*Journal of Information & Optimization Sciences*
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 44 (2023), No. 3, pp. 529–539
DOI : 10.47974/JIOS-1412

# An approach for predicting the price of a stock using deep neural network

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**Abstract**

For the prediction of any stock price and its fluctuations in prices, researchers have suggested several versions of machine learning techniques. Machine learning-based techniques fail to achieve good prediction and in turn, their accuracy is not adequate to predict the stock price. For sentiment analysis related to the financial domain BERT model is quite useful. The score generated by BERT is useful to get more insight. Few research works which have incorporated financial news, have not used financial corpus for training and testing. FinBERT is quite useful to solve stock pricing fluctuations as it is specially trained on corpus related to the financial domain. The stock market usually gets fluctuated during any impactful news either positive or negative sentiments. In this work, highly fluctuating stock price movement is predicted efficiently which is validated by experiment analysis. Further, in existing research works, stock prices are predicted for a specific company only. In this paper, A hybrid method to predict fluctuations in stock prices has been suggested using FinBERT and Long Short-term Memory (LSTM) along with news that impacted the

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market. The proposed method using news score and hybrid approach outperforms existing approaches significantly.

***Subject Classification:*** *68T07.*

***Keywords:*** *Deep learning, Price prediction, Machine learning, Data analytics, FinBERT, LSTM.*

## 1. Introduction

Financial Technology (FinTech) based solutions have tried to improve analytics for better decision-making. For example, Machine learning has improved analytics by FinTech significantly [1]. Recurrence and multiple regression are not possible in the architecture of machine learning. There is a need for deep neural networks which can perform analytics on complex non-linear data. In this research work, BERT and LSTM hybrid model is employed for analyzing time-series data with very high variations. In our approach, it is validated that if advanced models are applied with efficient hyper-parameter tuning, then even high variations can be analyzed effectively.

The prediction of stock prices was assumed impossible in earlier research works [2]. However, due to advancements in computing, stock prices can be predicted with adequate accuracy now [2, 3]. In the current era of advanced computing, stock price prediction is considered a hybrid of computer science and finance [4] Stock prices fluctuate when company information is out [5] [6]. External news which is unstructured needs to be analyzed to predict stock price [7, 8]. Social media, reviews, and news have a significant effect on stock price variations [9] Stock prices are predicted based on time series of stock price technical indicators and textual data requires an efficient solution [10]. Further, sentiments in news feed also affect stock price [11, 12]. Several NLP techniques on textual news are used for financial forecasting [14-16]

It is concluded in several research works that deep learning approaches provide better prediction as compared to traditional machine learning approaches [13] It is because the traditional technique is not able to learn dependencies due to its shallow architecture [14]. Researchers have proposed deep neural networks to learn long-term dependencies to provide adequate accuracy. In the stock market, large-scale transaction data is generated every day which can be used in deep learning models for better prediction [10].

The rest of the paper is structured as follows. In Section 2, related work on stock price prediction using technical indicators and financial news is surveyed. The proposed approach is elaborated on in Section 3. Section 4 covers the experiments with a discussion of the results. Finally, Section 5 concludes the paper with future directions.

## 2. Related Work

Several research works have focused on predicting stock prices using technical indicators only. It is non-trivial to predict stock prices using historical data only [15]. Existing research works have predicted stock prices using either numerical or textual information only [16]. Company and stock information is not limited to numerical data only [17]. Stock price prediction based on historical prices is not efficient due to certain events which change stock prices [18]. In [19], authors have stated that news and technical indicators are important factors that affect stock price variations. The hybrid model is composed of CNN and LSTM as SI-RCNN and LSTM as I-RNN are proposed by the authors. Experiment analysis has proved that the proposed model provides reasonable profit as compared to other strategies. In [20], the stock price is predicted using twin fuzzy logic using SVM. It is observed by authors that high/low variations are not classified accurately by traditional approaches. The accuracy of the proposed approach is compared with traditional SVM and fuzzy SVM approaches. Emotional, topic and embedding factors are used in this paper. It is also estimated that the proposed approach using emotional, topic, and embedding factors is better than using these features individually. In [15], it is stated that historical data is not sufficient to predict stock prices. Large-scale price and news data are collected for S&P 500 companies and applied to ARIMA and RNN. Furthermore, the RNN-LSTM model is used for different strategies such as price only, price, and text polarity. Stock market predictions are applied based on the relationship between companies [21]. It is stated in this paper that previous studies have focused on news articles from an individual companies. Korean market dataset is used and F1 and accuracy are used as evaluation metrics. In [22], the significance of news in stock price prediction is stated. Feature extraction, selection, and representation are described in detail. Authors have used SVM for classification and a 2-gram approach is used for feature extraction. It is also stated in the paper that the 2-gram approach is better than the 3-gram approach, therefore the 2-gram approach is used. In [23], textual news data is used to predict the class of future news articles. It is

