found great success in various fields as a powerful machine learning method. In the financial field, deep learning is widely used in stock forecasting, risk management and quantitative trading. This paper aims to study quantitative investment strategies based on deep learning and explore their specific application methods in the financial field.

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2. LSTM network structure and principles

LSTM is a kind of recurrent neural network belonging to the recursive neural network, compared with the RNN neural network structure, the gated self-recycling unit (GRU) is introduced to effectively overcome the problem of gradient vanishing, which is especially suitable for processing and predicting the important events with relatively long intervals and delays in the time series, and it is now widely used in the time series prediction problem [5].

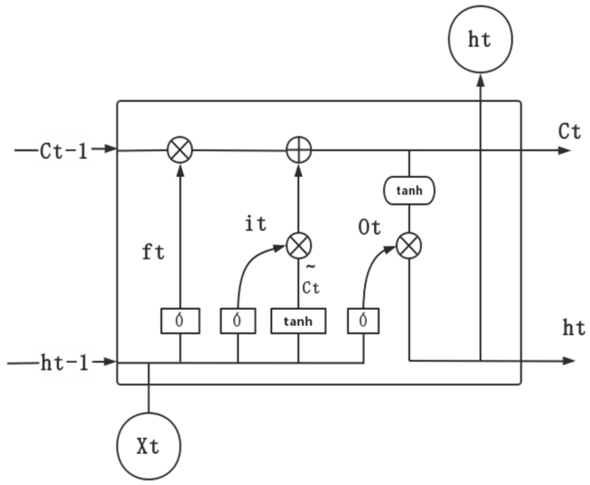

Figure 1 Internal structure of LSTM neural network

The above *(Figure 1)* shows the internal structure diagram of the LSTM neural network.The LSTM neural network is mainly composed of four key parts including update gate (i_t), forget gate (f_t), output gate (o_t) and cellular unit state (c_t), where each gate represents a fully connected network and each gate takes a value between (0, 1), and c_t is a vector rather than a numerical value, x_t representing the moment t of the input, σ represents the gated cell (in the presence of an activation function), $\tanh$ is a hyperbolic tangent function, and h_t is the hidden state at moment t.

The cell unit state and hidden state of the previous moment are passed to the current stage, at this time the forgetting gate controls the degree of forgetting of the cell state of the previous moment, and the updating gate controls the degree of updating of the new information of the cell state of the previous moment, and then the new cell state information is calculated by the hyperbolic tangent function, and finally, the LSTM output gate is based on the new cell state information, and the final measurement is obtained by calculating using the hyperbolic tangent function and the gating unit and outputting it or passing it to the next moment.Below is the formula for the inner workings of the LSTM neural network:

$$\mathrm{f}_t = \sigma(W_f \mathrm{x}_t + U_f h_{t-1} + b_f) \tag{1}$$

$$\mathrm{i}_t = \sigma(W_\mathrm{i} x_t + U_i h_{t-1} + b_i) \tag{2}$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{3}$$

$$\mathrm{c}_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{4}$$

$$\mathrm{o}_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$\mathrm{h}_t = o_t * \tanh(c_t) \tag{6}$$

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where W_f, W_i, W_c, W_o represent the weights of the inputs to the oblivion gate, the update gate, the new unit state, and the output gate, respectively; U_f, U_i, U_c, U_o represent the weights of the hidden state to the oblivion gate, the update gate, the new unit state, and the output gate, respectively; and b_f, b_i, b_c, b_o represent the bias vectors of the oblivion gate, the update gate, the new unit state, and the output gate, respectively.

3. The methodology for stock forecasting

3.1 Stepwise regression algorithm based on decision trees

Stepwise regression algorithm (SWR) is a regression algorithm that is widely used. The basic idea of the SWR is to introduce the independent variables one by one, and each introduction of the independent variable has the most significant effect on the dependent variable Y. Each time a new independent variable is introduced, the old independent variables previously introduced into the regression equation are tested one by one, and the non-significant independent variables in the current equation are eliminated one by one, starting with the independent variable that has the least impact on the dependent variable Y, until no new independent variables can be introduced. The final independent variables retained in the regression equation have a significant effect on the dependent variable Y, while the independent variables not in the regression equation have a significant effect on Y, and such a regression equation is called the optimal regression equation.

3.2 Linear regression algorithm

The most used method is logistic regression (LR), LR uses Sigmoid transformation to map function values to the 0~1 interval, and the mapped function value is the estimate. LR is a linear model, easy to parallelize, can easily process hundreds of millions of pieces of data, but the learning ability is very limited, and a lot of feature engineering is required to increase the learning ability of the model. However, a large number of feature engineering is time-consuming and labor-intensive, and does not necessarily lead to improved results. Therefore, how to automatically discover effective features and feature combinations, make up for the lack of manual experience, and shorten the experimental cycle of LR features is an urgent problem to be solved.

