

LM jump detection-high frequency grid trading model based on LSTM prediction

Haowei Sun ^{*}, Wei Li, Chenghuan Ou

School of South China University of Technology, Guangzhou, China

^{*} Corresponding author: shwlvv@163.com

Abstract. In the computer era, high frequency trading is one of the hottest topics in the financial investment market. In order to develop a high-frequency trading strategy model with specific validity for different types of stocks, this paper proposes a LM jump detection-grid trading model based on LSTM prediction to construct a trading strategy for three types of stocks: blue chips, volatile stocks and stable stocks. The proposed model is a combination of a black-box model and a white-box model, which not only has the powerful learning capability of LSTM Model and but also the excellent scalability of LM Jump Detection Model and Grid Trading Model. These allow the model to have greater advantages in terms of trading strategies and the convenience of optimizing anomaly detection.

Keywords: High Frequency Quantitative Trading, LSTM Model, Grid Trading Strategies.

1. Introduction

High frequency trading refers to computerized trading that seeks to profit from extremely short-lived market movements that people cannot take advantage of. In the computer age, high-frequency trading is one of the hottest topics in the financial investment market. It is central to the design of sound high-frequency trading algorithms that can extract important information from complex market environments and use it to evaluate the market in reverse.

This paper classifies stocks in the current market into three types: blue chips, volatile stocks and stable stocks. Blue chip stocks are issued by companies with high visibility and good creditworthiness, and therefore have relatively stable profitability and are better able to withstand cyclical fluctuations. Volatile stocks have the highest uncertainty in price movements and the highest risk, but their potential output return is the highest. Stable stocks, on the other hand, are nonvolatile stocks with stable price movements, low levels of profit and loss and minimal risk. Of these, both blue chips and stable stocks have low share price volatility, while blue chips have higher long-term expected returns than non-blue chip stable stocks. Therefore, in order for the strategy to better suit the stock characteristics, different types of stocks are studied separately in this paper.

For high frequency quantitative trading methods for different stocks in the market, existing studies have specified high frequency quantitative strategies using three main ideas: pure mathematical methods, traditional machine learning methods, and deep learning. mathematical models and indicators such as MACD Indicator [1], BOLL Indicator [2], and LM jump Model [3] are used to optimize quantitative trading systems. Traditional machine learning models such as Support Vector Machines [4], Decision Trees [5], and Plain Bayes [6], as well as integrated machine learning models such as Random Forests [7] and LightGBM [8] have also been successfully used to enhance high frequency quantitative returns. In addition, with the development of deep neural networks, more and more studies have successfully demonstrated the significant superiority of fully connected neural network models [9], LSTM models [10], convolutional neural network models [11] and reinforcement learning methods [12] in high-frequency quantitative trading.

2. Analysis and solution of high frequency quantitative trading

2.1. Task analysis and model overview for high frequency quantitative trading

In order to make high-frequency quantitative trading returns maximized, it is necessary to construct high-frequency trading strategies for stocks with different characteristics, which puts certain requirements on the generalization ability and specificity of the model. In this paper, we propose a LM jump detection-grid trading model based on LSTM prediction to construct trading strategies for three types of stocks, namely blue chips, volatile stocks and stable stocks respectively. Among them, the LSTM price prediction model has strong generalization ability and can predict price changes well for different types of stocks, while the LM jump detection-grid trading method has strong scalability and can make specific optimization according to different stock types. The overall flow of the LM jump detection-high frequency grid trading model based on LSTM forecasting is shown in Figure 1.