observed in this paper that previous studies have focused on numerical data. There is a need to analyze text data efficiently. Naïve Bayes classifier is used to train news articles Summarization at the sentence level is applied to financial news articles in [24]. Authors have stated that a lot of mixed information is present in the complete news article text. There is a need to summarize the relevant text from news articles. Further, SVM is used for text classification. It is concluded that the proposed approach SPSR outperforms existing approaches and SPSR using WordNet performs the best as compared to other approaches.

It is observed from a comprehensive literature survey that traditional approaches are used for sentiment analysis of news articles. Even though neural networks are employed in some techniques, but these neural networks are unidirectional. We have overcome this limitation by using BERT which uses a bidirectional technique for sentiment analysis and provides improved results.

In this research work, news about various indices is scraped from the web, and sentiments about the index are computed which is merged with technical indicators to predict stock price.

**Proposed Approach**

Existing research works have employed Bag-of-words [25] [21] and n-grams [22] approaches. The limitation of existing techniques is that complex computations for sentiment analysis are not performed effectively. Our proposed architecture is composed of 2 input layers. The first layer is textual news about a particular company and the second layer is numerical technical indicators. In our proposed model, the time window of 60 days and the close price are used as technical indicators. Training of the model is based on a close price that indicates fluctuations due to the previous 60 days' price. Experiment analysis validates that a time window of 60 days is suitable for training the model efficiently. Furthermore, our proposed model is robust as the polarity of textual news from BERT is combined to predict stock price. NLP techniques such as stemming, lemmatization, POS tagging, and tokenization are applied to textual news using the NLTK library to preprocess the text of news.

It is also observed that news affects stock prices in 1-5 days. It is not necessary that stock prices fluctuate on the same day when news is out in the press. It takes some time for the stock market to analyze and react to the news.

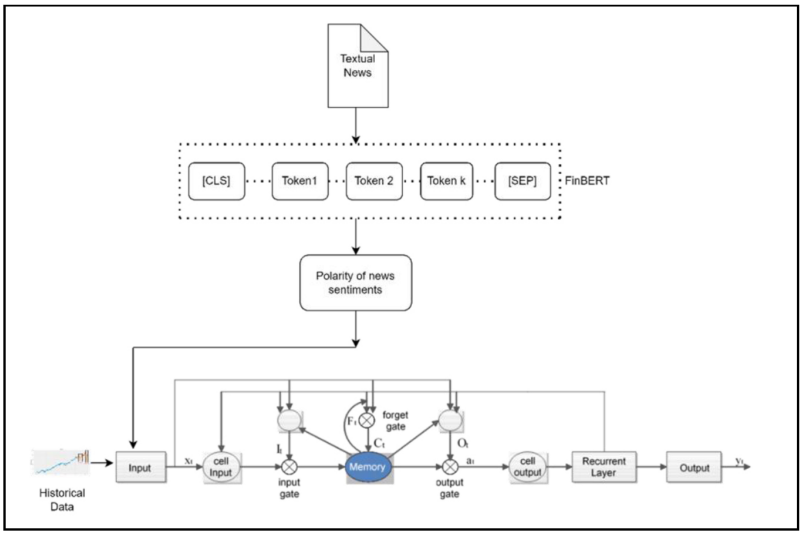


**Figure 1**

**Proposed model using the hybrid approach**

In our proposed work, textual news is fed into the BERT model for sentiment analysis.

