International Journal of Recent Innovations in Academic Research
E-ISSN: 2635-3040; P-ISSN: 2659-1561
Homepage: https://www.ijriar.com/
Volume-5, Issue-12, December-2021: 88-99

Research Article

Big Data-Driven Predictive Analytics in the Financial Sector: A Stock Market Forecasting Approach

[*a]Niharika Katnapally, [b]Purna Chandra Rao Chinta, [c]Kishan Kumar Routhu, [d]Vasu Velaga, [e]Varun Bodepudi and [f]Laxmana Murthy Karaka

[a]Amazon AWS, BI Developer, [b]Microsoft, Support Escalation Engineer, [c]AT & T, Sr Openstack Administrator, [d]Cintas Corporation, SAP Functional Analyst, [e]Applab Systems Inc, Computer Programmer, [f]Microsoft, Senior Support Engineer
[*]Corresponding Author Email: niha791@gmail.com

Received: December 11, 2021 **Accepted:** December 23, 2021 **Published:** December 31, 2021

Abstract
Stock investing is a rigorous monetary technique that relies on demand. As a result, the study of stock projections, or more specifically, the predicting of stock prices, is critical to the stock market. Mistakes in projecting share prices have a huge influence on global finance, necessitating an effective way of anticipating share price movements. ML is one method that may be used to forecast stock values. This research examines how ML and DL models, especially Long Short-Term Memory (LSTM), ARIMA, and Linear Regression (LiR), forecast Google stock prices employing historical data from 2013 to 2018. The effectiveness of the model was measured using the metrics of determination coefficient R^2, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Evaluation of the models reveals that the LSTM model is of high accuracy with a high R-squared of 94.21 percent but observes high errors (RMSE 17.79 and MAE 13.13 relative to traditional models. Nevertheless, the results from ARIMA and LiR models are more accurate with lower RMSE and MAE than the other models. Future work will include the processes of refining the proposed LSTM model for fewer mistakes and better performance for stock price prediction as well as experiment with the proposed hybrid model implementation of LSTM with ARIMA or other models for even more accurate results.
Keywords: Component, Big Data, Financial Sector, Stock Market Forecasting, Predictive Analytics, Machine Learning, Market Trends, Google Stock Price Data.

I. Introduction

There has been an exponential growth of big data across industries globally, creating new opportunities to solve multifaceted problems with data driven solutions. Big data, which is characterised by volume, velocity and variety, refers to information collected by social media, financial transactions and IoT devices, among others [1]. The ever-growing pool of information has significantly disrupted conventional decision-making steps and made it possible for firms to sort out useful knowledge and even detect hidden trends [2].

Big data has become a force in the financial sector; it concerns data driven strategies in aspects such as operational management, risk management and market predictions. The financial sector on its own is very fluid and volatile with markets producing large volumes of data on daily basis. In particular, stock market differs from other financial markets due to its paramount impact on national and worldwide economies. Stock markets are important indicators of economic performance and principally offer a process of wealth generation and management [3]. The stock market forecast has great economic significance as it provides investors, brokers and policymakers with useful information [4]. The problem, though, is that trends in the stock price are not always linear and fluctuate depending on many factors, such as macroeconomic releases, sentiment, and global events [5].

Essentials about stock market predictions may now be effectively solved through predictive analytics [6]. The exact mathematical modelling that transforms current and historical data into future trends is a definition of predictive analytics [7]. Predictive analytics has been utterly transformed in the last few years by the employ of AI and ML. The AI and ML methods can be flexible with the newly learnt data, can work on large and complex data and find hidden patterns [8, 9]. When it comes to predicting the stock market, the overall performance of the ML methods, especially DL, has been rather outstanding.

A. Significance and Contribution

This work is inspired by the desire to enhance the accuracy in the prediction of stock prices, specifically Google, to enhance accurate future eruption since the existing mechanisms in the financial market do not excel, particularly during the period of market fluctuation. In this case, through the use of the most current and innovative machine learning technologies, the goal is bettering the reliability of forecasting as well as delivering improved and stronger tools to investors and traders. The emphasis is placed on reliable data preprocessing and accurate criteria for assessment to promote the use of the models. This work adds to the existing literature by conducting a thorough analysis of several ML and DL models for predicting stock prices employing the Google Stock dataset.

