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Stock Trend Prediction Based on Technical Indicator Graph Attention Network

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***Abstract*—In recent years, deep learning technology has been widely used in the financial industry, especially in the research of stock trend prediction. Aiming at the two aspects that most stock prediction algorithms do not make full use of the data and the model does not pay enough attention to the relationship between stocks, this paper establishes a graph attention network model based on technical indicators to better predict the stock trend. On the CSI 300 data set, we compare the model with the existing deep learning model and the single factor model in factor investment. A large number of experiments show that our model not only has higher prediction accuracy, but also has better profitability in practical application.**

***Index Terms*—Stock market, Graph Attention Network, Technical Indicators, Stock relation**

I. Introduction

Stock has been invented for many years. Investors who participate in it all hope to get more benefits with the same investment. The research of stock trend prediction has a history of decades. It has attracted many investors and researchers for a long time. It has broad application prospects in avoiding risks and maximizing benefits. However, the trend of stock price is nonlinear and unstable, so the prediction of stock trend has always been a difficult problem for many researchers. Lo et al. proved in his early research that the stock price does not follow the random walk theory [1], which proves the predictability of the stock price.

In recent years, deep learning has developed rapidly, and many scholars began to apply it to the analysis of time series data such as stocks. For technicians, stock prices are regarded as typical time series data with complex patterns. Through appropriate pretreatment and modeling to analyze the operation mode, so as to profit from it. The information used for technical analysis mainly includes closing price, income and trading volume. Since the movement of stock price is unstable and nonlinear, technical analysis focuses on reducing randomness and capturing consistency. Common models such as Long Short-Term Memory (LSTM) directly use algorithms to capture the timing information in the stock basic data through learning [2]. In addition, some scholars directly use the traditional stock technical indicators to capture the timing information instead of neural network [3].Although the above methods can be modeled from the perspective of temporal correlation, they usually regard each stock as independent, ignoring many explanatory factors in the stock market. With the development of stock market, there are extensive connections between enterprises, so that the stock price change of the target company may be affected by relevant companies.

Recently, with the rise of Graph Convolutional Neural Network (GCN) [4], researchers use relational data to model the explicit correlation between stocks for stock market prediction. The research shows that the rich relationship between stocks contains valuable signals conducive to trend prediction [5]. GCN treats the relationship between nodes equally. Although it can aggregate the characteristics of neighbor nodes to the central node, it focuses on the feature update of the whole graph rather than the relationship of each node. Therefore, Graph Attention Network (GAT) is proposed [6]. It aggregates the features of neighbor nodes to the central node in the way of attention coefficient, and better integrates the correlation between node features into the model.

Inspired by this, this paper mainly studies how to reasonably apply the relationship between stocks to predict the stock trend, and puts forward the attention network model of technical indicators graph. The model captures the time series characteristics of stocks through technical indicators, and models the weighted relationship between stocks through graph attention network, so as to predict the stock trend. Following are the main contributions of our work:

1) Proposed a Technology Indicator Graph Attention Network, in which the technology indicators extracts the temporal feature and the graph attention extracts the relationship feature between stocks, so as to predict the stock trend from end to end.
2) Constructed a technical indicators graph data set based on CSI 300, including the daily market data from 2020 to 2021 and the calculated technical indicators data, and converted the unstructured data such as stock industry data and sector concept data into structured data, so as to study the stock trend prediction model based on different relationships.
3) Designed a stock selection simulation backtesting experimental framework based on stock prediction classification, and verified that compared with the baseline model, our model can get more ideal prediction effect and has

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stronger profitability.

The rest of this paper is organized as follows: "Related work" briefly reviews some important work that has been carried out in the direction prediction of the stock market. A detailed overview of our model is given in "Methodology". "Experiments" provides a detailed report on the process and results of the experiment. Finally, we summarize this paper and look forward to the future work in the "Conclusion" part.

II. Related work

In the research of stock market, it has been proved that the prediction of stock price trend is closely related to the characteristics of stock time series data [1]. Therefore, the main research methods of stock price prediction are based on historical series. Financial scholars introduce various evaluation indexes to predict the price fluctuation of the stock market. From the initial opening price, closing price and other direct indicators, indirect indicators such as kinetic energy that effectively show a certain characteristic are gradually derived. For example, Jegadeesh et al. proposed that the stock price has the trend of continuing the original movement direction [8], and the volume indicator is derived from the trading volume and turnover rate to predict the stock price trend. Fama et al. constructed a indicator pricing model using derivative index indicators such as total market value and book to market ratio to explain the cross-sectional change of expected stock return [9].