In Figure1, our proposed model is depicted which is based on FinBERT and LSTM models. Textual news is fed into the FinBERT model to extract the polarity of news sentiments. This polarity and historical data are fed into the LSTM model to predict stock prices. LSTM model is trained on polarity as well as numerical historical data which is quite better as compared to training based on numerical data only.

In our proposed model, LSTM is used as it is the most suitable model for time-series analysis. In existing research works, RNN was used, but the limitation of RNN is that gradient descent issue exists and long-term dependencies are not effective in RNN. In LSTM, the time window of 60 days is used in the model.

## 2.1 *BERT*

Bidirectional Encoder Representations from Transformers (BERT) is introduced by Google to develop models such as language inference, sentiment analysis, etc. Transformers are employed to analyze sentiments using an encoder for input and a decoder for output. BERT has gained unprecedented attention in recent days [1].

The phases of BERT are as follows.

(i) Pre-training: In this phase, context learning is achieved using unsupervised learning. In the Mask language model (MLM), the mask of words is assigned is also used for left and right training of sentences.

(ii) Fine-tuning: In this phase, various NLP tasks can be solved using supervised learning. The parameters are fine-tuned during this phase. [CLS] is used for every sentence and [SEP] is used to separate different sentences.

### 2.2 *LSTM*

The LSTM model is used for long-term dependencies and time-series analysis. It overcomes the limitation of the Recurrent Neural Network (RNN). Input, Forget and Output Gate are the main components of LSTM.

## 3. Experiment Analysis

In this section, sentiment analysis of financial news is analyzed using BERT. The combined sentiments and numerical prices are trained using LSTM which results in better prediction. In the next subsections, the experiment setup, dataset, and discussion of results are presented.

$$MAPE = \frac{1}{n}\sum_{i=0}^{n}\left|\frac{y_{acti} - y_{predictedi}}{y_{acti}}\right| * 100 \tag{1}$$

MAPE score is calculated as a difference between whatever value we get during prediction and the original value as mentioned.

### 3.1 *Experiment setup*

NLTK library is used for preprocessing such as stop words removal, stemming, lemmatization, POS tagging, etc. Keras 2.3.0, Pandas 1.2.3, and Numpy 1.20.1 libraries are used for our neural network architecture. This preprocessed text is fed into BERT for sentiment analysis. This merged data frame is sent as input into LSTM. Training and testing in LSTM are done based on a time window of 60 days. Earlier, training was based on numerical prices in traditional implementations. In our proposed approach, sentiment score is applied in synchronization with numerical prices to enhance prediction. The duration from the Year 2012-2020 is used for training purposes and the Year 2020-2021 is used for testing purposes.

The reason for selecting stock prices from the 2020-2021 year for testing is very high fluctuations in stock prices were observed during this duration.

BERT base model is used for experiment analysis which contains 12 encoder layers, 12 bi-directional self-attention heads, and 768 hidden units. In LSTM, 60 units are used in the first layer with a dropout of 0.2, in the next layer, 80 units are used with the same dropout. In the next layers, 80 and 120 units are used with the same dropout.

### 3.2 *Dataset*

The news articles are scraped using Finviz API and merged with numerical prices. Yahoo finance API is used for extracting numerical prices. The numerical prices are extracted from the years 2012 to 2021.

### 3.3 *Results& Discussion*

Stock prices are predicted for various stock indexes and results are presented in this subsection. In Figure 2-3, the results of prediction for NSE, and BSE are depicted. It is clearly shown during testing that even high variations are predicted with adequate accuracy.


**Figure 2**

**Prediction of NSE stock index**

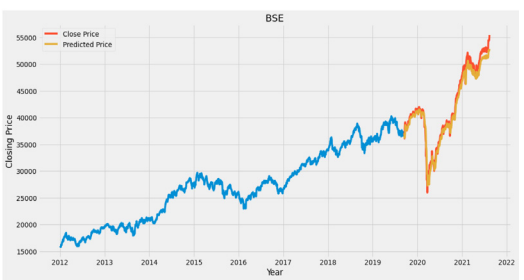


**Figure 3**

**Prediction of BSE stock index**

The MAPE score of the proposed schemes is presented in table 1 and it is compared with existing approaches. SVR is used for stock price prediction in Extreme Learning Machine (ELM) is used in LSTM. The results shown in table2 validate the better performance of our proposed approach. Several other approaches are available in literature for stock price related issues [26-30].