The main contributions are:

- ✓ Develop effective ML and DL models for stock market forecasting by Google stock dataset.
- ✓ Implementing robust data cleaning techniques, including handling null values, removing duplicates, and normalising data to enhance model performance.
- ✓ Demonstrating the effectiveness of machine learning models like LSTM, ARIMA, and linear regression for stock price prediction.
- ✓ Using multiple performance metrics (MAE, RMSE, and R^2) to assess model accuracy and fit, providing a clear benchmark for stock prediction models.

B. Structure of the Paper

The study is structured as follows: Section II presents relevant work on predictive stock forecasting. Section III details the procedures and materials used. Section IV presents the experimental findings of the proposed system. The inquiry is summarised and concluded in section V.

II. Literature Review

This section discusses the surveys and reviews articles on predictive analytics in the financial sector. This study, Yang and Chen [10] used the financial stock of Taiwan as an illustration. January through September 2017 was the time frame used for the simulation. Both CNYES.com and Money DJ are examples of external information providers. The first step was to determine an initial weighted ratio of 8:2 for the internal and external data. Then, from October to December 2017, modifications were made using rolling learning to anticipate the monthly volatility. The empirical data reveal that conventional forecasting has a 62.25% accuracy rate when it comes to anticipating the real pattern of fluctuations. The data reference for the examination of the technical and basic aspects is the internal information. Following the integration of chip facet analysis and subsequent examination of all three aspects, the weighted forecasting-derived accuracy of individual stock swings is 73.55%. As a whole, weighted forecasting may be used to determine monthly stock movements, improve the accuracy of such predictions, and provide a point of reference for professionals and investors [10].

This study, Beyaz, et al. [11] assesses how ML stock price forecasts are affected by explicitly recognising and accounting for stock market states. Market mood indicators, such as the VIX, are clustered to define different stock market states, and prediction models are created for the chosen businesses for each market condition. Results from experiments using 85 S & P 500 companies over a 126-day forecasting horizon show that taking market sentiment into account improves prediction accuracy (lower RMSE) in 47% of cases [11].

This study, Singh and Srivastava [12] that an employ of DL may enhance the precision of stock market predictions. In this regard, the advance technique 2D-2PCA + RBFNN is contrasted with the (2D) 2PCA + DNN approach. The suggested technique outperforms the modern RBFNN method with a 4.8% improvement in accuracy for Hit Rate at a 20-window size. A comparison of the suggested model's performance with that of the RNN reveals a 15.6% improvement in Hit Rate accuracy. In comparison to RBFNN and RNN, DNN has a 17.1% higher correlation coefficient among actual and anticipated return, and it outperforms RNN by 43.4% [12].

This study, Vargas, et al. [13] give priority to designs like RNNs and CNNs, which have proven effective in more conventional NLP applications. Results show that RNN is great at understanding context and making accurate predictions about the stock market based on complex temporal features, whereas CNN could be better at extracting meaning from texts [13].

This study Dingli and Fournier [14] use of CNNs for the purpose of predicting the direction of prices relative to the existing price in the short term. Predicting the direction of prices one month from now has a 65% accuracy rate, while predicting prices one week from now yields a 60% accuracy rate. Though these outcomes are definitely not arbitrary, they still can't compete with or even beat the outcomes produced by market-leading methods like SVM and LR [14].

This study, Usmani et al. [15], the prediction model takes several variables into account while making market predictions, which may be either positive or negative. The model incorporates the following attributes: oil, gold, silver, interest, foreign exchange (FEX), news and social media feeds. SMA and ARIMA, two of the more traditional methods of statistical analysis, are also used. The following ML methods are contrasted: SVM, RBF, SLP, and MLP. Separate studies are also conducted on all of these characteristics. When tested against competing methods, the MLP algorithm proved to be the most effective [15].

Table 1 provides a comparative analysis of different previous reviews on stock price prediction based on the datasets, findings, limitations, and future work.

Table 1. Overview of studies on predictive analytics for stock market prediction using machine learning methods.