Some scholars also start with statistical methods to study the trend of stock price. Cao et al. used Autoregressive Moving Average (ARMA) method to predict stock price based on the statistical characteristics of time series [11]. Wang et al. further used the optimized Autoregressive Integrated Moving Average (ARIMA) method and Threshold Autoregressive (TAR) model to predict the stock trend [7]. With the rapid development of artificial intelligence, stock trend prediction has gradually changed from machine-aided prediction to computer-based iterative learning prediction. Machine learning methods such as Support Vector Machine [12] and Random Forest [13] have made good progress in stock forecasting. With the integration of deep learning and traditional time series models, the traditional modeling method has been substantially improved by using a large amount of data to estimate the global model parameters in the whole time series. Due to the unique directed cyclic connection between hidden layers, Recurrent Neural Network (RNN) has the memory function of time series data, and has been widely used in natural language processing and time series data analysis [14]. However, RNN model is a gradient based algorithm, and there may be gradient disappearance or gradient explosion when dealing with long-time series data. Therefore, derived variants such as LSTM and Gated Recurrent Unit (GRU) are more commonly used [14]. Chen et al. used LSTM to predict prices based on time series data generated from stock market history [15]. Zhang et al. proposed a method based on State Frequency Memory (SFM) to decompose the hidden state of LSTM storage unit into multiple frequency components to find multi frequency transaction patterns [16]. Althelaya et al. used stacked GRU and bidirectional GRU to compare with the corresponding LSTM respectively to verify the performance of a variety of RNN variants in short-term and long-term stock market prediction [17]. The above methods based on time series modeling improve the accuracy of stock price prediction. However, these methods only model the time series correlation and ignore the dynamic linkage of the stock market.

Recently, the deep learning method based on graph structure data has attracted extensive attention of researchers [4]. Different from the traditional Convolutional Neural Network (CNN), GCN can encode the relationship graph structure of different input data, so as to use the relationship data between stocks for stock market prediction. Feng et al. proposed a time graph convolution component to modify the stock sequence embedding in combination with the relationship between industry and Wikipedia to implement the Relational Stock Ranking (RSR) model [5]. Kim et al. proposed a hierarchical attention network for stock market prediction using relational data to predict the trend of individual stock prices and market indexes [19]. Albahli et al. used HANet to classify the news text extracted by DCWR to predict the change of stock trend [20]. Yin et al. used GCN to extract the correlation data between stocks and integrated it into the sequence prediction model based on RNN [18]. These methods often pay more attention to the stock data itself, extract the time series characteristics of the data through the model, and make relatively little use of a large number of mature technical indicators applied to the stock market. Agrawal et al. proved the effectiveness of stock technical indicators in predicting stock prices based on deep learning [21]. Li et al. tried to use hypergraph to construct multiple relationships between stocks, and achieved good results [23]. Albahli et al. experimentally verified the effect of DenseNet using stock technology indicators on multiple stocks [3].

Therefore, we propose a stock trend prediction model based on stock technology indicators and GAT. Among them, as a mature financial statistical method, stock technology indicators extracts the characteristics of stock time series data, generates graph data through stock relationship, and uses GAT to fuse the weighted correlation of the characteristics of each node, so as to finally realize the end-to-end stock trend prediction.

III. Methodology

In this section, we introduce and explain the proposed method utilized for stock trend prediction. The CSI 300 index is composed of 300 most representative securities with large scale and good liquidity in the Shanghai and Shenzhen markets. It can reflect the overall performance of securities of Listed Companies in Shanghai and Shenzhen markets. Initially, the industry classification and sector concept data of stocks were obtained from China Stock Market and Accounting Research (CSMAR) and Royal Flush Finance database, and the daily trading data of CSI 300 were obtained from the financial data interface of Tushare and Baostock. Then, the stock relationship diagram is constructed through the above data, and the technical indicator data of each stock every day is calculated in a rolling manner. Finally, the GAT classifier is trained over the computed features for predicting the stock trend. The whole flow of the proposed scheme is presented in Fig.1.

