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Deep Learning Application in Stock Price Prediction

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***Abstract*—Stock market prediction has a great significance for investment decision-making. However, such a prediction task is notoriously difficult given the intricate nature of the variations in stock price. Many pieces of research have been proposed in the field of stock price prediction. And numerous reviews of stock price prediction have been done. However, the deep learning methods, especially the newest attention-based methods, have not yet been reviewed. Therefore, in this paper, we supplement some of the newest studies for review. A series of deep learning methods for predicting stock price has been compared on the metrics of accuracy and robustness. In summary, the more information the method could take advantage of, the better performance of methods would have.**

Keywords-component; Stock market prediction; Deep Learning; Accuracy and Robustness

I. Introduction

Stock market prediction is a topic of perennial interest in modern finance. Stock prices are determined by the marketplace, where seller supply falls short of, excess, or rarely matches the buyer demand [1-3].

High-performance stock index prediction models have the benefit of reducing investment risk and help investors select the most profitable stocks [4]. One main difficulty that lies in the heart of stock prediction is the low signal-to-noise ratio [5] and the heavy-tailed [6] nature of stock market data. Additionally, the problem is complexed by a multitude of factors, such as macro-economic factors, financial series inherent changes, etc., that all play a role in influencing the stock market. Besides, investors sometimes irrational behavior adds to the intricacy of the forecasting task.

Generally, the scientific community purposes two ways to forecast the stock market [7]. One way is technical analysis, where major predictive attributes are historical prices and volumes. The other way is fundamental analysis, which uses underlying factors affecting industries or companies, such as Gross Domestic Production, interest rate, Consumer Price Index, or social network as predictive attributes. Traditionally, scientists have used the Autoregressive (AR) Mode [8], Autoregressive Moving Average (ARMA) Model [9], Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model [10], Vector Autoregressive model [11], and Box–Jenkins [12] to make stock market prediction. However, these statistically supported models are based on the subjective model and experience of the data sequence to make predictions, and there is no guarantee in terms of the accuracy or stability of the prediction. The stock market is a complex system with many influencing factors and various uncertainties. Price changes are affected by the dynamic nonlinearity problem, the high noise of data, human intervention, policy intervention, and other various factors. The mechanism of mutual influence is also very complicated. In order to make accurate predictions, it must be ensured that the prediction method can handle a large amount of information. At the same time, it must be a method of induction and reasoning. This is why traditional methods cannot prove satisfactory for a lot of stock market forecast tasks.

Recently, with the advance in computing power and machine learning techniques, more studies are conducted in the quest for higher performance in a stock market forecast using machine learning algorithms. Specifically, deep learning, which is a subset of artificial neuron networks, has the strength of better explanation of the non-linear relationship between features and stock price [7] compared to traditional models. Furthermore, deep learning eliminates the need for feature engineering as a data preprocessing step [7] and enables the use of non-traditional data to serve as predictors. Scientists have implemented deep learning methods such as CNN, LSTM, DNN, RNN, and Transformer in the realm of stock market prediction.

As of now, there are several literature reviews summarizing the application of deep learning in stock market prediction [13-15]. However, newer studies are not included in these works. Thus, we feel a need to give a supplementary review of recent development on this topic.

In section 2 of this review, we present both classic and new deep learning methods, describe research inputs and outputs, and model techniques used. Section 3 examines the performance of different deep learning methods against common metrics of accuracy and robustness. Finally, the article discusses challenges and future research recommendations.

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II. DEEP LEARNING FOR STOCK PRICE PREDICTION

A. Stock Price Prediction Using CNN

Convolutional Neural Network (CNN) was based on human visual perception of recognizing things and was proposed by Yann LeCun in the 1900s [16]. Some researchers have made successful attempts to utilize CNN to predict the stock price. For example, Andriyanto A et al. [17] proposed CNN and candlestick approach to recognize an image to identify the strength of a trend pattern in the prediction movement of stock. Their results show the CNN with candlestick approach can produce up to 99.3% accuracy overall. However, this CNN-based method was only tested on one dataset (e.g., Yahoo financial data). Thus, it is still questionable whether this CNN and candlestick approach could prove powerful using another dataset. In addition, Hyun Sik Sim et al. [18] proposed a stock price prediction model based on CNN to validate the applicability of new learning methods in stock markets. What's more, Jiasheng Cao et al. [19] use the CNN-based method to forecast the stock index in a two-step process. Firstly, a CNN stock index prediction model is constructed; secondly, the stock index prediction model based on CNN-support vector machine (SVM) is established. Their results show that the two prediction models are feasible and effective. In summary, based on the above pieces of research and many others, we conclude that the CNN-based method generally can effectively capture the information from images or important indexes to predict the stock market price.