Paper	Methods	Dataset	Key findings	Limitations/future work
Yang and Chen [10]	Weighted forecasting using internal and external information, rolling learning	Taiwan's financial stock data (Jan-Sep 2017) from CNYES.com and MoneyDJ	Improved accuracy of stock fluctuation prediction from 62.25% (traditional methods) to 73.55% with weighted forecasting	Limited to Taiwan's financial market, future work could explore the model's scalability to other markets or industries
Beyaz, et al. [11]	Clustering methods for market mood indicators (e.g., VIX), forecasting models for	85 companies from the S&P 500	Accounting for market mood indicators improves forecasting accuracy (lower RMSE) in 47% of cases for a 126-day forecasting horizon	Limited improvement percentage, future work could focus on refining market mood indicators or incorporating other financial variables

	each market state using machine learning			
Singh and Srivastava et al. [12]	(2D)2PCA + DNN, compared with RBFNN and Recurrent Neural Network (RNN)	Stock data	DNN improves hit rate accuracy by 4.8% over RBFNN and 15.6% over RNN, correlation coefficient improved by 17.1% over RBFNN and 43.4% over RNN	Limited dataset details, future work could expand on datasets, improve scalability, and apply methods to other stock markets
Vargas, et al. [13]	CNN, RNN	Finance data	CNN performs better at capturing semantics, while RNN excels at modelling complex temporal characteristics for stock market forecasting	Dataset not specified, future work could involve hybrid models combining CNN and RNN for better performance
Dingli and Fournier [14]	CNN, comparison with LR and SVM	Stock market data	Achieved 65% accuracy for next-month price direction forecasting and 60% for next-week price direction forecasting	Performance lower than industry-leading techniques; future work could enhance CNN architectures or combine with other methods for better results
Usmani et al. [15]	SLP, MLP, RBF, SVM, ARIMA, SMA	Market attributes (oil, gold, silver rates, interest rate, FEX rate, NEWS, social media feed)	MLP outperformed other methods in predicting positive and negative market trends	Limited attribute inclusion, future work could incorporate additional attributes, such as geopolitical events or macroeconomic indicators, to improve model robustness

III. Methodology

The methodology for this study involves several key steps to develop and evaluate models for predicting Google stock prices. Initially, the Google Stock Prediction dataset, sourced from Kaggle and covering the period from 2013 to 2018, is preprocessed by handling null values and duplicates and normalising the data within the range of [0, 1] using a Min-Max normalisation formula. The dataset is divided into two parts: the training set uses 80% of the data, while the testing set uses 20%.

The training set contains characteristics like date, open price, high price, low price, closing price, adjusted closing price, and trade volume. The models considered include LSTM, ARIMA, and LiR. Three metrics are utilised to measure the effectiveness of a model: MAE, RMSE and the R^2. A lower R^2 number indicates a better fit to the data, while lower MAE and RMSE values indicate higher predicted accuracy.

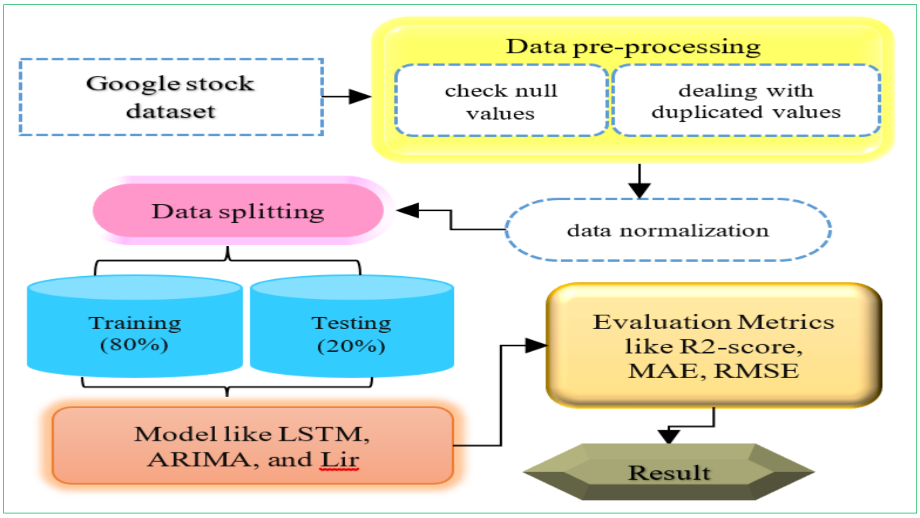

Figure 1. Flowchart for stock market forecasting.

The following steps of the flowchart are briefly explained below:

A. Dataset Description and Visualization

Datasets from Google Stock Prediction were used in the research. Information used was sourced from Kaggle ML. The Google dataset spans the years 2013 to 2018. The combined dataset contains 10,272 occurrences (rows), with 6,000 of them being Google stock projections. The date field, range of prices, adjusted closing price, trading volume, and high and low prices are all attributes of a dataset. The Google stock daily returns percentage is shown in Figure 2.