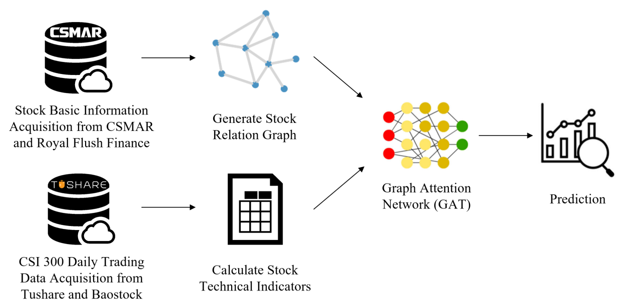

Fig. 1. Proposed method diagram

A. Stock Relation

We use two kinds of stock basic information to generate the relationship graph: stock industry and sector concept. The stock industry classification data comes from the industry classification of China Securities Regulatory Commission in 2012, including 19 major categories and 90 sub categories. We get the data from CSMAR (https://www.gtarsc.com/). Table I lists the industries to which part of stocks belong.

TABLE I
PART OF STOCKS AND INDUSTRIES

Stock Code	Industry Code	Industry Name
sh.600000	J66	Monetary and financial services
sh.600009	G56	Air transport industry
sh.600011	D44	Electricity, heat production and supply
sh.600015	J66	Monetary and financial services
sz.000001	J66	Monetary and financial services
sz.000002	K70	Real estate industry

We select stocks in the same sub industry category as the adjacent nodes in the relation graph.

The sector concept can be found in Royal Flush Finance (https://www.10jqka.com.cn/). The concept of stock comes from the concept stock plate, which is often used in the stock market. The concept is the collection of stocks with common characteristics. There are many classifications in the concept section, including regional classification, policy classification, listing time classification, hot economy classification, etc. Part of stocks and concepts are listed below.

- sh.600000: S&P Dow Jones A shares, trust concept, MSCI concept, Shanghai Stock connect, margin trading
- sh.600009: S&P Dow Jones A shares, Shanghai state owned assets reform, MSCI concept, Shanghai Stock connect, Shanghai Free Trade Zone, Disney, margin trading
- sh.600010: Data center, S&P Dow Jones A shares, Belt and Road, small metal concept, MSCI concept, gold holding, Shanghai Stock Exchange, rare earth permanent magnet, margin trading and margin trading.
- sh.600011: Green power, nuclear power, S&P Dow Jones A shares, photovoltaic concept, MSCI concept, state-owned assets reform of central enterprises, power reform, Shanghai Stock connect, wind power, margin trading
- sh.600015: S&P Dow Jones A shares, MSCI concept, Shanghai Stock connect, margin trading

Each stock selects the five stocks with the largest conceptual cosine similarity as its adjacent nodes in the relation graph.

B. Stock Technical Indicators

Stock technical index is the statistical feature of stock data. It establishes a fair estimation of price and trading volume through various mathematical formulas. In this paper we choose 13 basic indicators and 93 technical indicators. Basic indicators include: open, close, high, low, preclose, volume, amount, turn, total share, float share, free share, total market value, circulation market value. In the appendix "Appendix III. Part of Stock Technical Indicators" we list part of stock technical indicators we used.

C. Graph Attention Network

The GAT structure we use contains two layers of graph attention layer. Fig.2 shows its structure. First we will start by explaining a single graph attention layer. Similar to the work of Velickovic et al. [6], the input of our layer is a set of node features, $\mathbf{s}=\{\vec{s}_1,\vec{s}_2,\ldots,\vec{s}_N\}, \vec{s}_i \in \mathbb{R}^F$, where N is the number of stock nodes 290, and F is the number of each node's features, it's the input feature number 106 in the first GAT layer. And the layer produces a new set of node features as its output: $\mathbf{s}'=\{\vec{s}'_1,\vec{s}'_2,\ldots,\vec{s}'_N\}, \vec{s}'_i \in \mathbb{R}^{F'}$, where F' may be different from F.

