Stock Price Trend Prediction Model Based on Deep Residual Network and Stock Price Graph

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***Abstract*—Consider that people often use stock price graph to make decisions, this paper introduce a deep residual network (ResNet) model for prediction, using the stock price graph as input. The results show that the ResNet model has the average accuracy of 0.40, which is higher than the stochastic indicator of 0.33.**

Keywords-Stock price time series; ResNet; Stock price graph

I. INTRODUCTION

In the field of financial time series prediction, traditional statistical methods usually assume that a time series is generated by a linear process [1]. Ayodele et al. [2] used the ARIMA model to establish a stock price prediction model. However, the stock price data is complex in nature, it has non-linearity, non-stationary, selective and dynamic characteristics [3], and the behavior of stock price fluctuation is often controlled by the random walk process, stock price data also has high noise [4]. Traditional time series prediction statistical models are limited [5].

With the development of computational intelligence, researchers have continually proposed machine learning algorithm models to predict the future development of a single stock or a specific portfolio, such as the hybrid ARIMA and support vector machines model [6]. These machine learning techniques can learn the nonlinear relationships between features without having to be familiar with the input data in advance. In addition, the artificial neural network has excellent learning ability in the case of a large amount of data. Sureshkumar et al. [7] used ANN to predict stock prices in 2012. In order to further improve the training speed and prediction accuracy, various algorithms combining machine learning and neural network have been proposed [8,9].

Recently more and more researchers have applied deep learning models to stock prediction problems, and many studies have shown that deep learning models have strong learning ability and prediction accuracy [10-13]. In 2015, He et al. [14] proposed a special convolutional neural network called deep residual neural network, which can increase the number of network layers to hundreds or even thousands easily, while training time is within the acceptable range, greatly improving the accuracy of image recognition.

In this paper, we focus on deep residual network and stock price graph and explore their potential in stock price trend prediction problem. Specifically, our contributions are as follows:

- Propose using graph features of stock prices.
- Apply the residual network model with stock price graph features to the stock prediction problem.
- Show the feature extraction ability of the ResNet in the images and improve the prediction accuracy.

II. DATA DESCRIPTION

This article used two data sets (10 China Market Index stocks and 10 White Horse stocks) to evaluate the general performance of the model comprehensively. For daily data, the training set is from January 2006 to December 2016, and the test set is from January 2017 to August 2017. For minute data, the training set is from January 2016 to December 2016, the test set is from January 2017 to August 2017.

TABLE I. STOCK DATA DETAILS: 10 WHITE HORSE STOCKS AND 10 CHINA MARKET INDEX STOCKS

Stock Code	*Name List*	*Stock Code*	*Name List*
SH600009	Shanghai Airport	SH000001	SSE
SH600056	Chinese medicine	SH000002	A-share index
SH600104	SAIC	SH000003	B-share index
SH600176	Chinese boulder	SH000010	SSE 180
SH600887	Yili	SH000011	SSE 180
SZ000418	Little Swan A	SH000012	Treasury bond index
SZ000513	Livzon Group	SH000013	Corporate bond index
SZ000538	Yunnan Baiyao	SH000016	SSE 50
SZ000651	Gree Electric	SH000300	CSI 300 Index
SZ000858	Wuliangye	SZ399004	CSI 100 Index

In order to avoid the class imbalance problem, this paper uses a flexible method to divide the price category:

$$label_d = \begin{cases} 0, & if\ \ return\_next\_day_d < h_1 \\ 1, & if\ \ h_1 < return\_next\_day_d < h_2 \\ 2, & if\ \ return\_next\_day_d > h_2 \end{cases} \quad (1)$$

$label_d$ is determined by the next day's price increase $return\_next\_day_d = close_{d+1,240} - close_{d+1,1} - 1$ and $close_{d,i}$

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represents the closing price of the ith minute on day d. We rank $return\_next\_day_d$ from small to large, setting h1 as the 33% of the sequence, and h2 as the 66% of the sequence. The number of samples in the three categories (fall, flat and rise) is almost equal.