Figure 2. Google stock daily returns percentage.

Figure 2 demonstrates that the majority of the daily return percentages fall within the range of-0.05 to 0.05, with the top and bottom returns not exceeding 0.2. The accuracy of price predictions will, therefore, be enhanced, as the price movement the next day will be quite minor.

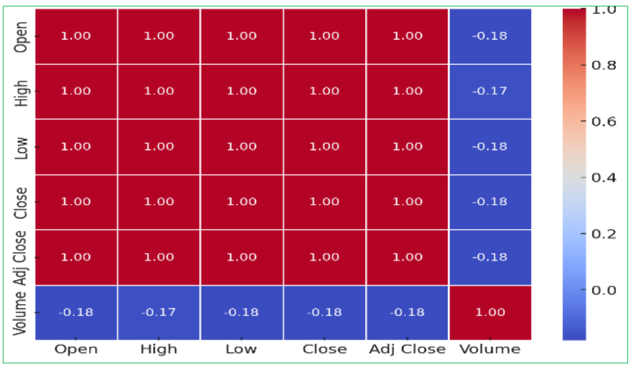

Figure 3. Data correlations for the prediction model.

Figure 3's data correlation diagram allows us to see which characteristics significantly impact stock price prediction by looking at the data on the right side. Influence grows as the value rises closer to 1. Importantly, a feature's relevance in forecasting stock prices is diminished with lower correlation values.

B. Data Preprocessing

The analysis of data is an essential stage in the construction of trustworthy forecasting models, particularly when comparing them [16]. In addition to improving the model's correctness, structure, and performance, it also makes sure the data are cleaned and presented correctly [17]. As mentioned before, this research used a robust dataset for training ML models that was created by collecting and processing data from different sources.

The following pre-processing steps are listed below:

- Check Null Values: A field with spaces or a zero value is not the same as a NULL value [18]. When a record is created, any field that does not have a value assigned to it is marked as NULL.
- Dealing With Duplicate Values: Duplicate data might be helpful in certain cases, but it can also make your data more difficult to analyse in others. Get rid of duplicate data by highlighting it using conditional formatting.

C. Normalization

The optimisation of the training model weights in subsequent phases may have been influenced by the significant variations found among the five parameters of each kind of stock [19]. The current research used a normalisation formula (Formula (1)) to bring the data down to a range of [0, 1] in order to remove these effects.

$$X_i^n = \frac{X_i - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

Where the value before processing the feature, value is represented by xi, the minimum of all the original characteristics is represented by xmin, and the maximum of all the original characteristics is represented by xmax. The mapping interval's maximum value is high, while its minimum value is low.

D. Data Splitting

The training and testing datasets were kept separate. The training set was used to train the models, while the test set was used to assess their performance. The data is split between training and testing, with 80% going into training and 20% into testing.

E. Classification with LSTM Model

The model makes use of a stateful LSTM neural network with four hidden layers; the characteristics listed above make up the input dataset for this layer [20]. Each hidden layer has h cells that are completely connected to the layers below it, both for input and output [21]. The projected price for a second minute after the current event is included in a single cell that makes up the output layer [22]. The model was built to be stateful so that it may take use of LSTMs' most important feature: the capacity to remember previous states. This is because, in stock price prediction, prior prices are vital for predicting future prices [23].

At time t, xt is an input data of an LSTM cell, the preceding moment's output of the LSTM cell is represented by $ht{-}1$, a value of a memory cell is represented by ct, and the LSTM cell's output is represented by ht. There are several steps to the LSTM unit's computation process. Figure 4 shows the summary of LSTM.

First, determine the value of the potential memory cell $\tilde{c}t$; Wc stands for a weight_matrix, and a bias is represented by bc.

$$\tilde{c}t = tanh(W_c[h_{t-1}, x_t] + b_c) \quad (2)$$

Find out what the input gate's value is it; the input gate regulates the updating of the present input data to the memory cell's state value, σ represents the sigmoid function, Wi is the matrix of weights, and bi is a bias.

$$i_t = \sigma(W_t[h_{t-1}, x_t] + b_i \quad (3)$$

Determine a forget gate's value ft; the forget gate regulates the updating of the memory cell's state value with past data, Wf describes the weight_matrix, and bf is a bias.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f \quad (4)$$

Determine a value of a moment memory cell ct; at this instant, a state value of a final LSTM unit is ct−1.

$$c_t = f_t * [c_{t-1} + i_t] * \tilde{c}t \quad (5)$$

Where ∗represents the dot product [24]. The candidate's cell and the last cell's state value determine the memory cell's update, which is managed by the input gate and the forget gate.