In order to obtain sufficient expression ability and convert the input features into higher-level features, we need a learnable linear transformation. Each node has a linear transformation $\mathbf{W} \in \mathbb{R}^{F' \times F}$ of shared parameters. Then we perform *self-attention* to each node. The *attention coefficients* can be calculated by:

$$cof_{ij} = \text{LeakyReLU}\left(\overrightarrow{\mathbf{a}}^T\left[\mathbf{W}\vec{s}_i \| \mathbf{W}\vec{s}_j\right]\right) \tag{1}$$

Where $\overrightarrow{a} \in \mathbb{R}^{2F'}$ and the negative input slope α of nonlinearity LeakyReLU is 0.2. The $\cdot^T$ represents transposition and $\|$ is the concatenation operation. The cof_{ij} shows the importance of j'features to node i. In this way, we can calculate the impact of each stock on all other related stocks, so as to fuse their features through their correlation, so as to better predict their trend. In the above way, we use *masked attention* to calculate the coefficient for each j directly connected to node i. In order to make the coefficients between different nodes easy to compare, we use softmax function to normalize all the coefficients of j adjacent to i:

$$\alpha_{ij} = \text{softmax}_j\left(cof_{ij}\right) = \frac{\exp\left(cof_{ij}\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(cof_{ik}\right)} \tag{2}$$

After the normalized attention coefficient is obtained, the linear combination of the transformed features of each node and adjacent nodes can be calculated, and after a nonlinear

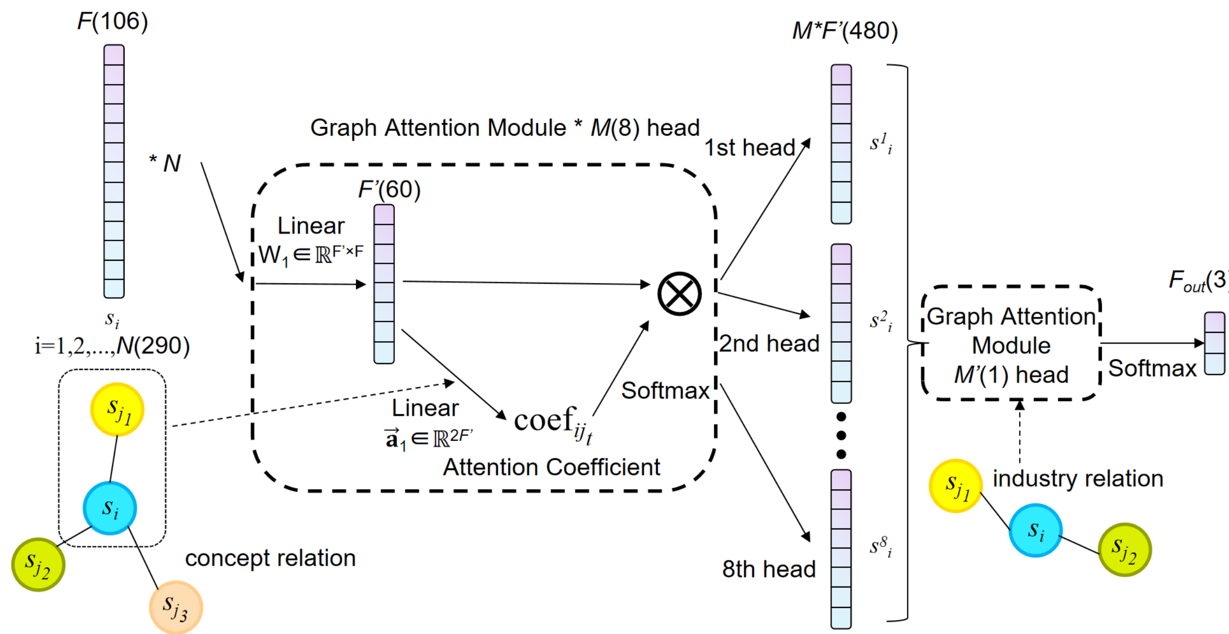

Fig. 2. Overall structure of GAT model. The features are initially extracted through a linear layer, and fused after calculating the attention weight of each edge. Finally, the new features fused with all adjacent node features are obtained.

transformation σ the final output features of the node are obtained.

$$\vec{s}_i' = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W} \vec{s}_j\right) \tag{3}$$

In order to extract a variety of related information from features, we use *multi-head attention* to improve the performance of self-attention. Specifically, Equation 3 is transformed by using k independent attention mechanisms, and then their output features are concatenated, as shown below:

$$\vec{s}_i' = \|_{k=1}^{K} \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij}^k \mathbf{W}^k \vec{s}_j\right) \tag{4}$$

Where $\|$ is the concatenation operation and the $\cdot^k$ is the k-th attention mechanism. The output will be $\vec{s}_i' \in \mathbb{R}^{K \cdot F'}$ instead of $\mathbb{R}^{F'}$.

