Stock Price Prediction Using Machine Learning Strategies

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Abstract. Being able to foresee the potential opportunities or crisis in stock market has always been desirable among investors. Especially during the Covid-19 global pandemic, the skill of risk management is of great importance to sustain in such an unstable environment. Apart from various kinds of strategies in traditional business analysis, a robust intelligent system that can correctly predict stock price is desired to determine investment strategies. At present, much related research involve with predicting the stock price trend, and most of them use deep learning methods. Although these research managed to achieve an ideal result of their tasks, seldom surveys focus on the summary of deep learning methods employed in stock price prediction. As a result, the aim of this paper is to summarize the machine learning methods used in forecasting stock price, the development context of the task, and, finally, analyze the development trend of the task based on previous published papers. These papers were classified by deep learning methods, which included Long Short-Term Memory (LSTM); Gated Recurrent Units (GRU); Recurrent Neural Network (RNN); and other hybrid deep learning methods. Furthermore, this paper identifies some of the dataset, variable, model, and results of each article. The survey adopted presents the results through the most used performance metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Mean Square Error (MSE).

Keywords: machine learning; deep learning; stock price prediction; LSTM; GRU

1. Introduction

The fluctuation of stock prices, to some extent, reflects the environment of the global economy – whether it's prosperous or in a recession. Some traditional stock traders discredit the authenticity and accuracy of stock price prediction with modern machine learning techniques, deeming that the complicated nature of stock market deny the possibility of making reliable prediction.

In fact, previous research have revealed the practicability of these machine learning models. With the hope of predicting potential risks that might need immediate action of buying or selling, researchers even developed a series of hybrid models attempting to predict the tendency of Candlestick charts of a single stock. The previous success of machine learning methods application in other time series prediction problems indicates their ideal prospect for stock market analysis. Previous researchers vastly employed Support vector machines (SVM) and neural networks for price trends forecasting not merely in the stock markets. The features largely determine the overall performance of a prediction model, so previous research on stock price prediction with ML strategies focus on the features from historical stock data. In order to collect and analyze the influence of public and private information, scholars have been dedicating on leveraging textual information from social media, news and official company announcements. Information from various types of resources is fed into the ML systems.

A model performed based on deep learning, on the other hand, might differ from this structure and can include all these steps into an end-to-end training model. Recent years have witnessed the success of deep learning not only in achieving excellent results in many computer-visioning tasks, but also in its surprising performance in natural language processing. Similarly, deep learning has been applied to a versatile range of tasks by researchers in recent years. The initial machine learning methods in early years first constructed features manually, and then were used for classification or regression. However, the performance of these methods depends on the quality of artificially constructed features. If the quality of feature construction is poor, it will have a negative impact on the effect of classification or regression. Fortunately, deep learning can solve this problem well. Through deep neural networks and nonlinear transformations, the model can automatically learn the relevant features of the task through a large number of parameters. The fact that deep learning did manage to work well on giving the correct prediction results draws the world's attention to the power of these techniques. In general, if correctly set up, deep learning will serve as a highly effective tool in a wide range of academic research and industrial fields, bringing a cherry on top of human civilization.

Although researchers have successfully applied deep learning methods such as GNN, GRU, and LSTM, etc., to fulfill the forecasting tasks, there is still a lack of a review which provides a comprehensive summary of these latest works done in stock price prediction. Therefore, in this article, first a detailed introduction to the task-related background was given, including the subtasks of the task, and the datasets and variables it uses. Then, we introduce some of the latest neural network models adopted in each task, including the principles of the model. In addition, we review some of the latest work and demonstrate which problems and methods the task focuses on solving. Finally, based on the analysis of the previous work, we put forward some possible challenges in the task. Our review can provide a good guide for beginners.

2. Background

2.1 Stock Price Prediction (The overall task)

With an attempt to effectively trace the empirical evidence of stock market prediction based on machine learning and deep learning models, the survey is dedicated to dividing the general task into a few subtasks. Five research questions are constructed and are listed as: 1) What datasets are normally used for forecasting in stock market? 2) What models are usually adopted to predict the stock market? 3) What different performance parameters are used during the process of the experiment? 4) What metrics are set to serve as a standard to evaluate the effectiveness of these models? 5) What are the most representative works and contributions for stock market forecasting? All these questions will be answered sequentially in the remaining survey.