Calculate a value of an output gate ot; the output of the memory cell's state value is controlled by the output gate, Wo is a weight_matrix, and bo is a bias.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o \quad (6)$$

$$h_t = o_t * tanhc_t \quad (7)$$

Finally, determine the LSTM unit's output (ht).

Model: "sequential_9"

Layer (type)	Output Shape	Param #
lstm_4 (LSTM)	(None, 60, 50)	10400
lstm_5 (LSTM)	(None, 50)	20200
dense_10 (Dense)	(None, 25)	1275
dense_11 (Dense)	(None, 1)	26

Total params: 31,901
Trainable params: 31,901
Non-trainable params: 0

Figure 4. Summary of long short-term memory (LSTM).

Figure 4 outlines an architecture of an LSTM-based sequential DL model. A model has a total of 31,901 parameters, all of which are trainable, with no non-trainable or pre-trained parameters included.

F. Evaluation Metrics

MAE, RMSE, and R^2 were utilised to evaluate a model's performance. Relative accuracy between the actual and forecast values may be more accurately anticipated when the MAE and RMSE values decline [25]. As the coefficient of determination (R^2) gets closer to one, the model's fit should improve [23]. The formula for RMSE (8), MAE (9) and R^2 (10) is shown below.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (8)$$

If ŷi shows the forecasted value and yi shows the real value, and N stands for a total number of observations.

$$MAE = \frac{1}{N}\sum_{j=1}^{N}\left|x_j - \hat{x}_j\right| \quad (9)$$

Meaning that at time j, the real value is xj and the forecasted value is $\hat{x}\, j$.

$$R^2 = \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \overline{y_i})^2} \quad (10)$$

The average of the real values is represented by y¯.

IV. Result Analysis and Discussion

The suggested model is tested in an experimental setting using the Python programming language and the Jupyter Notebook plugin. Computer hardware requirements for running the LSTM include an Intel Core i7, 2.2 GHz CPU, "Microsoft Windows 10" operating system, and 16 GB of RAM. This experimental outcome demonstrates how well the LSTM algorithm performed on the Google stock dataset. A number of assessment measures are taken into account, including R^2-score, MAE, and RMSE. The outcomes of these assessment metrics are shown in Table 2. Then, LSTM model performance compare with ARIMA [26], and LiR [27] that present in Table 2.

Table 2. LSTM model performance for stock price forecasting on the Google stock dataset.

Performance matrix	Long short-term memory (LSTM)
R^2-score	94.21
RMSE	17.79
MAE	13.13

The results of the model's stock price forecast are displayed in Table 2. The model's ability to accurately describe the variation in stock prices is shown by its remarkable R^2-score of 94.21. However, the error metrics reveal some challenges, with an RMSE of 17.79 and an MAE of 13.13, suggesting that the LSTM model captures the underlying trends effectively. These results highlight the model's strong predictive capability, though finer tuning may be necessary to further reduce the error margin and enhance forecasting precision [28-35].

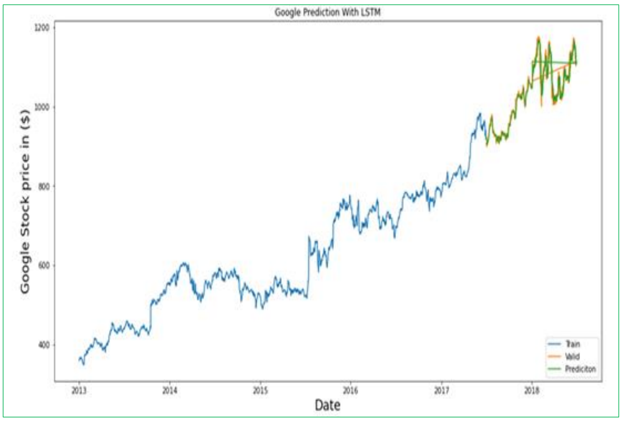

Figure 5. Stock forecasting with LSTM model.