In our model, we use two layers of GATLayer, in which the first layer uses 8-heads attention, and the output of a single attention module is 60-dimensional feature. The second layer is single-head attention and removes the output nonlinear activation function in order to output the final prediction result.

IV. Experiments

A. Data

We choose the most representative CSI 300 as the research object, and obtain all daily data from January 2020 to December 2021 from the daily trading interface between Tushare (https://tushare.pro/) and Baostock (http://baostock.com/). Since the overall trend of China's stock market after the COVID-19 is quite different from that before [25], so we only choose the data after January 2020. A total of 290 stocks are taken as the basic data after removing the 10 stocks that have not been established for a long time. The 2020 data is selected as the training set, and the 2021 data is selected as the validation set and the simulated transaction test data set. After calculating the technical factor, each stock has a total of 106 features as input every trading day. Follow the practice of Fuli et al. [22], the label is obtained according to the moving percentage of the closing price. Those with a moving percentage greater than or equal to 0.5% are marked as "up", those with a moving percentage less than or equal to -0.5% are marked as "down", and the rest are "remain". We choose the above three categories in the prediction of stock rise and fall, which can better distinguish between small-scale rise and fall, large rise and fall, and has more practical significance.

B. Evaluation Parameters

In this paper, we select accuracy, precision, recall and F1 score (Harmonic average between accuracy and recall) as the evaluation indexes of model prediction. It is calculated according to true positions (TP), true negatives (TN), false positives (FP) and false negatives (FN). The specific definitions are as follows:

$$\text{accuracy} = \frac{tp + tn}{tp + fp + tn + fn} \tag{5}$$

$$\text{precision} = \frac{tp}{tp + fp} \tag{6}$$

$$\text{recall} = \frac{tp}{tp + fn} \tag{7}$$

$$F1\_\text{score} = 2\frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{8}$$

The above indicators are only used to measure the prediction ability of the model based on classification, and what is really important in the real market is profitability. In the simulated trading test, we use the widely used Return (R), Annual Return (AR), Sharpe Ratio (SR) and Maximum Drawdown (MDD) in the financial industry as the measurement indicators of the stock selection model.

The cumulative income in simulation period T is recorded as $Profit_T$, $Profit_T = Portfolio_T - Portfolio_{t_0}$, where $Portfolio_T$ represents the total value of assets in simulation period T, $Portfolio_{t_0}$ represents the total value of t_0 at the beginning of simulation period, and the rate of return (R) and annual rate of return (AR) are calculated as follows:

$$R = \left(\frac{Profit_T}{Portfolio_{t_0}}\right) * 100\% \tag{9}$$

$$AR = (1 + R)^{\frac{244}{T_s}} - 1 \tag{10}$$

Where: T_s is the total time span of the simulation period (days), and 244 is the average number of trading days in a year.

In addition, Sharpe Ratio (SR) considers both return and risk. SR is defined as the ratio of average excess return to risk fluctuation:

$$SR = \frac{R_t - R_f}{\sigma} \tag{11}$$

Where: R_t is the Return within t, and the Annual Return is generally adopted. R_f is the risk-free return rate, in this paper we choose the bank's general term return rate of 3% as the risk-free return rate.

Similarly, the Maximum Drawdown (MDD) is another important risk measurement index, which is used to describe the maximum loss that the investment may face. It is calculated as:

$$MDD = \frac{\mathrm{Max}\left(P_t - P_{t+i}\right)}{P_t} \tag{12}$$

Where: P_t is the total value of assets on day t, and P_{t+i} is the total value of assets on day $t+i$ after t. this indicator measures the range of the total value of assets falling from the highest point to the lowest point in a certain period of time.