B. Stock Price Prediction Using RNN

Apart from CNN-based models, RNN-based models are also widely used in stock prediction tasks. In fact, due to RNN's ability to make predictions using the information from the past, past scholars had shown a great amount of interest in using RNN in prediction tasks, including stock trend prediction. Saad et al. investigated the performance of three different kinds of models: time delay, recurrent, and probabilistic neural networks, which are represented by TDNN, RNN, and PNN, respectively. In this relatively early experiment, they use the false alarm rate as the evaluation metric, and these three models were tested on the past record of the stocks of several companies, including Apple, IBM, Motorola, etc. Their result shows that all three models achieve a very low false alarm rate and have an obvious improvement compared to the baseline models, linear classifiers. They also concluded that RNN is the most powerful model among these three due to its internal recurrence. Though the metric is relatively weak compared to our current metrics, this experiment shows RNN's potential in the task of prediction.

Since the 2000s, there have been many improvements made to the RNN models, as well as many successful attempts of combining it with other models. One of those improvements was made by Deng et al. [20]. This research team proposed the Recurrent Deep Neural Network (RDNN) that uses the idea of both deep learning and reinforcement learning, to outperform human expertise in the task of financial asset trading. Their model is composed of a DNN structure to learn from the input features and an RNN structure for reinforcement learning. The model was trained on stock-IF data calculated from the top 300 stocks in the exchange centers in Shenzhen and Shanghai. The training process of RDNN includes the layer-wise parameter initialization and the fine-tuning process. They also introduced a novel derived model, the fuzzy deep direct reinforcement model, which is based on the RDNN. In this model, they manage to reduce the high transaction cost by choosing to forgo RNN's ability to track historical feature information and to only pay attention to the current market conduction and past trading history. In comparison to other models, including LSTM and RNN, FDDR achieves a significantly better performance in stock price prediction.

C. Stock Price Prediction Using LSTM

Long short-term memory (LSTM) is an artificial RNN architecture, but it is different from standard feedforward neural networks. It can not only process single data like pictures but also can process whole sequences of data like video. Thus, it can be used to make predictions by processing time-series data. A prime example of LSTM's application in stock price prediction is Guangyu Ding and Liangxi Qin's research, where they established three different deep learning models to predict the trend of the stock market based on LSTM [21]. The first one is the original LSTM model; The second one is an LSTM-based deep recurrent neural network (DRNN) which enhance the expressiveness of the model, where the loop can be repeated multiple times at each moment; The third one is an Associated neural network model based on LSTM, which calculates the opening price, the lowest price, and the highest price separately because these three values are not related to, and separate calculations can prevent mutual interference. Ding and Qin use these three models to analyze two different stocks (Petro China and ZTE) history data to test the model performance. And the results show that the original LSTM has the lowest accuracy, which is around 79%; DRNN have high accuracy, which is over 95%. Thus, the improved LSTM model has better performance. In addition, the model is more accurate in predicting stocks with less volatility, and more iterations are required for stocks with large volatility to improve accuracy.

D. Stock Price Prediction Using DNN

Besides the CNN-based, LSTM-based, and RNN-based methods, there are also attempts to use DNN-based models for stock price prediction. One model for stock prediction tasks based on DNN was proposed by Singh and Srivastava [22], which is composed of a 2D PCA for dimension reduction and a DNN model that utilizes the PCA results for predicting the closing price. Their input data set was collected from NASDAQ from 2004 to 2015, and the model performance was evaluated with multiple error measures, including Root mean square error (RMSE), Hit Rate (HR), Mean Absolute Percentage Error (MAPE), etc. In comparison to the SOTA method, 2D PCA + Radial Basis Function Neural Network (RBFNN), the DNN model achieves a better HR performance and a better correlation coefficient for the predicted return and the ground truth value, besides having comparable results in other error measurements. However, one drawback for the DNN based model is that its performance on the total return and RMSE does not achieve the level of performance of the RBFNN model. Additionally, when comparing with another baseline model based on RNN, the DNN model and the

RBFNN model have a significantly better performance in most error measurements. Thus, we propose that possible improvements for the DNN approach can be made by doing experiments with other algorithms like Deep Belief Network (DBN) or advanced optimizations.

Predicting the buy-sell points in the stock market is also an important aspect of stock market prediction. One attempt made by Sezer et al. [23] was to create a stock trading system that combines the optimized technical analysis indicators and Deep Neural-Network, DNN, based model for generating buy-sell points. Their model first uses a genetic algorithm to compute the best RSI values and then uses the algorithm output as the training set for MLP. This novel approach did not outperform SOTA methods but had a comparable result relative to the Buy-Hold and other trading systems.