Figure 5 shows the LSTM predictions for Google stock prices, showcasing the model's performance in forecasting trends over time. The graph plots the train data (historical prices used for training), validation data (used to evaluate model accuracy), and predicted prices generated by the LSTM model. The graphic shows that the LSTM model is successful for time-series forecasting, with stock prices in USD on the y-axis and a range of 2013–2018 on the x-axis. Predictions made by the model closely match the validation data [36-40].

Table 3. ML and DL models comparison on the Google stock dataset for stock price prediction.

LSTM	17.79	13.13
ARIMA	0.55	0.36
LiR	0.014	0.021

Table 3 is presented to compare the ML and DL-based models for the forecasting of Google stock prices with the help of the most commonly used error measures like RMSE and MAE. Here, they also find that the LSTM, a commonly used DL method in time-series forecasting, has relatively higher RMSE 17.79 and MAE 13.13 than other methods, suggesting less accurate predictions. The presented results show that the chosen ARIMA model works best for linear time-series data because it has the lowest RMSE of 0.55 and the MAE of 0.36. As for the majority of error values, the Linear Regression (LiR) model yields the lowest RMSE value of 0,014 and MAE of 0,021 while remaining fairly simple for this given dataset. In summary, though LSTM may accommodate detailed characteristics, the conventional model of ARIMA and LiR provide better forecast precision in comparison to LSTM for this kind of stock data set.

V. Conclusion and Future Work

Stock market forecasting is an entailing subject because of the large sums of money involved in the shares. ML techniques that may be used to stock market forecasting have garnered more attention because to the inherent complexity and volatility of the financial industry. This study takes a close look at the literature on stock market forecasting approaches that rely on machine learning. The research identifies the strengths and weaknesses of using LSTM in forecasting Google stock prices.

The R^2 score obtained by LSTM, 94.21, was sufficient to demonstrate that the model could find hidden patterns in stock prices. However, its performance was hindered by relatively high error metrics, with an RMSE of 17.79 and an MAE of 13.13, when compared to traditional models such as ARIMA and Linear Regression, which achieved significantly lower RMSE and MAE values (ARIMA: RMSE = 0.55, MAE = 0.36; LiR: RMSE = 0.014, MAE = 0.021).

One weakness of this study is that only Google stock has been used in this study for the periods 2013 to 2018 and therefore, the findings of this study may not be generalisable to other firms or other years. In future work to improve the LSTM models for predicting stock prices, more features are going to be added, hyperparameters are going to be tuned, and investigating hybrid models that combine deep learning with traditional ML techniques.

Declarations

Acknowledgments: We gratefully acknowledge all of the people who have contributed to this paper.
Author Contributions: All authors have contributed equally to the work.
Conflict of Interest: The authors declare no conflict of interest.
Consent to Publish: The authors agree to publish the paper in International Journal of Recent Innovations in Academic Research.
Data Availability Statement: The data presented in this study are available upon request from the corresponding author.
Funding: This research received no external funding.
Institutional Review Board Statement: Not applicable.
Informed Consent Statement: Not applicable.
Research Content: The research content of manuscript is original and has not been published elsewhere.