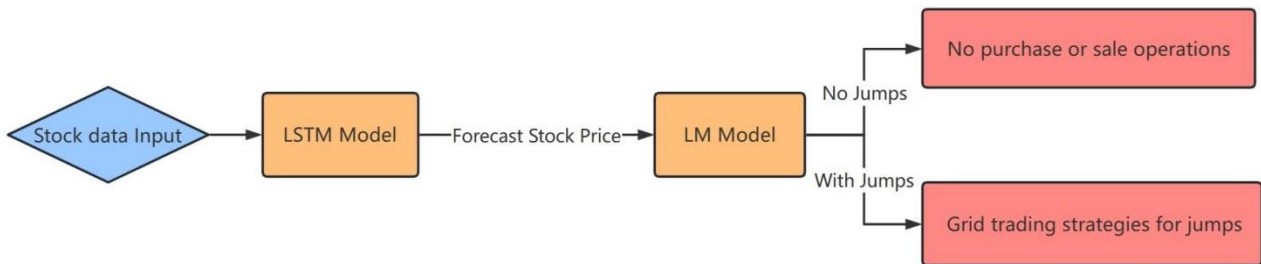


Figure 1. General flow of LM Jump Detection - High Frequency Grid Trading Model

2.2. Task analysis and model overview for high frequency quantitative trading

2.2.1. LSTM Price Forecasting Model

This paper argues that although stocks with different characteristics have different degrees of increase and volatility on minute level data, their price movements still follow certain patterns, and such high-dimensional features can be well mined out using deep learning algorithms. Among them, the long short-term memory (LSTM) model controls the flow of information and the state of neurons through three logical units: input gate, output gate and forget gate, which can effectively use the long-range temporal information and is very suitable for processing data with time series. Therefore, the LSTM model is used in this paper to extract and analyze the important factors affecting stock price movements and predict the future stock price movements.

The individual structural units that make up the LSTM model are shown in Figure 2.

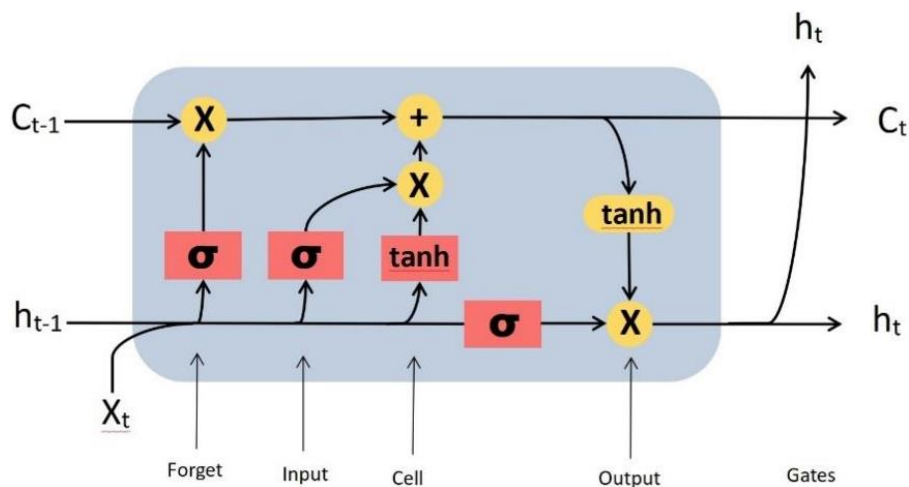


Figure 2. Schematic diagram of a single structural unit of the LSTM model

(The output gate is used to read the elements in the memory cell; the input gate is used to decide when to read the data into the memory cell; the forget gate is used to decide whether to forget the

contents of the memory cell; X_t is the input at this moment; C_{t-1} and C_t are the states of the neuron before and after the update; h_{t-1} and h_t are the hidden states before and after the update.)

The definitions and values of parameters for the LSTM model implemented in this paper are shown in Table 1 and Table 2.