C. Prediction Results

We conducted a series of comparative experiments to evaluate the model. Through the comparative experiment with the existing stock prediction methods SFM [16], RSR [5] and GRU-HGCN [23]. For each method, repeat three times and report the average performance to eliminate fluctuations caused by different initialization. The time period of the experiment is selected from [23]. The experimental results are shown in Table II. Where “industry” refers to the use of industrial relations, “concept” refers to the use of conceptual relations, and “Hybrid” refers to the use of two kinds of relations at the same time. It can be seen that the methods which using the relationship between stocks are better than SFM, and the effect is better than RSR and GRU-HGCN after using technical factors to extract temporal features and using attention to selectively tend the relationship between each stock, and our method is better when using two relationships at the same time than using a single relationship.

TABLE II
COMPARISON WITH EXISTING METHODS

Methods	accuracy	precision	recall	F1 score
SFM	35.40±0.20	26.50±6.91	33.34±0.01	29.21±4.06
RSR	37.56±1.01	34.47±9.58	35.50±0.72	34.55±5.71
GRU-HGCN	38.85±0.36	39.59±1.26	**35.65±0.37**	37.51±0.69
GAT(concept)	37.76±0.55	40.33±3.91	35.61±1.14	**37.79±2.37**
GAT(industry)	36.51±0.79	36.12±1.13	35.06±1.77	35.72±1.56
GAT(hybrid)	**40.17±0.41**	**40.85±1.64**	34.98±0.90	37.69±1.22

D. Simulated Trading Results

In order to further evaluate the performance of the proposed model in the stock market, we simulate the behavior of traders based on prediction to test whether the model can make a profit. On each trading day, input the technical factor data generated according to the data of the previous 60 trading days into the model, continue to hold or buy the stocks judged as ”up” by the model, continue to hold ”remain” stocks, and sell the ”down” stocks in the holdings. In addition to the neural network models of CNN, LSTM, GRU, ResNet [24] and DenseNet [3], three Factor Investment models of Book-to-Mark [9], Momentum Factor and Unusual Turnover Rate [10] are added for comparison. The final return result is obtained by operating all stocks during the simulation of the test set, taking into account the transaction handling fee of 3 / 10000. The simulated trading results are presented in Fig.3.
It can be seen from the income curve that the return rate of the strategy based on prediction is basically higher than that based on factor investment model, and the Maximum Drawdown is lower, indicating the effectiveness of trading using the prediction results of the model. In addition, our model has the highest cumulative return in the test trading span. In particular, our model has an overall return close to the bull market in a stable market environment. Table III shows the experimental results of the profitability of each model, and makes a quantitative analysis of the above indicators. Among them, SR of our model is higher than other baseline models. Under unit risk, a larger SR corresponds to a higher return. The Maximum Drawdown is lower than other baseline models, indicating that the loss risk of the portfolio is the smallest.

V. CONCLUSION

In this paper, we propose a technology factor graph attention network, in which the technology factor extracts the temporal feature and the attention graph extracts the relationship feature between stocks, so as to predict the stock trend from end to end. Stock technology factors are used to extract the preorder sequence timing features of graph attention network prediction model. Through a large number of technology factors covering different signals, we can obtain the timing feature information of a series of stocks in the past period as