3.3 Deep learning algorithms

Through a variety of different vector representation learning methods, the features are extracted from different angles, and each feature is processed individually by using the multi-channel recurrent neural network, making full use of the obtained data information, and finally the features are spliced together to predict the stock price. Neural networks are divided into many types, BP neural network (BP) is a multi-layer feedforward neural network trained according to the error reverse propagation algorithm, and it is also the most widely used neural network; Convolutional neural network (CNN) extracts input features by constructing convolutional layers, and then uses feedforward connections to complete the output of features, which is one of the representative algorithms of deep learning; RNN is suitable for data whose input is a sequence, which is a kind of neural network that is recursive in the direction of the evolution of the sequence, and the recurrent units are connected in a chain[6].

4. Model building and dataset description

LSTM is an improvement on RNN, which solves the problem of long-term dependence on information that cannot be realized by introducing a gate mechanism to build special memory neural units. LSTM structures include gate structures such as input gates, output gates, and forget gates, which update the cell state through the following recursive equation while activating the mapping from input to output.For the goal of predicting the rise or fall of a stock, it is converted into a multi-classification task to process. There are many factors that affect the rise and fall of stocks, and the basic trading data related to the information of the stock itself are its basic trading data, such as opening price, closing price, high price, low price, trading volume, rise and fall, etc., as well as some statistical technical indicators derived from trading data, such as turnover rate. In addition to trading data, stock market

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volatility is usually related to factors such as public opinion and policy. However, these characteristic information cannot be intuitively and immediately reflected in the subsequent stock price, and whether this information is coupled with the basic information of the stock has not yet been demonstrated. Therefore, this article only features such basic trading data for stocks as input[7].

Firstly, the experimental samples are pre-processed separately, the noise data are detected and processed, and then standardised uniformly after processing. In this paper, we use the fitted Scaler normaliser and construct the Scaler normaliser specifically for the feature of closing price, which is used to reduce the magnitude of the prediction results, which can help the LSTM stock prediction model to better understand and deal with the data differences between different features. The constructed LSTM stock prediction model is then trained using the Sequential model, which consists of a total of 50 LSTM units, with a fully connected layer with 20 neurons and an output layer, using the mean square error as the loss function, and the Adam optimiser for updating and adjusting the model parameters. The number of training rounds is 4000 and an EarlyStopping callback function is created to monitor the changes in the validation loss on the validation set and end the training early according to the set conditions to prevent the data from overfitting conditions. The sample dataset is predicted using the trained LSTM stock prediction model respectively and the prediction results are shown below(*Figure 2 to Figure 4*).

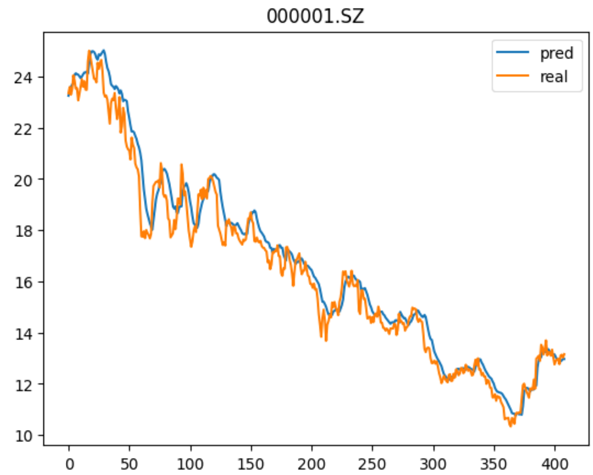

Figure 2 Ping An Bank Stock Forecast Chart

Figure 3 Pudong Development Bank Stock Forecast Chart

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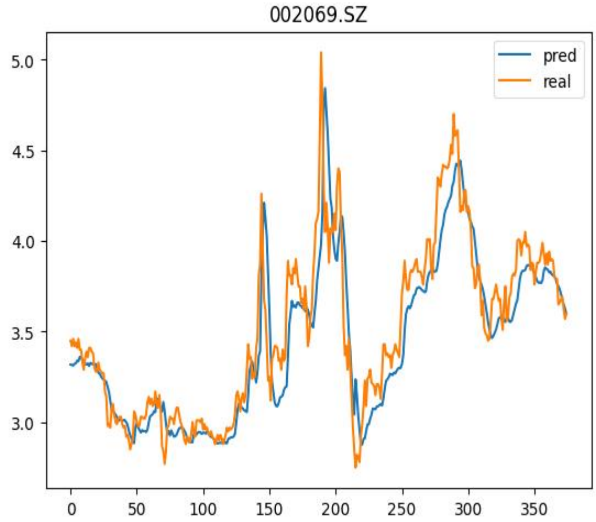

Figure 4 Roebuck Island Stock Forecast Chart

5. System development and application

After the model is developed[8], it can be arranged on the WEB website for easy use by users online.The usage steps and setting methods are as follows (*Figure 5 to Figure 8*).