Table 1. Parameters definitions of the LSTM model

Parameters	Meaning of parameters
input_size	Number of input neurons
Rnn_unit	Number of neurons in a LSTM unit
Lstm_layers	Number of LSTM units
output_size	Number of output neurons
lr	Learning Rate
epochs	Number of training rounds
batch_size	Number of training samples in each batch
time_step	Prediction model step size

Table 2. Parameters values for the LSTM model

Parameters	input_size	Rnn_unit	Lstm_layers	output_size
Value	n1	256	4	1
Parameters	lr	epochs	batch_size	time_step
Value	0.00065	65	32	20

The data used for training and testing of the LSTM model in this paper are the 1-minute level quotes of Wuliangye (000858.SZ), China Merchants Bank (600036.SH), Poly Development (6000.SH), China Guodian (600795.SH) and Yili (600887.SH) from 09:30 on 10 October 2022 to 15:00 on 16 October 2022. Minute level quotation data including opening price, closing price, high price, low price, volume and turnover. All data are obtained from the Flush platform.

In this paper, the LSTM model does not need to predict the exact value of the price, but only the trend (up or down) by predicting the price. The price trend prediction of the test dataset Guizhou Maotai (600519.SH) is shown in Figure 3. The price change trend accuracy is 67.68% and the relative error is 0.4673%.

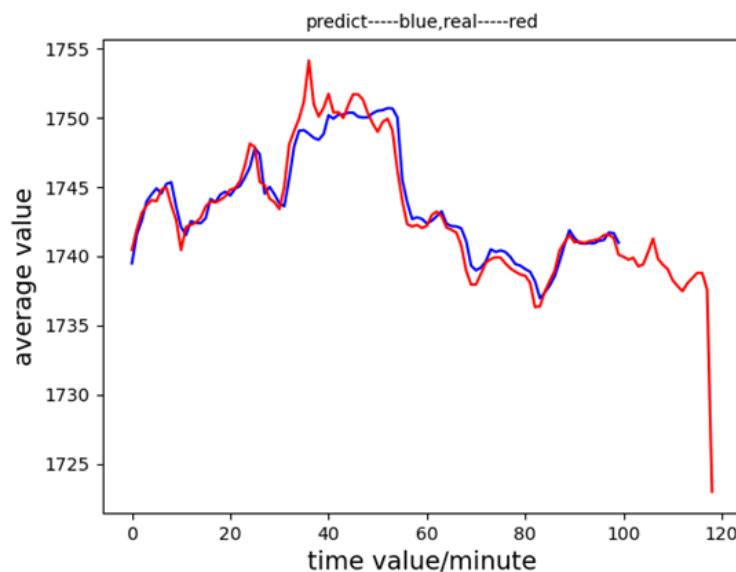


Figure 3. LSTM model for price trend prediction on test dataset

2.2.2. LM Jump Detection Model

In order to make full use of the price prediction results of the LSTM model in the grid trading model, this paper refers to the LM detection method proposed by Lee and Mykland [13] to convert

the price prediction data into a prediction of price jumps. The LM method is easy to use and time consuming, which is a necessary condition for the effective execution of high frequency strategies.

The definitions of parameters for the LM Jump Detection Model implemented in this paper are shown in Table 3.

Table 3. Parameters definitions of the LM Jump Detection Model

Parameters	Meaning of parameters
Y	Average price by minute
R	Logarithmic average price
K1	Data cleaning window values
V	Local volatility
K2	Local volatility observation window values
n	Number of observations in the observation cycle
α	Significance level
β	Statistical thresholds

(1) Data re-processing

In order not to misclassify data outliers as price jumps, a sliding window approach is used to filter and estimate the data, while controlling for market microstructure noise is considered, resulting in the construction of the following pre-averaged log returns.

$$R_t = \frac{1}{K1} \sum_{i=1}^{K1} \log Y_{t-k+i} - \frac{1}{k} \sum_{i=1}^{K1} Y_{t-2k+i} \tag{1}$$