III. Methodology

A. Stock price candlestick graph

Stock price graph is often used as an aid map for investors in analyzing stocks. By integrating information on the price-volume characteristic, the graph records a number of price patterns in a line segment, reflecting price movements and fluctuations. Stock price candlestick graph consists of three parts:

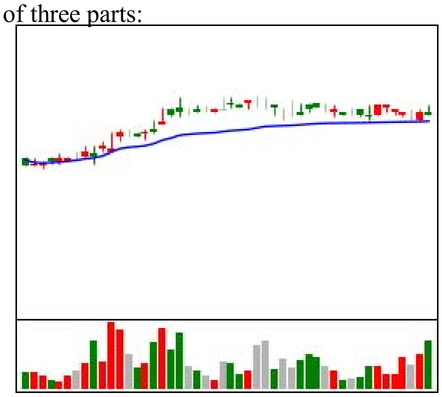

Figure 1. Candlestick graph of stock SH600004 on May 3, 2016. The stock price is normalized by a range of 5% every 5 minutes, and the vertical axis of the picture is -5% ~5%.

Average price line. Represented by the blue line, it reflects the average shareholding cost of the investor on the day. It is calculated by dividing the current accumulated transaction amount by the current accumulated transaction volume.

K line chart. The figure is based on the four features of Open, Close, High and Low in the specified period (5 minutes), reflecting the price fluctuations and trends, in the upper part of the figure. The positive line represented by a red entity represents the closing price is greater than the opening price. The negative line represented by a green entity represents the opening price is greater than the closing price. And the neutral line represented by a gray entity represents the opening price equal to the closing price. The entity length of the K line depends on difference between the opening price and the closing price.

Volume histogram. Changes in volume can be used to analyze volume-price relationships in the lower half of the figure. The histogram is used to characterize the volume of the transaction. The height of the column represents the volume: the higher the column, the larger the volume.

B. Deep Residual Network

We use a ResNet network with a 32-layer convolution kernel to process stock price graph feature. ResNet consists of 15 residual blocks in *Fig. 2,* which places both the Relu and Batch Normalization nodes in a pre-activation item.

The main training steps are as follows. First we randomly select a small batch, that is, the input image order of each epoch is random. Randomly disturbing the input order is to ensure the independence between data blocks. Second multi-class cross entropy is used as the loss function, and L2 regularization is added to the loss function to avoid overfitting. In addition, the parameters are updated using the Mini-batch Gradient Descent Algorithm, which uses momentum to speed up convergence and reduce oscillation.

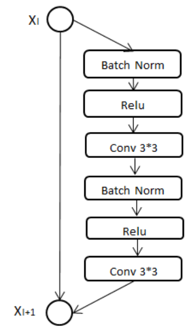

Figure 2. Residual block structure

For this experiment, cross entropy is chosen as the loss function. After L2 regularization, the cross entropy is as follows：

$$E(w) = -\sum_{n=1}^{N} e_n(w) + \frac{\lambda}{2N}\sum_{w} w^2, en(w) := \sum_{k=1}^{K} y_{k,n} \ln(\hat{y}_{k,n}) \quad (2)$$

The first term is a conventional cross-entropy expression, where K is the number of categories and N is the total number of samples. $y_{k,n}$ is one when the category of the nth sample is k, else zero. $\hat{y}_{k,n}$ represents the probability that the nth sample belongs to the category k. The second term is the sum of the squares of all the weights in the model, where λ is the regularization parameter (λ>0), and $1-\frac{\eta\lambda}{N}$ is used to adjust the weight w.

C. Traditional Numerical Feature

Linear feature refers to the time series feature of the closing price. In order to ensure the stability of the sequence, we use the sequence as follows:

$$feature_d = close_d - close_{d-1} \quad (3)$$

Volume price indicator refers to the six characteristics (open, high, low, close, amount, and quantity) of the original stock data set for the DNN, CNN_Price, and SVM_Price models.

$$feature_d = [price_1, price_2, ..., price_{240}] \quad (4)$$

Where $price_d$ represents the characteristic value of the d-minute (a total of 240 minutes per day).

$$price_d = [open_{d,t}, high_{d,t}, close_{d,t}, low_{d,t}, volumn_{d,t}, amount_{d,t}] \quad (5)$$

Stock technical indicator is a statistical indicator based on stock price indicator, rise index and fall index. According to the paper [13], we use nine common indicators as the technical indicator feature set. For example, RSI provides strength or weakness of stock market for recent period:

$$RSI=100-\frac{100}{(1+\frac{averagegain}{averageloss})} \quad (6)$$

IV. EXPERIMENTAL

We selected three widely used financial time prediction models: SVM, DNN, and CNN compared to the ResNet model. Two SVM models: SVM_Tech takes technical features as input, SVM_Price takes volume and price features as input. Three CNN models: CNN_Price takes volume and price features as input, CNN_Ca5 takes graph features as input and CNN_2D [13] takes feature matrixes of 28*28 as input.