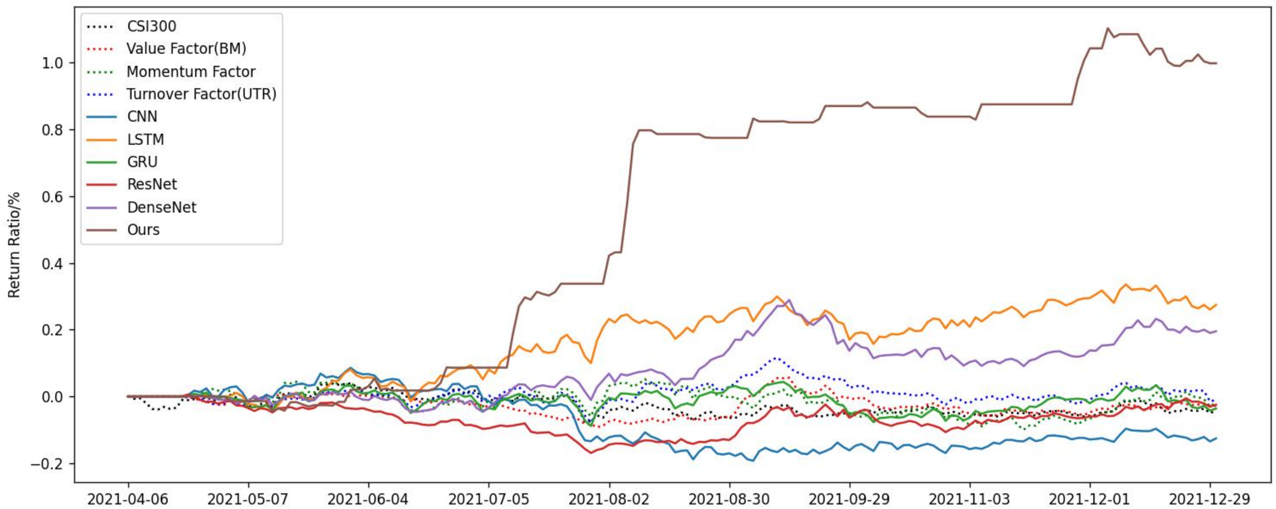

Fig. 3. Simulated trading results

TABLE III
PERFORMANCE COMPARISON OF MODELS

Methods	R	AR	SR	MDD
Value Factor(BM)	2.44%	3.29%	0.2326	12.01%
Momentum Factor	2.30%	3.10%	0.2364	10.06%
Turnover Factor(UTR)	1.27%	1.71%	0.1658	10.75%
CNN	17.19%	23.70%	0.5504	8.34%
LSTM	27.42%	38.39%	0.5211	10.96%
GRU	5.00%	6.76%	0.3670	10.55%
ResNet	5.13%	6.93%	0.3792	9.23%
DenseNet	19.53%	27.02%	0.3631	15.38%
Ours	**84.92%**	**128.00%**	**0.9096**	**6.87%**

comprehensively as possible. We have constructed the basic factor and technical factor data set based on CSI 300, and built a complete simulated transaction test system on it. A large number of experiments have been carried out on it to prove the effectiveness and practical application ability of our method.

There are still some deficiencies in the work of this paper for follow-up research: Possible over learning problems caused by a single dataset. Intraday trading data not used due to unavailable data source and calculation quantity. The types of stock relations can be increased. The most important thing is to get better results and apply them to the actual stock market.

APPENDIX A
PART OF STOCK TECHNICAL INDICATORS

1) **Moving Average:** Average value of n-day closing price
2) **Moving Standard Deviation:** Standard deviation of n-day closing price
3) **Exponential Moving Average:** The exponential moving average is a type of moving average that gives more weight to recent prices in an attempt to make it more responsive to new information.

$$EMA_{\text{Today}} = \left(\text{Value }_{\text{Today}} * \left(\frac{\text{Smoothing}}{1+\text{ Days}} \right) \right) + EMA_{\text{Yesterday}} * \left(1 - \left(\frac{\text{Smoothing}}{1+\text{ Days}} \right) \right) \tag{13}$$

4) **Displaced Moving Average:** A displaced moving average (DMA) is any moving average (MA) that has all its values shifted forward (positive displacement) or back (negative displacement) in time.
5) **Directional Movement Index:** The directional movement index (DMI) is a technical indicator that measures both the strength and direction of a price movement and is intended to reduce false signals.

$$\begin{aligned} +\text{DI} &= \left(\frac{\text{Smoothed } +\text{DM}}{\text{ATR}} \right) \times 100 \\ -\text{DI} &= \left(\frac{\text{Smoothed } -\text{DM}}{\text{ATR}} \right) \times 100 \\ \text{DX} &= \left(\frac{|+\text{DI} - -\text{DI}|}{|+\text{DI} + -\text{DI}|} \right) \times 100 \end{aligned} \tag{14}$$

Where: $+DM = CurrentHigh - PreviousHigh$
$-DM = CurrentLow - PreviousLow$

6) **Moving Average Convergence Divergence:** Moving average convergence divergence (MACD) is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA.
7) **Stochastic Indicator:** Stochastic Indicator KDJ is generally a statistical system used for stock analysis. According to the statistical principle, the immature random value RSV of the last calculation cycle is calculated through the highest price, lowest price and the closing price of the last calculation cycle in a specific cycle