(2) Construction of the LM statistic

Following the idea of Lee and Mykland, the LM statistic is constructed to detect the jumping behavior of stock prices on minute level data:

$$L_T = \frac{|R_T|}{\sqrt{V_j}} \sim N(0,1) \tag{2}$$

In order to distinguish between the two scenarios of jumping and increasing volatility, local volatility V is introduced to normalize the absolute value of returns:

$$V_j = \frac{1}{K2-2} \sum_{j=i-K2+2}^{i=1} |R_{j-1}| |R_j| \tag{3}$$

Since this method can only determine whether there is a price jump at a certain point in time, Lee and Mykland proposed a statistic that can be used to detect data within a certain market, based on the principle of the maximum value function and the threshold principle. The statistic is constructed as below:

$$\frac{\max(L_j) - C_n}{S_n} \rightarrow \xi \tag{4}$$

Where ξ has a cumulative distribution function $P(\zeta \leq x) = \exp(-e^{-x})$.

$$C_n = \frac{(2 \times \log n)^{1/2}}{c} - \frac{\log n + \log(\log n)}{2 \times c(2 \log n)^{1/2}} \tag{5}$$

$$S_n = \frac{1}{c(2 \log n)^{1/2}} \tag{6}$$

Where n is the number of observations.

If there is no jump at the testing time, the test statistic follows approximately a normal distribution. If there is a jump, however, it becomes very large. So, the key question is that how large the test statistic can be accepted when there is no jump. β is the rejection domain of the model. When $\frac{|L_i| - Cn}{S_n} > \beta$, the price will be considered to have jumped and classify the jump compared with the price at the previous moment. If the price increases, it is a positive jump. And if the price decreases, it is a negative one. The values of parameters for the LM Jump Detection model implemented in this paper are shown in Table 4.

Table 4. Important parameters values of the LM Jump Detection Model

Parameters	K1	K2	Cn
Value	10	10	1.6825
Parameters	Sn	n	α
Value	0.6985	5	0.01

2.2.3. High-frequency grid trading model for jumps

Using the models described in 2.2.2 of this paper, it is possible to better predict whether the stock price will produce a positive or negative jump in the next minute. The jump generation means that the stock price has fluctuations, while the grid trading method is suitable for the market with large fluctuations.

Therefore, this paper combines the grid trading method with the LM jump detection model and proposes a grid trading method for the jump. The main process is: use the LM jump detection model to determine whether there is a jump. If a positive jump is detected, a positive grid is established, and if a negative jump is established, a negative grid is established. And then the funds are put into the grid in pieces, and if the upper (lower) grid line of the grid is exceeded, a buy (sell) trade will be made using the funds. According to different characteristics of the stock, we can set different grid parameters and get a grid trading model with specificity.

The grid parameters are set as follows:

(1) Grid reference zero line, upper and lower limits

The base zero line of the grid is the market price of the stock in the previous minute. The upper and lower limits of the grid are obtained by calculating the upper and lower trigger points according to the Dual Thrust model, and then the total judgment space can be determined. The grid is constructed as shown in Figure 4.