2.2 Datasets/Benchmarks

2.2.1 Time Series Data in Finance

The task focuses on time series stock data, a time-series dataset which consists of the different price at the stock's closing, opening, the current closing period, and include price change, volume, and daily closing offer price. The prevailing research mainly focuses on indexes such as Dow Jones, Nasdaq, NYSE, S&P 500, and Hong Kong Index. These data are opened to be downloaded for different time span (frequencies). Various studies have leveraged these resources from Google Finance, Bloomberg, and Yahoo Finance.

Aside from the prices in different frequency level, the volume that represents the total number of traded stocks within the period, another widely used price component is called adjusted closing price that factors the stock's dividends, stock splits, and the new stock offerings. For instance, in [15], researchers took advantage of volume at different trading period for S&P 500 and Dow Jones indices. Additionally, in [16], researchers focus on high and low prices and incorporate them using LSTM analysis to give predictions of prices of soybean futures – fully electronic, exchange-traded contracts on the Chicago Board of Trade (CBOT).

Among a variety of papers dealing with the problem of forecasting the financial markets, different frequencies of the trading data were used. For instance, article [17] and [18] both adopted daily stock data in their datasets for the research. In [19], researchers also employed data from both Nikkei 225 and S&P 500 to make prediction with the help of deep learning models. Researchers in [17] leverage data from Google Finance with a frequency of per 15 minutes. Additionally, they derive technical indicators and incorporate sentiment embeddings for financial market prediction. In [20], financial news are used to perform experiments on data in the Hong Kong Stock Exchange.

2.2.2 Textual Data

The task then takes textual data into account. In mentioning Twitter and other sources of social media, previous research has demonstrated that textual data, with historical prices, manage to improve the performance of a forecasting model. Textual data come within various forms and sources - comments from the Internet, news sources and company reports or more specifically, financial reports of a company and blogs, etc., Textual information from news, financial blogs and sentiments online and discussion boards in stock trading applications have been used for stock market prediction.

News data coming from journals, newspapers, and websites are some of the most prevalent sources of textual data. Financial news data were extracted in [28] and [29] from different financial news website to predict future stock price trends. A sentiment analytical tool was constructed in [24] to applied it in a financial news article prediction system. [25] applied both news data and technical features on a simple regressive model to make predictions.

Moreover, nowadays influential people commonly share their opinions about certain political or financial events on social media and thus might influence other stock traders' decisions. For example, [22] shows that President Trump's tweets, to some extent, indicate information for short-term market movements. Social media have widely been used as examples for sentiment analysis due to their ability to capture personal opinions. In particular, researchers in [21] adopted Twitter data for evaluation of the effect of public Manuscript. Similarly, [27] also used tweet data to analyze the relationship between textual data and stock price trends, and hence used it on market prediction.

Company disclosures, on the other hand, are more trustworthy resources since they usually include the latest officially confirmed information. They usually report information regarding quarterly earnings, adjustment of the board of the directors and challenges of the business. Particularly, textual data from company announcements was extracted in literature [23] to understand their impact on both short-term and long-term stock index predictions. Moreover, based on instant announcement from the website of Thomson and Reuters, literature [26] construct a decision supporting model. They also set up sentiment analysis that focuses on negation scope detection.

2.3 Metrics

After the process of collecting data and placing them into each machine learning or deep learning model assigned, a standard for evaluating the performance of the models is expected. In the remainder of section 2, four of the most popular performance metrics for model evaluation are briefly introduced to help axialite the understanding of tasks. The performance metrics commonly adopted in most research is MAPE, MAE, MSE and RMSE.

2.3.1 MAPE

Also known as mean absolute percentage deviation (MAPD), the mean absolute percentage error (MAPE) is a standard to evaluate the accuracy of a prediction model. It usually expresses the performance of the model as a ratio defined by the formula:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{1}$$

A_t stands for the actual value and F_t is the forecast value. The difference of A_t and F_t is divided by the actual value A_t. The absolute value in this ratio is summed for every forecasted point in time and divided by the number of fitted points n. MAPE is widely used in stock market forecasting.