(usually 9 days, 9 weeks, etc.) and the proportional relationship between the three, and then the K value, D value and J value are calculated according to the method of smoothing the moving average.

$$
\begin{aligned}
&\mathrm{RSV}=\frac{C-L_n}{H_n-L_n}\times 100\\
&K_i=\frac{2}{3}K_{i-1}+\frac{1}{3}\mathrm{RSV}_i\\
&D_i=\frac{2}{3}D_{i-1}+\frac{1}{3}K_i\\
&J_i=3K_i-2D_i
\end{aligned}
\tag{15}
$$

8) **Relative Strength Index:** The relative strength index (RSI) is a momentum indicator used in technical analysis that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset.

$$
\begin{aligned}
&gain'_i=\begin{cases} gain_i & ,i=0\\ \frac{gain_i+(n-1)gain'_{i-1}}{n} & ,i>0\end{cases}\\
&loss'_i=\begin{cases} loss_i & ,i=0\\ \frac{loss_i+(n-1)loss'_{i-1}}{n} & ,i>0\end{cases}\\
&RSI_i=\frac{gain'_i}{gain'_i+loss'_i}\times 100
\end{aligned}
\tag{16}
$$

9) **Stochastic RSI:** The Stochastic RSI (StochRSI) is an indicator used in technical analysis that ranges between zero and one (or zero and 100 on some charting platforms) and is created by applying the Stochastic oscillator formula to a set of RSI values rather than to standard price data.

$$
\text{StochRSI }=\frac{RSI-\min[RSI]}{\max[RSI]-\min[RSI]}\tag{17}
$$

10) **Volume RSI:** Compared with the RSI, the calculation method and judgment principle are basically the same, but it focuses on the factor of quantity. According to the principle of quantity price first, it can better judge the price trend in advance.
11) **Bollinger Band®:** A Bollinger Band® is a technical analysis tool defined by a set of trendlines plotted two standard deviations (positively and negatively) away from a simple moving average (SMA) of a security's price, but which can be adjusted to user preferences.

$$
\begin{aligned}
&\mathrm{BOLU}=\mathrm{MA}(\mathrm{TP},n)+m*\sigma[\mathrm{TP},n]\\
&\mathrm{BOLD}=\mathrm{MA}(\mathrm{TP},n)-m*\sigma[\mathrm{TP},n]
\end{aligned}
\tag{18}
$$

Where TP (typical price) = (High + Low + Close) $\div 3$

12) **BBIBOLL:** BBIBOLL is a track line with multiple empty lines as the center line and the standard deviation of multiple empty lines as the bandwidth.

$$
\text{BBIBOLL}=\frac{(MA_3+MA_6+MA_{12}+MA_{24})}{4}\tag{19}
$$

13) **Williams %R:** Williams %R, also known as the Williams Percent Range, is a type of momentum indicator that moves between 0 and -100 and measures overbought and oversold levels.

$$
\text{Williams }\%R=\frac{\text{Highest High }-\text{ Close}}{\text{Highest High }-\text{ Lowest Low}}\tag{20}
$$

14) **BIAS:** BIAS is percentage difference between closing price and a moving average.
15) **Accumulative Swing Index:** The Accumulative Swing Index (ASI) is a trendline indicator used by technical traders to gauge the long-term trend in a security's price, drawing on candlestick charts by collectively using its opening, closing, high, and low prices.
16) **Volatility Volume Ratio:** Volatility Volume Ratio (VR) is an indicator of the strength of trading volume.

$$
\text{VR}=(AVS+1/2CVS)/(BVS+1/2CVS)\tag{21}
$$

Where AVS is cumulative daily trading volume of stock price rise in n days. BVS is the cumulative value when the stock falls, and CVS is the cumulative value when the stock is flat.

17) **ARBR:** The popularity intention index ARBR is given by

$$
\begin{aligned}
&AR=\sum_i^n\frac{High_i-Open_i}{Open_i-Low_i}\\
&BR=\sum_i^n\frac{High_i-Preclose_i}{Preclose_i-Low_i}
\end{aligned}
\tag{22}
$$

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