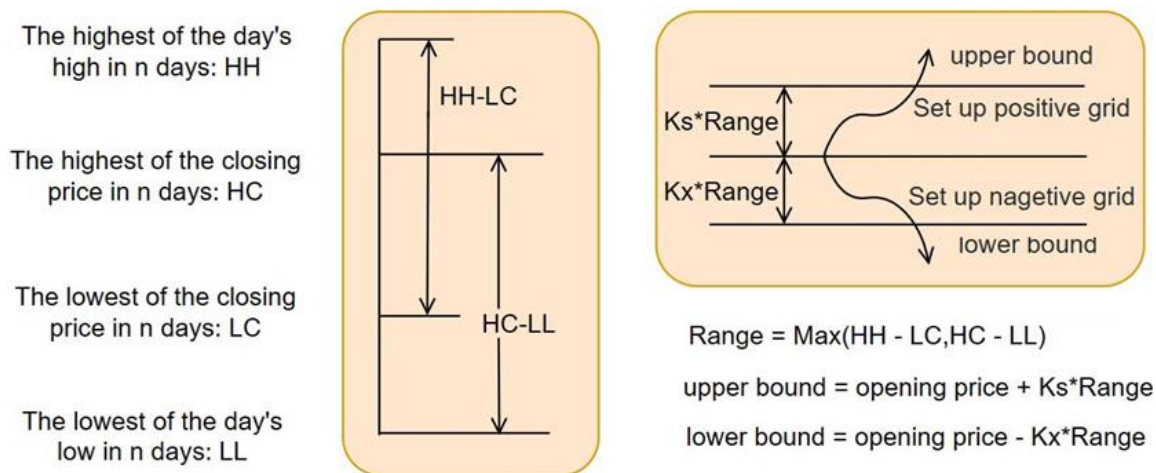


Figure 4. Schematic diagram of grid reference zero line, upper and lower limits

The Ks and Kx in the formula can be adjusted according to the situation.

(2) Number of grids and funds allocated per grid

In the grid trading method, the denser the grid, the more frequently you buy and sell, the more stable the return will be. But at the same time, the increase in the number of transactions will bring

an increase in fees. The sparser the grid, the higher the risk, but the corresponding fee will be reduced. For blue-chip stocks, the risk is relatively small, so a sparse grid is used. For stable stocks, a dense grid should be set up. And for volatile stocks, a medium level of sparsity is chosen as a compromise between risk and fees.

For the three target stock types selected in this paper: blue-chip stocks, volatile stocks and stable stocks, the number of grids and the allocated funds should be optimized idiosyncratically according to their different characteristics. For the amount of funds allocated per grid, blue-chip stocks have steadily increased prices, so the amount of funds put in each grid is larger. Stocks with small fluctuations have relatively few moments of jumping changes, and thus the amount of funds put in each grid is relatively small. And stocks with high volatility choose the middle amount of money.

This model is not only applicable to the three stocks used in this paper. For stocks with other characteristics, a grid matching their characteristics can still be designed for trading.

3. Backtest Results

In this paper, we use the trading of Midea Group Co., Hisense Home Appliances Group CO., and Mys Group Co. from 9:30 on October 28, 2022 to 15:00 on November 4, 2022 as backtest data for blue chips, volatile, and stable stocks, respectively. The backtest results are shown in the figures below.

(1) Blue chip stocks

Total Return: 3.66%, Sharpe Ratio: 17.79, Maximum Drawdown: 1.19%.

The backtest results of this paper’s strategy on blue chip stocks are shown in Figure 5 and Figure 6.

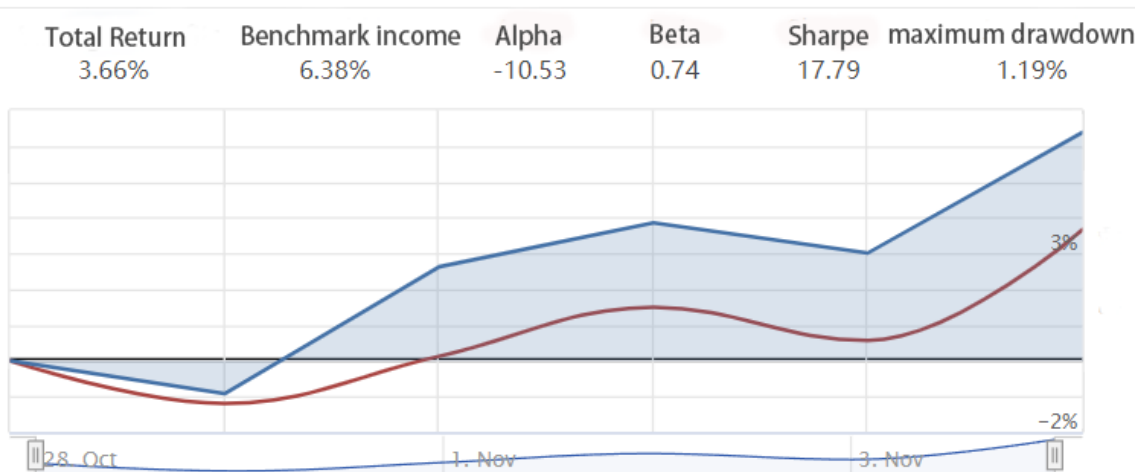


Figure 5. Overview of backtest results of this paper’s strategy on blue chip stocks