E. Stock Price Prediction Using Transformer

Transformer is a deep learning model launched in 2017 that uses the attention mechanism, and since then, there has been multiple attempts of using transformer-based models for the task of stock market prediction. Ding et al. [24] proposed Hierarchical Multi-Scale Gaussian Transformer (HMG-TF) based on the basic transformer to predict the stock movement. The difference between HMG-TF and the basic transformer is that they added a multi-scale Gaussian prior, an orthogonal regularization, and a trading gap splitter for the transformer. In their experiment, LSTM, CNN, Attentive LSTM, and HMG-TF were tested on the NASDAQ data and the China A-share data. The result shows that HMG-TF outperforms the current SOTA approaches, and Ding concluded that the Multi-Scale Gaussian Prior and the Trading Gap Splitter has a greater effect on the improvement of HMG-TF compared to the effect of Orthogonal Regularization. Additionally, they also proposed future research recommendations, including increasing the amount of cross-sectional features of financial data, regularization, and using data augmentation to make the model more robust.

Another attempt of using transformer is made by Liu et.al, which they proposed the Capsule network based on Transformer encoder (CapTE) [25]. Different from other experiments they use the social media as their input dataset to collect information for predicting the movement of the stock market. Their idea was to use the transformer encoder and take the semantics and relations for different stock into the process of stock movement prediction. The capsule network is introduced as a way to evaluate similar features extracted by the transformer encoder, which would help the model to have a categorical information of the dataset and thus become capable of paying attention to important events. Their result shows that CapTE was able to get better performance than the state-of-the-art methods.

III. Performance Analysis of Different Methods for Stock Price Prediction

In this section, we analyze the performances of the different deep learning methods on the basis of accuracy and RMSE. The comparison of different deep learning methods is shown in Table 1.

Table 1. The performance of different deep learning methods

Methods	accuracy	RMSE
CNN [17]	99.32%	0.0124
LSTM [21]	96.75%	0.014983
DNN [22]	68.21%	0.010119
DNN [23]	59.98%	N/A
Transformer [24]	58.70%	N/A

Table 1 shows the accuracy of different deep learning methods for stock price prediction. The first column shows the different methods to be compared; the second column presents the accuracy of stock price prediction using deep learning methods; the third column summarizes the RMSE of different methods, which evaluates the robustness of methods. These properties can help us analyze the performance of these stock prediction models.

We conclude that CNN-based methods have the highest accuracy of stock price prediction, with RMSE being the second lowest. Obviously, the CNN-based method for stock price prediction has a good performance accuracy and robustness. Such successful results could be partially accounted for by the fact that CNN uses the whole picture of stock price variation trend and thus takes advantage of more variation information to predict the price. On the other hand, two pieces of research based on DNN both exhibit accuracy much lower than the CNN-based and LSTM-based methods. This is because the DNN-based classifier could not capture the sequence information effectively. Besides, the LSTM-based method can also achieve a good performance, proving that the calculation characteristic of LSTM is suitable for sequence processing. However, the accuracy of the transformer-based method only achieves 58.7%. This may be because this complicated method requires a lot of data for training, while the data stock price prediction is too small to satisfy the requirement of the transformer-based method.

IV. Conclusion

In this paper, an analysis of stock price prediction using different deep learning methods has been given. Some deep learning methods have achieved very successful result in prediction compared with traditional methods. However, more research is needed to refine training process as well as validate the high performance of sophisticated models. Specifically, the CNN-based method has a prominent advantage over other methods, but the test data set of this model is very simple. Thus, more tests are needed to determine whether this CNN model can accurately analyze the stock market. The LSTM-based method (Associated Net) performs closely to the CNN-based method, and this model tested two different data sets, which get a good performance. Therefore, its stability and reliability should be higher than that of the CNN model. However, the DNN, RNN, and transformer models are not nearly as good as LSTM. In summary, the more information the deep learning method could capture, the better performance the models could achieve.

Considering the general trend of stock market prediction using deep learning methods, it is to be expected that more research works focus on finding new meaningful sources of information to extract from. At present, technical indicators are favored over fundamental analysis because of the directness of such information, however, we anticipate as interests are aroused around social network sentiment, more research considering a combination of technical predictors and social network predictors will be conducted. From current studies available, only social network data does not perform better than technical analysis, while a combination of both types of input improves model performance. We also believe that including more variables, such as topics discussed in social platform, besides sentiment scores, which are the most commonly looked at predictor in stock prediction right now, have considerate potential in improving deep learning model performance.

Moreover, it is expected that new studies will eventually cover more datasets of different nature, for example, stock market data in developed countries versus in developing countries, price of stock belonging to different sectors, etc. Such comparisons have significance in the future application of stock market prediction in various contexts in revealing which methods and what kind of information is most helpful in stock prediction under changing circumstances.

We hope our review of deep learning methods for stock price prediction in recent years provide a clear view of past research and point out directions and promising areas to explore for future research in this field.

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