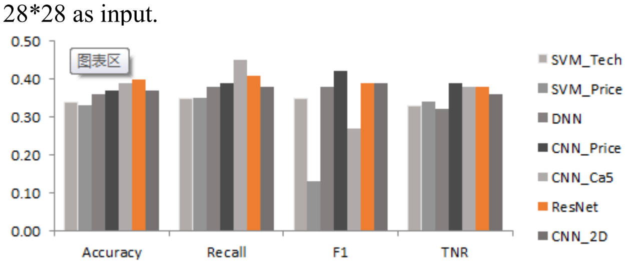

Figure 3. Average performance on 10 White Horse stocks

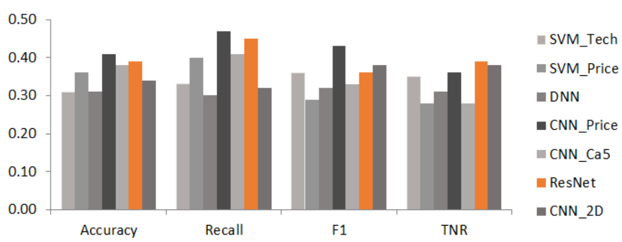

Figure 4. Average performance on 10 Market Index stocks

Accuracy represents the ratio of the number of samples accurately classified to the corresponding category to the total number of samples. Taken together, ResNet, CNN_Ca5 and CNN_Price have the highest accuracy. The averages are 0.40, 0.39 and 0.39, which are all higher than the stochastic indicator of 0.33.

Recall is the coverage rate predicted by the positive example. The average recall of ResNet, CNN_Price and CNN_Ca5 are both 0.43 shows that these models have strong ability to identify positive classes.

F1-Score comprehensively considers the accuracy and the recall, and is used to evaluate the ability of the classifier to recognize the rise category. We can see CNN_Price performs best both on the stock index data set and the white horse stock data set, with an average of 0.43. CNN_2D ranks second with an average of 0.39 and ResNet has an average F1 of 0.38. It shows that these three models have strong recognition ability.

TNR is used to evaluate the ability to recognize the fall category. The average TNR of ResNet is the highest 0.39. CNN_Price and CNN_2D perform well overall, with average values of 0.38 and 0.37 respectively.

Overall, the ResNet and CNN models are the most stable in the classifier evaluation index, whether in the market index data set or the white horse stock data set. CNN_Ca5 is slightly better than CNN_Price and better than CNN_2D. SVM_Price and SVM_Tech have the lowest classification accuracy and precision, and DNN performance is in the middle. This is consistent with theoretical analysis. First, the deep learning model can capture the hidden dynamics of stocks because of its more complex network structure, so ResNet, CNN, and DNN are better than SVM. Secondly, CNN and ResNet filter the features through convolution operations, optimize the learning process, avoid over-fitting compared to DNN, and improve the accuracy. Finally, ResNet and CNN_Ca5 perform best because they contain more information than volume price indicators, and CNN_Ca5 is better than CNN_Price. The feature set of CNN_2D is a matrix of 28*28, and the total number is 784. It maybe contains redundant information, resulting performance second to CNN_Ca5 and CNN_Price.

V. CONCLUTION

In this paper, we introduce a deep residual network model for stock price prediction using the stock price graph as input. And in order to comprehensively consider the performance, we analyze seven models' performance based on the different model classification indicators. It is found that compared with numerical values, stock graph feature is able to provide more effective information. In addition, the results show that ResNet model can excavate the hidden trend of stock price concealment and be more stable and efficient than other models.

However, there are still some shortcomings and improvements in our models. Future work might deal with integrated models, which can combine the performance of different models and use voting mechanism to determine the forecast results. Further work might also try to make use of other factors that probably affect the stock price, such as the correlation between stocks.

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