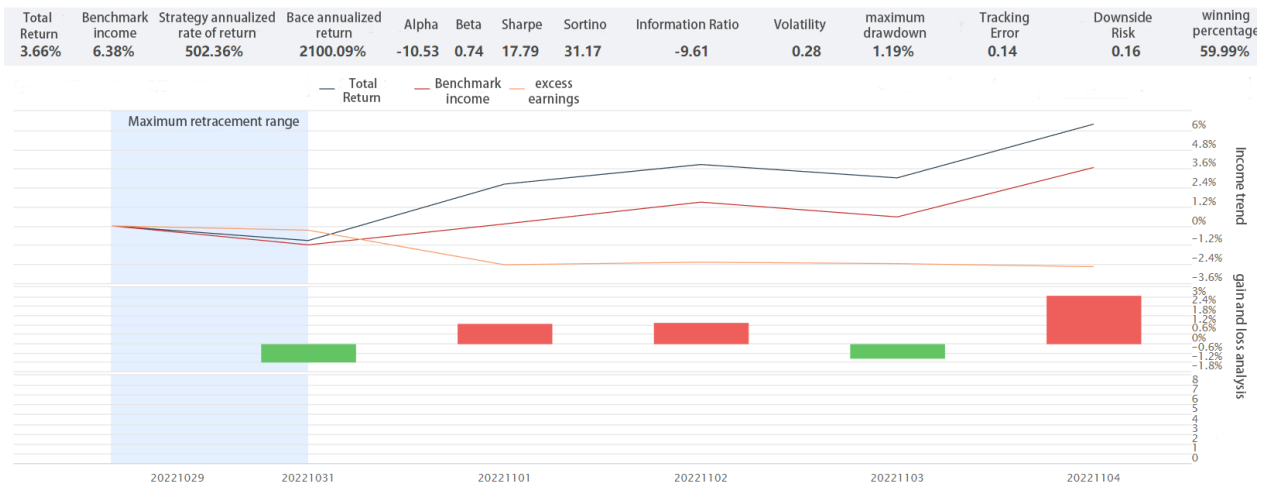


Figure 6. Data analysis of backtest results of this paper’s strategy on blue chip stocks

(2) Volatile stocks

Total Return: 9.11%, Sharpe Ratio: 305.76, Maximum Drawdown: 0.30%.

The backtest results of this paper’s strategy on volatile stocks are shown in Figure 7 and Figure 8.

Total Return	Benchmark income	Alpha	Beta	Sharpe	maximum drawdown
9.11%	6.38%	67.74	0.46	305.76	0.30%