2.3.2 MAE

Mean absolute error (MAE), on the other hand, is a measure of errors between paired observations expressing the same phenomenon.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{2}$$

Where y_i is the prediction and x_i represents the true value. The mean absolute error shares the same scale as the data being measured. The MAE is a widely used standard for computing forecast error in stock analysis, and sometimes used in coordinates with the more standard definition of mean absolute deviation.

2.3.3 MSE

The next common measure for the difference/distance between two datasets is the *mean squared error (MSE)*. MSE is computed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 \tag{3}$$

As the value of MSE approaches zero, the predicting model that predicts observations is gradually approaching to a relatively high accuracy. MSE is usually used for comparative purposes. Two or multiple results from ML or DL models may be compared using their MSEs as a measure indicating how well they give a prediction to a certain dataset – usually the model with the smallest variance is the best unbiased estimator.

2.3.4 RMSE

Root-mean-square deviation (RMSE) is defined as the square root of the mean squared error (MSE). The RMSD of predicted values for times *t* of a regression's dependent variable with variables observed over *T* times, is calculated for *T* different predictions as the square root of the mean of the squares of the deviations:

$$RMSE(\theta) = \sqrt{MSE(\theta)} = \sqrt{\frac{\sum_{t=1}^{T}(Y_i - \widehat{Y}_i)^2}{T}} \tag{4}$$

The effect of each error on RMSD is proportional to the size of the squared error; As a result, larger errors have a disproportionately large effect on RMSD. Consequently, RMSD is sensitive to outliers.

3. Neural Network Models

Various types of methods and techniques applied to price prediction analysis are presented in the literature. The literature also considered and sorted some statistical techniques, machine learning as well as deep learning methods. Although a subset of machine learning, deep learning techniques have also been specifically introduced due to their popularity in recent years.

As a particular type of machine learning techniques, deep learning displays great potential and flexibility by acquiring information to split the task into a nested hierarchy of concepts, representing the overall task as different concepts, and every single concept is defined in relation to less complicated concepts, and more obscure notations are computed in terms of less obscure ones, more comprehensible ones. The dominant characteristic of deep learning methodology is the ability to represent the semantic composition provided by the vectorization as well as neural processing. Nonlinear network topology in neural networks manage to model complicated real-world data by extracting features which capture the distinguished information to create a more robust business than traditional methods. In various fields that conduct the successful application of deep learning models such as speech processing and image recognition made them an ideal alternative for time series analysis. The successful adoption of different learning models such as Artificial neural networks (ANN), convolutional neural networks (CNN), deep belief networks (DBN), recurrent neural networks (RNN) [30], and Long Short-term Memory (LSTM) has again spoken for the ability of deep learning algorithms in real-world applications. In [30], researchers apply RNN for learning characteristics as well as applying a reinforcement learning composition for making trading decision with deep representations. A lot of experiments have been operated based on the above ML strategies. Below, the paper mainly elaborates on two of deep learning architectures commonly used in predicting the trend of future stock market – LSTM and GRU.

3.1 Long-short term memory (LSTM)

Long Short-Term Memory (LSTM) would be a good approximation in predicting sequence prediction problems because of its gate structure and its efficiency to extract useful information and remove outdated ones. Overall, the LSTM is evolved around a memory cell that can maintain its state over time and nonlinear gating units which regulate the flow of information either into or out of the cell. We can visualize LSTM with a stock market scenario. Since the stock price of a given day will be most likely to rely on:

a) The pattern that the stock has been following in the previous few days, and it can be an uptrend or a down trend.

b) The price of the stock on the previous day.

c) Some factors that might influence the price for today. This can be some disturbance in the stock market, changes in senior leadership of the company or a drop in company's profit.

d) Global disturbance such as war and pandemic.

These dependencies can be summarized as to any problem as:

a) The previous cell state (The information that were previously stored in the cell -- i.e., price of the stock in the previous days)

b) The previous hidden state *(the same as the output of the previous cell)*

c) The input at the current state *(the new information that is fed in now)*

The operation formula of LSTM is as follows:

Forget gate:

$$f_t = (W_f * [h_{t-1}, x_t] + b_f) \tag{5}$$

Input gate:

$$i_t = (W_i * [h_{t-1}, x_t] + b_i) \tag{6}$$

$$\widetilde{c_t} = \tanh(W_c * [h_{t-1}, x_t]) + b_c \tag{7}$$

$$c_t = f_t * c_{t-1} + i_t * \widetilde{c_t} \tag{8}$$

Output gate:

$$t = (W_o * [h_{t-1}, x_t] + b_o) \tag{9}$$

$$h_t = o_t * \tanh(c_t) \tag{10}$$

While simple model of RNN is able to address with original text data in sequentially to acquire context-based features, problems such as vanishing gradient and dependencies on short context may still impact the forecasting performance. Hence, An LSTM-RNN hybrid model has been introduced to address the issue. Specifically, LSTM adopts memory cells to process imported data with long dependencies [31]. Hierarchical structures are taken advantage of and multiple hidden layers for feature engineering. In [32], scholars constructed an LSTM based model that takes in parameters such as stock prices and backlog as input for predicting a single stock price. In [35], a hybrid of CNN and LSTM is implemented -- CNN is applied for stock selection while LSTM is responsible for price prediction. In [34] technical indicators and stock data are used as the data imported for LSTM and the result is tested on Bovespa index from the BM&F Ibovespa stock exchange. Moreover, researchers in [36] utilized LSTM model for a single stock market index forecasting. Their experiments reveal that LSTM manages to outperform most memory-free models such as random forest and logistic regression classifier. Paper [33] incorporated paragraph vectors with LSTM in their model which is later tested on textual data from different companies in Tokyo Stock Exchange. The paper also show that LSTM can learn even when the input has large dimensions.

3.2 Gated Recurrent Units (GRU)

GRU is a variant derived from RNN and was proposed in paper [11]. Like LSTM, by implementing gate structure, it successfully addresses some issues that RNN encounter with long-distance information acquisition. Unlike LSTM, GRU only have two gate structure -- update gate z_t and reset gate rt. In a GRU structure, the update gate determines the amount of input x_t and last output h_{t-1} to be escorted to the following cell structure and the reset gate decides which of the previous information to forget, and only information with great necessity is left. The content stored in current memory guarantees that only the relevant content will be filtered to the next iteration, which is determined by the weight W. The main operations in a GRU training model are defined by the following formula:

Update gate:

$$z_t = (W_z * [h_{t-1}, x_t]) \tag{11}$$

Reset gate:

$$r_t = (W_r * [h_{t-1}, x_t]) \tag{12}$$

When finishes constructing and updating the gate, the candidate status value of GRU unit is $\widetilde{h_t}$ and the final output status value is h_t, and they are computed by formula below:

$$\widetilde{h_t} = \tanh(W_h * [r_t * h_{t-1}, x_t]) \tag{13}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widetilde{h_t} \tag{14}$$

A kind of similarity can be easily captured between LSTM and the GRU: it is certain that both models take advantage of a gate system for calculating the output value. Regarding the two models' performance, literature [12] demonstrated that GRU give a more desirable prediction output than does LSTM in a number of tasks, the result is also highlighted by other researches: Researcher in [13] discovered that GRU outperforms LSTM in a range of tasks excluding the task of language modeling. On the contrary, literature [14] finds that the LSTM provide a better predicting result than GRU does in the verbal recognition task, but they still conclude that the GRU classification is more lightweight and thus complete the task within a shorter amount of time. In general, both LSTM and GRU are relatively robust and suitable for predicting models to sequential data. Additionally, GRU, because of feeding with less parameters, has the advantage of faster optimization compared with LSTM.

However, there are always rooms for enhancement for a traditional GRU model. Particularly, some research has proposed changing the internal structure of GRU to eliminate local minima problem – ML algorithms may have the chance of struggling with local minima during model training process. Their experiment also suggests that the utilization of minibatch gradient descent –a neat balance between stochastic and batch gradient descent-- successfully reduced time complexity and other problems come with stochastic gradient descent. Theoretically, minibatch gradient decent is operating by dividing the training set into small batches for model error calculation and coefficients updates. In general, the slight modification on conventional GRU models, performing on actual dataset, managed to generate a desirable price prediction outcome as evaluated by RMSE. [38]