References

1. Parmar, I., Agarwal, N., Saxena, S., Arora, R., Gupta, S., Dhiman, H. and Chouhan, L. 2018. Stock market prediction using machine learning. In: 2018 first international conference on secure cyber computing and communication (ICSCCC) (pp. 574-576). IEEE.
2. Kumar, V.V., Liou, F.W., Balakrishnan, S.N. and Kumar, V. 2015. Economical impact of RFID implementation in remanufacturing: A chaos-based interactive artificial bee colony approach. Journal of Intelligent Manufacturing, 26: 815-830.
3. Kumar, I., Dogra, K., Utreja, C. and Yadav, P. 2018. A comparative study of supervised machine learning algorithms for stock market trend prediction. In: 2018 second international conference on inventive communication and computational technologies (ICICCT) (pp. 1003-1007). IEEE.
4. Sharaff, A. and Choudhary, M. 2018. Comparative analysis of various stock prediction techniques. In: 2018 2nd international conference on trends in electronics and informatics (ICOEI) (pp. 735-738). IEEE.
5. Kolluri, V. 2015. A comprehensive analysis on explainable and ethical machine: Demystifying advances in artificial intelligence. TIJER-International Research Journal, 2(7): a1-a5.
6. Kumar, V., Mishra, N., Vishwa, V.K., Felix, T.C. and Gnanasekar, B. 2010. Warranty failure analysis in service supply chain: A multi-agent framework. In: 2010 8th international conference on supply chain management and information (pp. 1-6). IEEE.
7. Selvin, S., Vinayakumar, R., Gopalakrishnan, E.A., Menon, V.K. and Soman, K.P. 2017. Stock price prediction using LSTM, RNN and CNN-sliding window model. In: 2017 international conference on advances in computing, communications and informatics (ICACCI) (pp. 1643-1647). IEEE.
8. Nelson, D.M., Pereira, A.C. and De Oliveira, R.A. 2017. Stock market's price movement prediction with LSTM neural networks. In: 2017 international joint conference on neural networks (IJCNN) (pp. 1419-1426). IEEE.
9. Tarafdar, R. and Han, Y. 2018. Finding majority for integer elements. Journal of Computing Sciences in Colleges, 33(5): 187-191.
10. Yang, S.J. and Chen, C.H. 2018. Using big data technology to analyze the fluctuation trends in stock price–as a practice of Taiwan financial stock market. In: 2018 IEEE/ACIS 17th international conference on computer and information science (ICIS) (pp. 549-555). IEEE.
11. Beyaz, E., Tekiner, F., Zeng, X.J. and Keane, J. 2018. Stock price forecasting incorporating market state. In: 2018 IEEE 20th international conference on high performance computing and communications; IEEE 16th international conference on smart city; IEEE 4th international conference on data science and systems (HPCC/SmartCity/DSS) (pp. 1614-1619). IEEE.
12. Singh, R. and Srivastava, S. 2017. Stock prediction using deep learning. Multimedia Tools and Applications, 76: 18569-18584.
13. Vargas, M.R., De Lima, B.S. and Evsukoff, A.G. 2017. Deep learning for stock market prediction from financial news articles. In: 2017 IEEE international conference on computational intelligence and virtual environments for measurement systems and applications (CIVEMSA) (pp. 60-65). IEEE.
14. Dingli, A. and Fournier, K.S. 2017. Financial time series forecasting-a deep learning approach. International Journal of Machine Learning and Computing, 7(5): 118-122.
15. Usmani, M., Adil, S.H., Raza, K. and Ali, S.S.A. 2016. Stock market prediction using machine learning techniques. In: 2016 3rd international conference on computer and information sciences (ICCOINS) (pp. 322-327). IEEE.

16. Boddapati, V.N., Galla, E.P., Sunkara, J.R., Bauskar, S., Patra, G.K., Kuraku, C. and Madhavaram, C.R. 2021. Harnessing the power of big data: The evolution of AI and machine learning in modern times. ESP Journal of Engineering and Technology Advancements, 1(2): 134-146.

17. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S.K. 2020. An effective predicting e-commerce sales and management system based on machine learning methods. Journal of Artificial Intelligence and Big Data, 1(1): 75-85.

18. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Exploring AI algorithms for cancer classification and prediction using electronic health records. Journal of Artificial Intelligence and Big Data, 1(1): 65-74.

19. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S.K. 2020. Navigating the complexities of cyber threats, sentiment, and health with AI/ML. Journal of Recent Trends in Computer Science and Engineering, 8(2): 22-40.

20. Kumar, V.V. 2014. An interactive product development model in remanufacturing environment: A chaosbased artificial bee colony approach. Masters Theses 7244. https://scholarsmine.mst.edu/masters_theses/724

21. Hasan, M.Z., Fink, R., Suyambu, M.R., Baskaran, M.K., James, D. and Gamboa, J. 2015. Performance evaluation of energy efficient intelligent elevator controllers. In: 2015 IEEE International conference on electro/information technology (EIT) (pp. 44-49). IEEE.

22. Kumar, V.V., Pandey, M.K., Tiwari, M.K. and Ben-Arieh, D. 2010. Simultaneous optimization of parts and operations sequences in SSMS: A chaos embedded Taguchi particle swarm optimization approach. Journal of Intelligent Manufacturing, 21: 335-353.

23. Kolluri, V. 2016. A pioneering approach to forensic insights: Utilization AI for cybersecurity incident investigations. IJRAR-International Journal of Research and Analytical Reviews, 3(3): 919-922.

24. Kumar, V.V., Tripathi, M., Tyagi, S.K., Shukla, S.K. and Tiwari, M.K. 2007. An integrated real time optimization approach (IRTO) for physical programming based redundancy allocation problem. In: Proceedings of the 3rd international conference on reliability and safety engineering, Udaypur, Rajasthan, India (pp. 692-704).