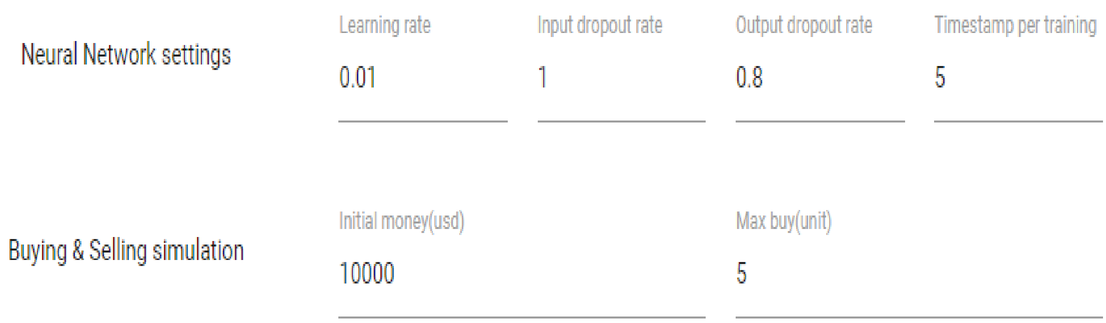

Figure 5 Setting parameter diagram

Figure 6 Training dataset visualization

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Figure 7 Modelling training

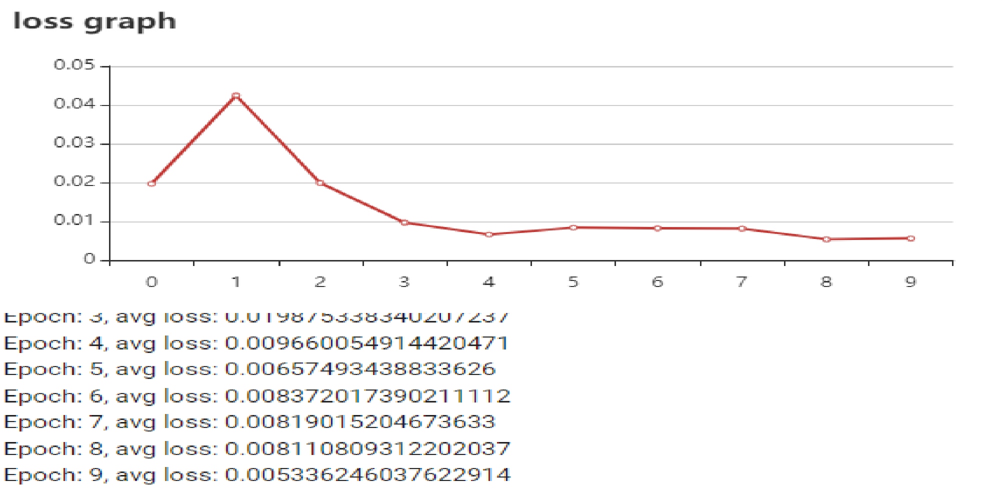

Figure 8 Plot of model loss function

6. Conclusions

Quantitative investment strategies based on deep learning models need to formulate clear trading rules and risk control strategies. These strategies include the generation of buy and sell signals, position adjustment rules, and stop loss and take profit strategies to ensure portfolio stability and yield levels. Through backtesting and empirical analysis of historical data, the performance and effectiveness of quantitative investment strategies based on deep learning are evaluated. The difference between indicators such as the return, volatility, and maximum drawdown of the strategy and the market benchmark can be compared, and statistical tests can be carried out to verify the effectiveness and stability of the strategy. Based on the results of backtesting and empirical analysis, we evaluate the performance of deep learning-based quantitative investment strategies. The results show that the strategy can obtain certain excess returns and has a certain degree of stability. However, attention also needs to be paid to the suitability of strategies and risk control to reduce investment risk and improve long-term investment returns. In this paper, a quantitative investment strategy based on deep learning is studied, and its performance and stability are evaluated through backtesting and empirical analysis. The results show that deep learning has certain application potential and value in quantitative investment. In the future, we can further study and improve models and algorithms, improve the performance of strategies, and explore more applications of deep learning techniques in the financial field.

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References

[1] Sun Ruiqi. Research on US stock index price trend prediction model based on LSTM neural network [D]. Beijing: Capital University of Economics and Business, 2016
[2] Yu Xiaojian,Liu Guopeng,Liu Jianlin et al. Stock index prediction based on LSTM network and text sentiment analysis[J/OL]. China Management Science:1-12[2023-08-26]. DOI:10.16381/j.cnki.issn1003-207x.2021.0084.
[3] PENG Yan, LIU Yuhong,ZHANG Rongfen. Modelling and analysis of stock price prediction based on LSTM[J]. Computer Engineering and Applications,2019,55(11):209-212.
[4]Md A Q, Kapoor S, AV C J, et al. Novel optimization approach for stock price forecasting using multi-layered sequential LSTM[J]. Applied Soft Computing, 2023, 134: 109830.
[5] Bao Zhenshan,Guo Junnan,Xie Yuan et al. Stock price rise and fall prediction model based on LSTM-GA[J]. Computer Science,2020,47(S1):467-473.
[6] Briola A, Turiel J, Marcaccioli R, et al. Deep reinforcement learning for active high frequency trading[J]. arXiv preprint arXiv:2101.07107, 2021.
[7] Sezer O B, Gudelek M U, Ozbayoglu A M. Financial time series forecasting with deep learning: A systematic literature review: 2005 –2019[J]. Applied soft computing, 2020, 90: 106181.
[8] https://github.com/huseinzol05/Stock-Prediction-Models