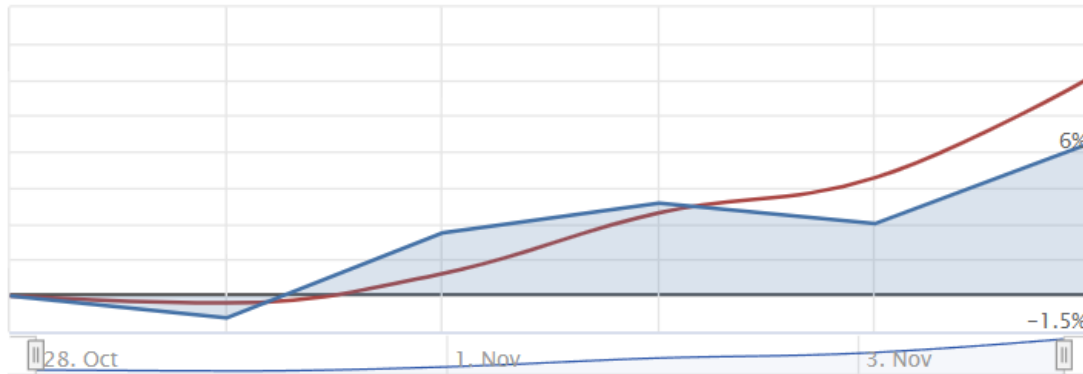


Figure 7. Overview of backtest results of this paper’s strategy on volatile stocks

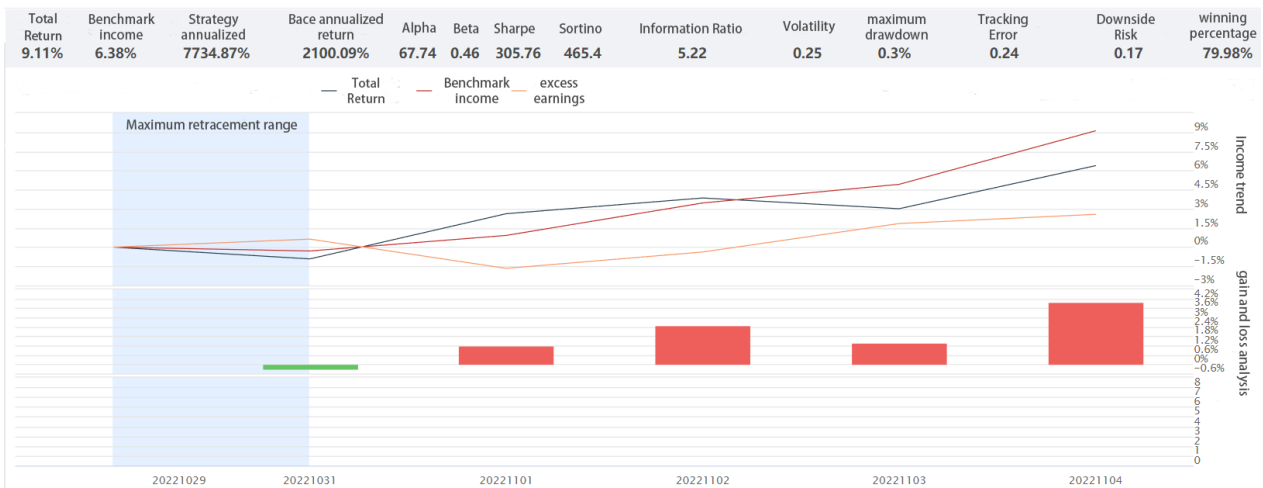


Figure 8. Data analysis of backtest results of this paper's strategy on volatile stocks

(3) Stable stocks

Total Return: 0.69%, Sharpe Ratio: 3.26, Maximum Drawdown: 0.79%.

The backtest results of this paper’s strategy on stable stocks are shown in Figure 9 and Figure 10.

Total Return	Benchmark income	Alpha	Beta	Sharpe	maximum drawdown
0.69%	6.38%	-6.48	0.33	3.26	0.79%