**Table 1**

**MAPE scores of existing approaches and proposed model**

| Stocks | Proposed model | SVR (Meesad & Rasel, 2013) | ELM (Mohanty, Parida, 2020) | (Mehtab & Sen, 2019) |
|---|---|---|---|---|
| NSE | 1.85 | 3.22 | 3.85 | 4.25 |
| BSE | 2.12 | 4.11 | 4.99 | 5.20 |

**Table 2**

**MAPE scores using different LSTM units and epochs**

| Stock Index | LSTM units | Epochs | MAPE |
|---|---|---|---|
| NSE | 100 | 300 | 1.98 |
| NSE | 120 | 350 | 1.89 |
| NSE | 140 | 400 | 1.85 |
| BSE | 100 | 300 | 2.55 |
| BSE | 120 | 350 | 2.30 |
| BSE | 140 | 400 | 2.12 |

## 4. Conclusion and Future Directions

Traditional approaches used only shallow architectures which do not provide adequate accuracy. In our approach, the recently introduced BERT and LSTM hybrid model is employed to predict stock prices. Our proposed hybrid model has predicted stock prices with very high variation which was experienced in lockdown. We have used FinBERT to enhance the accuracy as it is trained on a financial corpus that can understand the sentiments hidden in financial and technical terms. MAPE score is improved as compared to recent approaches. In future, training will be done on a more financial corpus to train and test the model more effectively.

**References**

[1] E. K. W. Leow, B. P. Nguyen and M. C. H. Chua, "Robo-advisor using genetic algorithm and BERT sentiments from tweets for hybrid portfolio optimization," *Expert Systems with Applications,* 179, p. 115060 (2021).

[2] M. Khashei and M. Bijari, "A novel hybridization of artificial neural networks and ARIMA models for time series forecasting," *Applied Soft Computing,* vol. 11, no. 2, pp. 2664-2675 (2011).

[3] E. Hoseinzade and S. Haratizadeh, "CNNpred: CNN-based stock market prediction using a diverse set of variables," *Expert Systems with Applications,* vol. 129, pp. 273-285 (2019).

[4] H. Rezaei, H. Faaljou and G. Mansourfar, "Stock price prediction using deep learning and frequency decomposition," *Expert Systems with Applications,* vol. 169, p. 114332 (2021).

[5] O. Boguth, M. Carlson, A. Fisher and M. Simutin, "Horizon effects in average returns: The role of slow information diffusion," *The Review of Financial Studies,* vol. 29, no. 8, pp. 2241-2281 (2016).

[6] N. Seong and K. Nam, " Predicting stock movements based on financial news with segmentation," *Expert Systems with Applications,* vol. 164, p. 113988 (2021).

[7] X. Li, X. Huang, X. Deng and S. Zhu, "Enhancing quantitative intra-day stock return prediction by integrating both market news and stock prices information," *Neurocomputing,* vol. 142, pp. 228-238 (2014).

[8] O. Bustos and A. Pomares-Quimbaya, "Stock market movement forecast: A Systematic review," *Expert Systems with Applications,* vol. 156, p. 113464 (2020).

[9] A. Thakkar and K. Chaudhari, " Fusion in stock market prediction: A decade survey on the necessity, recent developments, and potential future directions," *Information Fusion,* vol. 65, pp. 95-107 (2021).

[10] X. Li, P. Wu and W. Wang, "Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong," *Information Processing & Management,* vol. 57, no. 5, p. 102212, 2020.

[11] S. Bharathi and A. Geetha, "Sentiment analysis for effective stock market prediction," *International Journal of Intelligent Engineering and Systems,* vol. 10, no. 3, pp. 146-154 (2017).

[12] M. Lasek and J. Lasek, "Are stock markets driven more by sentiments than efficiency?," *Journal of Engineering, Project, and Production Management, 6* (2015).