4. Related Research

The fluctuation of stock prices, to some extent, reflects the environment of global economy – whether it's prosperous or in a recession. Even though traditional stock traders discredit the authenticity and accuracy of stock price prediction with modern machine learning techniques, deeming that the complicated nature of stock market deny the possibility of making reliable prediction, in fact, previous research have revealed the practicability of these machine learning models [3][4]. In [2], researchers demonstrated that the designing of appropriately chosen variables and models managed to capture the patterns of the stock price trend. Their paper presented a way of hybrid training for stock price using machine learning as well as deep learning methodology. Several deep learning-based regression models were built using LSTM networks, and we found that the LSTM-based univariate model, which uses data from a previous week as input for predictions, provides the most accurate result. [1][2]

Additionally, in [5], A hybrid of RNN and LSTM is constructed to make prediction of the stock price trend. Their comparison between the percentage of accuracy of both ARIMA and LSTM used on series data manifested that LSTM outperforms ARIMA. In [4], around ten classification models for predicting short-term stock price movement are set into place. Among these models including logistic regression, LSTM, Decision Tree, Random Forest, ANN, and Support Vector Machines (SVM) classifications, ANN generated the highest level of accuracy on average, and the most considerable prediction on short-term stock price movement is provided by LSTM. Indeed, as indicated in papers [6] and [7], many studies concluded that LSTM method helps improve the accuracy in stock prices prediction. Additionally, much research of stock price prediction favor ARIMA method due to its simplicity and wide acceptability, despite the fact that there exist other forecasting models that might provide more accurate prediction results, such as [8] and [9]. Generally, ARIMA models are the most commonplace models for forecasting a time series in stock market trend that can be made stationary by changing in combination with nonlinear transformations.

[10] aims to employ a CNN model for classification of the investors' sentiments that are collected from a specific stock forum. They then propose a hybrid model where within the model, LSTM approach is implemented for collecting the technical indicators, followed by the conduction of sentiment analysis. Overall, based on the experimental results, the hybrid model they invented performs more effectively and accurately in prediction results, and even outperformed the traditional LSTM model under certain circumstances.

5. Challenges to the Task

As presented above, previous literature extensively studies the machine learning methods on financial market prediction and propose variety of innovative models. Unfortunately, there are currently two main limitations existing in predicting stock price using machine learning algorithms. The first issue involves with the fact that although the textual features are employed in current models to better interpret the mainstream attitude towards a certain stock in social media, they usually collect information based on previous data mining tools (text mining technologies). The conventional text mining strategies usually fail to account for the semantic and other helpful resources that also improve the performance of machine learning models. Additionally, when determining the percentage of text or financial features to be adopted during data construction, the action to reduce dimensionality in feature sets is a of great necessity. Previous prediction models were mostly based on principal component analysis (PCA) and latent Dirichlet allocation (LDA) to reduce the feature dimensionality. Admittedly, they are both powerful tools for reducing dimensionally. However, both methods are somewhat problematic -- PCA method is prone to lose information and fails to process nonlinear data, while the LDA method is unable to evaluate semantic information in social media. Since both mechanisms will damage some of the information during dimensionality reduction, these two methods are, in general, not tailored for the stock price prediction. As a result, the challenge of employing machine learning models in real life financial market prediction is that better text mining tools and dimensionality reduction methods need to be invented.

There still exist several limitations regarding the variation of stock market environment. First, some studies take advantage of data only from a particular market environment with specific governmental trading restrictions. Hence the seemingly exceptional prediction accuracy may be biased and thus it is arbitrary to apply the model to other markets. For example, in [37], the predictability of their model partially relies on the fact that the strategy is impossible to implement due to the trading restrictions in a trading environment such as China. They apply the prices information from stock discussion forum of the current trading day to predict the closing price of next day. Usually, to achieve such predictability and implement trading strategies, a T + 0 trading is required, while it is prohibited in some region over the world. Predicting financial for those that are not implementable is relatively common. To make the result more persuasive, the experimental data adopted should be accommodated to other market as well.