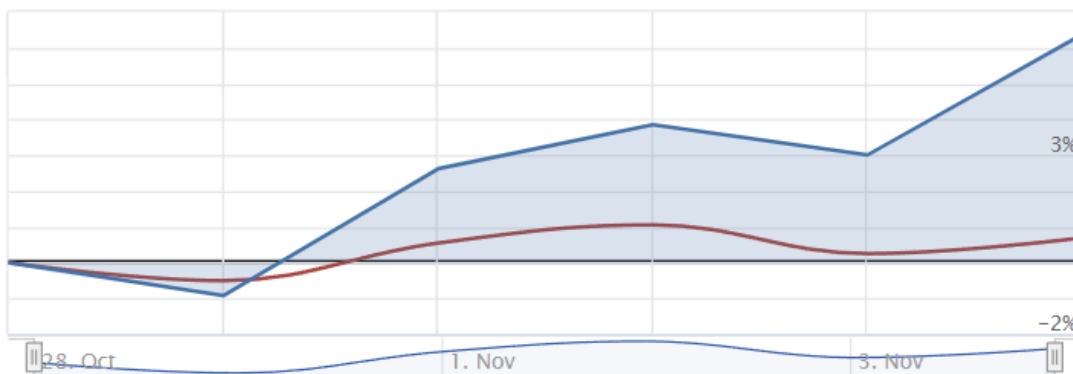


Figure 9. Overview of backtest results of this paper’s strategy on stable stocks

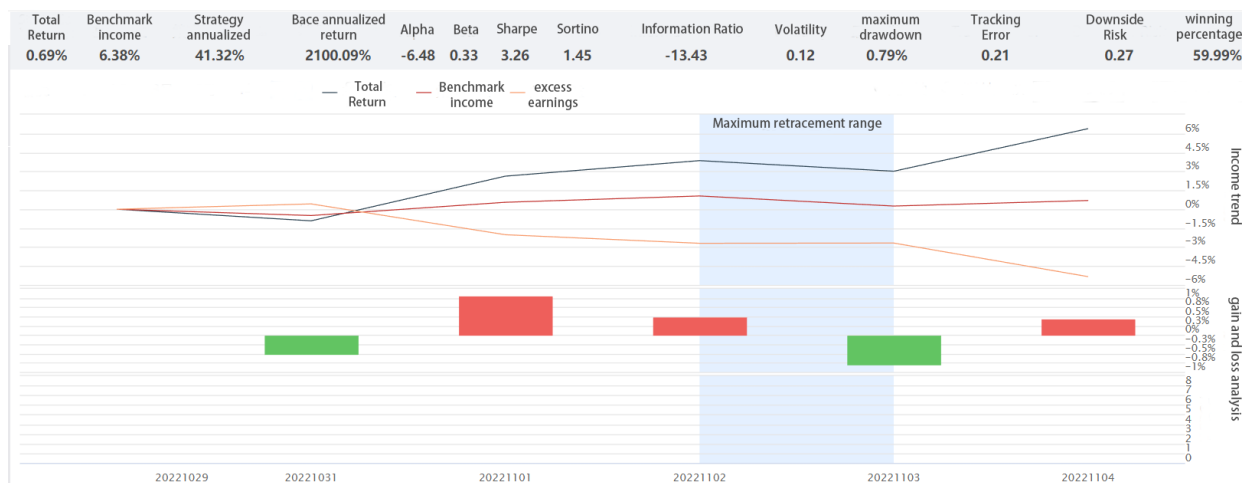


Figure 10. Data analysis of backtest results of this paper's strategy on stable stocks

4. Conclusion

In this paper, blue-chip, volatile and stable stocks are selected as the target stock types, and an innovative LSTM prediction-based LM jump detection-grid trading method is proposed. Firstly, an LSTM stock price prediction model is designed and trained. Then, a jump detection statistic LM is constructed to determine whether a positive (negative) jump in stock price occurs at the next moment. Finally, based on the Dural Thrust strategy, a better grid trading method for jump changes is proposed on top of the traditional grid trading method, and adapted to the characteristics of different stocks to achieve specific high frequency trading for three stocks. The proposed model is a combination of a black-box model and a white-box model, which has the powerful learning capability of the LSTM model and the excellent scalability of the LM jump detection and grid trading models, and has greater advantages in terms of trading strategies and the convenience of optimized anomaly detection. In the backtest, the returns of this strategy on blue chips, volatile stocks and stable stocks are 3.66%, 7.85% and 0.69% respectively.

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