[13] N. Jing, Z. Wu and H. Wang, "A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction," *Expert Systems with Applications,* vol. 178, p. 115019 (2021).

[14] X. Pang, Y. Zhou, P. Wang, W. Lin and V. Chang, "An innovative neural network approach for stock market prediction," *The Journal of Supercomputing,* vol. 76, no. 3, pp. 2098-2118 (2020).

[15] S. Mohan, S. Mullapudi, S. Sammeta, P. Vijayvergia and D. Anastasiu, "Stock price prediction using news sentiment analysis," in *2019 IEEE Fifth International Conference on Big Data Computing Service and Applications (BigDataService),* pp. 205-208 (2019).

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

[17] X. Li, H. Xie, R. Y. Lau, T. L. Wong and F. L. Wang, "Stock prediction via sentimental transfer learning," *IEEE Access,* vol. 6, pp. 73110-73118 (2018).

[18] D. L. Minh, A. Sadeghi-Niaraki, H. Huy, K. Min and H. Moon, "Deep learning approach for short-term stock trends prediction based on two-stream gated recurrent unit network," *IEEE Access,* vol. 6, pp. 55392-55404 (2018).

[19] M. Vargas, C. dos Anjos, G. Bichara and A. Evsukoff, "Deep leaming for stock market prediction using technical indicators and financial news articles," in *In 2018 International Joint Conference on Neural Networks (IJCNN),* pp. 1-8, IEEE (2018).

[20] P. Hao, C. Kung, C. Chang and J. Ou, "Predicting stock price trends based on financial news articles and using a novel twin support vector machine with fuzzy hyperplane," *Applied Soft Computing,* vol. 98, p. p.106806 (2021).

[21] K. Nam and N. Seong, "Financial news-based stock movement prediction using causality analysis of influence in the Korean stock market," *Decision Support Systems,* vol. 117, pp. pp.100-112 (2019).

[22] M. Hagenau, M. Liebmann and D. Neumann, "Automated news reading: Stock price prediction based on financial news using

context-capturing features," *Decision Support Systems,* vol. 55, no. 3, pp. 685-697 (2013).

[23] G. Gidofalvi and C. Elkan, "Using news articles to predict stock price movements," *Department of Computer Science and Engineering, University of California, San Diego.* (2001).

[24] X. Li, H. Xie, Y. Song, S. Zhu, Q. Li and F. L. Wang, "Does summarization help stock prediction? A news impact analysis," *IEEE intelligent systems,* vol. 30, no. 3, pp. 26-34 (2015).

[25] E. J. De Fortuny, T. De Smedt, D. Martens and W. Daelemans, "Evaluating and understanding text-based stock price prediction models," *Information Processing & Management,* vol. 50, no. 2, pp. 426-441 (2014).

[26] S. Farzana, Gayathri Harikumar, S. Shankaranarayanan & N. Vikram, "Study on the impact of service quality on the customer satisfaction due to e-banking services of public sectors banks in Chennai," *Journal of Statistics and Management Systems*, vol.25, no. 5, pp. 1205-1213, (2022).

[27] Ben Ebo Attom & Afzalur Rahman, "Empirical study of the relationship between working capital policies and firm financial performance (Profitability and market value)-Evidence from the manufacturing firms listed on the Ghana stock exchange (GSE)," *Journal of Statistics and Management Systems*, vol. 25, no. 4, pp.983-1000 (2022).

[28] Kuan-Min Wang, "The contagion effect of COVID-19 on stock markets," *Journal of Statistics and Management Systems,* vol. 25, no. 6, pp. 1379-1398 (2022).

[29] Talha Akbar Kamal, Shagufta Naaz, Rajeev Singh Bhandari, Hitendra Shukl & Rehan Khan, "Impact of trade openness and inflation on FDI in India: ARDL Approach," *Journal of Statistics and Management Systems*, vol. 25, no. 5, pp. 1103-1113 (2022).

[30] H. Bhardwaj, M.M. Jamal, "Effect of using Internet of Things for personalized advertisements on consumer buying behaviour," *Journal of Statistics and Management Systems,* vol. 25, no. 2, pp.1135-1146 (2022).