6. Conclusion

Stock market prediction has been a fascinating field of study largely because of its potential influence on personal financial management. But since financial markets usually come with noisy data and unstable fluctuation, modern forecasting models have been developed with an attempt to incorporate textual data for prediction. This paper provides a recap on many of machine learning strategies based on previous research paper. The main contribution this paper is to introduce the current techniques related to adapted methods using various performance metrices. It also identifies both financial time series data and textual data. The techniques used in the stock market prediction are categorized in different machine learning algorithms. Some of the selected surveys adopted the hybrid approaches in the financial market. Indeed, most of the hybrid methods did manage to combine the advantages of their original strategies and thus generated desirable outcomes. If operated correctly, hybrid models have significant potentials and can outperform traditional machine learning methods in some ways. Moreover, LSTM and GRU techniques are commonly used approaches for achieving the accurate stock market prediction. The main challenge that stock market prediction face is that the existing data mining strategies and dimensionality reduction methods cannot keep pace with the advanced machine learning algorithms. Also, some other factors such as domestic governmental decisions and consumer sentiments have influences on stock markets. In the future, researcher will strive to correct the existing problems and improve the mechanism for creating a more trustworthy stock market system that is more accurate and predictable.

References

[1] Ho, M., Darman, H., & Musa, S. (2021). Stock Price Prediction Using ARIMA, Neural Network and LSTM Models. *Journal of Physics. Conference Series, 1988*(1), 12041.

[2] Mehtab S, Sen J and Dutta A 2020 Stock Price Prediction Using Machine Learning and LSTMBased Deep Learning Models Second Symposium on Machine Learning and Metaheuristics Algorithms.

[3] Chan T, Sy A and Vc Y 2017 Prediction of Bursa Malaysia Equity Index using Artificial Neural Network Malaysian Finance Association Annual Conference 2017.

[4] Sen J 2018 Stock Price Prediction Using Machine Learning and Deep Learning Frameworks International Conference on Business Analytics and Intelligence.

[5] Moghar A and Hamiche M 2020 Stock Market Prediction Using LSTM Recurrent Neural Network Procedia Computer Science 170 pp 1168-73.

[6] Roondiwala M, Patel H and Varma S 2017 Predicting Stock Prices Using LSTM. International Journal of Science and Research (IJSR) 6.

[7] Chen K, Zhou Y and Dai F 2015 A LSTM-based method for stock returns prediction: A case study of China stock market 2015 IEEE International Conference on Big Data (Big Data), Santa Clara, CA, USA, pp. 2823-24.

[8] Jung-Hua W and Jia-Yann L 1996 Stock market trend prediction using ARIMA-based neural networks Proceedings of International Conference on Neural Networks (ICNN'96) 4 Washington, DC, USA pp. 2160-65.

[9] Alwadi S, Almasarweh M and Alsaraireh A 2018 Predicting Closed Price Time Series Data Using ARIMA Model. Modern Applied Science. 12. Simposium Kebangsaan Sains Matematik ke-28 (SKSM28) Journal of Physics: Conference Series 1988 (2021) 012041 IOP Publishing doi:10.1088/1742-6596/1988/1/012041 11

[10] Nan Jing, Zhao Wu, Hefei Wang, A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction, Expert Systems with Applications, Volume 178, 2021, 115019, ISSN 0957-4174.

[11] K. Cho, B. Van Merriënboer, C. Gulcehre et al., "Learning phrase representations using RNN encoder-decoder for statistical machine translation," 2014, arXiv preprint arXiv:1406.1078.

[12] Chung J, Gulcehre C, Cho K, Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv:14123555. 2014.

[13] Jozefowicz R, Zaremba W, Sutskever I. An empirical exploration of recurrent network architectures. In: International Conference on Machine Learning PMLR. 2015;2342–50.

[14] Shewalkar A. Performance evaluation of deep neural networks applied to speech recognition: RNN, LSTM and GRU. JArtif Intell Soft Comput Res. 2019;235–45.

[15] Ankit Thakkar and Kinjal Chaudhari. 2020. Predicting stock trend using an integrated term frequency-inverse document frequency-based feature weight matrix with neural networks. Appl. Soft Comput. 96 (2020), 106684

[16] Chenhao Wang and Qiang Gao. 2018. High and Low Prices Prediction of Soybean Futures with LSTM Neural Network. 2018 IEEE 9th International Conference on Software Engineering and Service Science (ICSESS) (2018), 140–143.

[17] A. Ratto, S. Merello, Y. Ma, L. Oneto, and E. Cambria. 2019. Technical analysis and sentiment embeddings for market trend prediction. Expert Syst. Appl. 135 (2019), 60–70.

[18] A. Oztekin, R. Kizilaslan, S. Freund, and A. Iseri. 2016. A data analytic approach to forecasting daily stock returns in an emerging market. Eur. J. Oper. Res. 253 (2016), 697–710.