25. Khare, K., Darekar, O., Gupta, P. and Attar, V.Z. 2017. Short term stock price prediction using deep learning. In: 2017 2nd IEEE international conference on recent trends in electronics, information and communication technology (RTEICT) (pp. 482-486). IEEE.

26. Kumar, V.V., Yadav, S.R., Liou, F.W. and Balakrishnan, S.N. 2013. A digital interface for the part designers and the fixture designers for a reconfigurable assembly system. Mathematical Problems in Engineering, 2013(1): 943702.

27. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Unveiling the hidden patterns: AI-driven innovations in image processing and acoustic signal detection. Journal of Recent Trends in Computer Science and Engineering, 8(1): 25-45.

28. Gollangi, H.K., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Sunkara, J.R. and Reddy, M.S. 2020. Echoes in pixels: The intersection of image processing and sound detection through the lens of AI and ML. International Journal of Development Research, 10(08): 39735-39743.

29. Sarisa, M., Boddapati, V.N., Patra, G.K., Kuraku, C., Konkimalla, S. and Rajaram, S. K. 2020. The power of sentiment: Big data analytics meets machine learning for emotional insights. International Journal of Development Research, 10(10): 41565-41573.

30. Reddy, M.S., Sarisa, M., Konkimalla, S., Bauskar, S.R., Gollangi, H.K., Galla, E.P. and Rajaram, S.K. 2021. Predicting tomorrow’s ailments: How AI/ML is transforming disease forecasting. ESP Journal of Engineering and Technology Advancements, 1(2): 188-200.

31. Madhavaram, C.R., Galla, E.P., Reddy, M.S., Sarisa, M. and Nagesh, V. 2021. Predicting diabetes mellitus in healthcare: A comparative analysis of machine learning algorithms on big dataset. Global Journal of Research in Engineering and Computer Sciences, 1(1): 1-11.

32. Hasan, M.Z., Fink, R., Suyambu, M.R. and Baskaran, M.K. 2012. Assessment and improvement of intelligent controllers for elevator energy efficiency. In: 2012 IEEE international conference on electro/information technology (pp. 1-7). IEEE.

33. Kumar, V.V. and Chan, F.T. 2011. A superiority search and optimisation algorithm to solve RFID and an environmental factor embedded closed loop logistics model. International Journal of Production Research, 49(16): 4807-4831.

34. Kumar, V.V., Tripathi, M., Pandey, M.K. and Tiwari, M.K. 2009. Physical programming and conjoint analysis-based redundancy allocation in multistate systems: A Taguchi embedded algorithm selection and control (TAS&C) approach. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 223(3): 215-232.

35. Baughman, M., Haas, C., Wolski, R.M., Foster, I. and Chard, K. 2018. Predicting Amazon spot prices with LSTM networks. In: ScienceCloud'18: Proceedings of the 9th workshop on scientific cloud computing (pp. 1-7).

36. Bhatt, A.K., Pant, D. and Singh, R. 2014. An analysis of the performance of artificial neural network technique for apple classification. AI and Society, 29(1): 103-111.

37. Patra, G.K., Rajaram, S.K. and Boddapati, V.N. 2019. AI and big data in digital payments: A comprehensive model for secure biometric authentication. Educational Administration: Theory and Practice, 25(4): 773–781.

38. Kuraku, C., Gollangi, H.K. and Sunkara, J.R. 2020. Biometric authentication in digital payments: Utilizing AI and big data for real-time security and efficiency. Educational Administration: Theory and Practice, 26(4): 954-964.

39. Galla, E.P., Madhavaram, C.R. and Boddapati, V.N. 2021. Big data and AI innovations in biometric authentication for secure digital transactions. Educational Administration: Theory and Practice, 27(4): 1228–1236.

40. Sunkara, J.R., Bauskar, S.R., Madhavaram, C.R., Galla, E.P., Gollangi, H.K. 2021. Data-driven management: The impact of visualization tools on business performance. International Journal of Management, 12(3): 1290-1298.

Citation: Niharika Katnapally, Purna Chandra Rao Chinta, Kishan Kumar Routhu, Vasu Velaga, Varun Bodepudi and Laxmana Murthy Karaka. 2021. Big Data-Driven Predictive Analytics in the Financial Sector: A Stock Market Forecasting Approach. International Journal of Recent Innovations in Academic Research, 5(12): 88-99.