[19] T. Matsubara, R. Akita, and K. Uehara. 2018. Stock Price Prediction by Deep Neural Generative Model of News Articles. IEICE Trans. Inf. Syst. 101-D (2018), 901–908.

[20] X. Li, J. Cao, and Z. Pan. 2018. Market impact analysis via deep learned architectures. Neural Computing and Applications (2018), 1–12.

[21] J. Bollen, H. Mao, and X. Zeng. 2011. Twitter mood predicts the stock market. ArXiv abs/1010.3003 (2011).

[22] Kun Yuan, G. Liu, J. Wu, and Hui Xiong. 2020. Dancing with Trump in the Stock Market. ACM Transactions on Intelligent Systems and Technology (TIST) 11 (2020), 1 – 22.

[23] S. Feuerriegel and J. Gordon. 2018. Long-term stock index forecasting based on text mining of regulatory disclosures. Decis. Support Syst. 112 (2018), 88–97.

[24] R. P. Schumaker, Y. Zhang, C. Huang, and H. Chen. 2012. Evaluating sentiment in financial news articles. Decis. Support Syst. 53 (2012), 458–464.

[25] J. L. Wu, C. Su, L. Yu, and P. C. Chang. 2012. Stock Price Predication using Combinational Features from Sentimental Analysis of Stock News and Technical Analysis of Trading Information. In Economics Development and Research.

[26] N. Pröllochs, S. Feuerriegel, and D. Neumann. 2016. Negation scope detection in sentiment analysis: Decision support for news-driven trading. Decis. Support Syst. 88 (2016), 67–75.

[27] B. Li, K. Chan, C. X. Ou, and R. Sun. 2017. Discovering public sentiment in social media for predicting stock movement of publicly listed companies. Inf. Syst. 69 (2017), 81–92.

[28] L. Shi, Z. Teng, L. Wang, Y. Zhang, and Alexander Binder. 2019. DeepClue: Visual Interpretation of Text-Based Deep Stock Prediction. IEEE Transactions on Knowledge and Data Engineering 31 (2019), 1094–1108.

[29] Y. Peng and H. Jiang. 2016. Leverage Financial News to Predict Stock Price Movements Using Word Embeddings and Deep Neural Networks. ArXiv abs/1506.07220 (2016).

[30] Y. Deng, F. Bao, Y. Kong, Z. Ren, and Q. Dai. 2017. Deep Direct Reinforcement Learning for Financial Signal Representation and Trading. IEEE Transactions on Neural Networks and Learning Systems 28 (2017), 653–664.

[31] S. Hochreiter and J. Schmidhuber. 1997. Long Short-Term Memory. Neural Computation 9 (1997), 1735–1780.

[32] S. Minami. 2018. Predicting Equity Price with Corporate Action Events Using LSTM-RNN. Journal of Mathematical Finance 08 (2018), 58–63.

[33] R. Akita, A. Yoshihara, T. Matsubara, and K. Uehara. 2016. Deep learning for stock prediction using numerical and textual information. 2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS) (2016), 1–6.

[34] D. Nelson, A. M. Pereira, and R. A. de Oliveira. 2017. Stock market's price movement prediction with LSTM neural networks. 2017 International Joint Conference on Neural Networks (IJCNN) (2017), 1419–1426.

[35] S. Liu, C. Zhang, and J. Ma. 2017. CNN-LSTM Neural Network Model for Quantitative Strategy Analysis in Stock Markets. In ICONIP.

[36] T. Fischer and C. Krauß. 2018. Deep learning with long short-term memory networks for financial market predictions. Eur. J. Oper. Res. 270 (2018), 654–669.

[37] Nan Jing, Zhao Wu, Hefei Wang, A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction, Expert Systems with Applications, Volume 178, 2021, 115019, ISSN 0957-4174.

[38] Mohammad Obaidur Rahman, Md. Sabir Hossain*, Ta-Seen Junaid, Md. Shafiul Alam Forhad, Muhammad Kamal Hossen, "Predicting Prices of Stock Market using Gated Recurrent Units (GRUs) Neural Networks"., IJCSNS International Journal of Computer Science and Network Security, VOL.19 No.1,2019