IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⪪ Peer-reviewed & Refereed journal ⪪ Vol. 12, Issue 4, April 2025
DOI: 10.17148/IARJSET.2025.12426

Real Time Analysis of Financial Market with AI Driven Trading Stratergies using React JS

N. Bhagya Lakshmi[1], K. Venisha[2], M. Amitha[3], G. Sri Lakshmi[4], B. Nirmala Kumari[5]

M.Tech, Asst.Professor, Computer Science & Engineering, Bapatla Women's Engineering College, Bapatla, India[1]

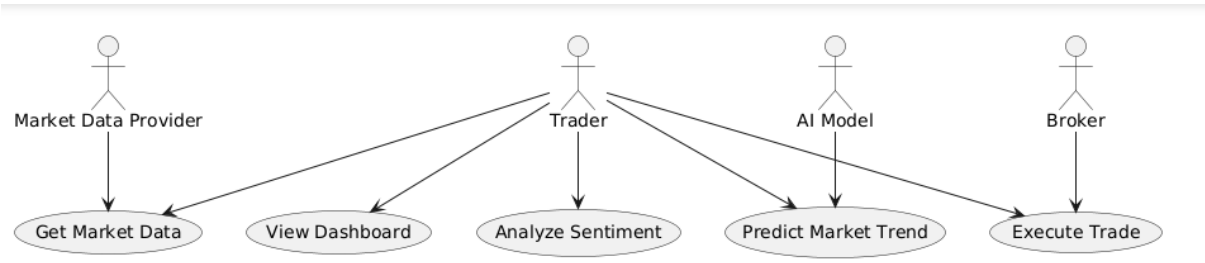
B.Tech, Computer Science & Engineering, Bapatla Women's Engineering College, Bapatla, India[2-5]

Abstract: This project aims to design and develop a real-time, AI-powered trading platform that integrates multiple external financial data APIs, a custom backend with AI inference and trading logic, and brokerage APIs for order execution. The platform leverages both REST and WebSocket protocols to handle live market data, financial news, and predictive AI models to make informed trading decisions. The system is designed for reliability, scalability, and automation, suitable for both retail and professional traders.

Keywords: React JS, Machine Learning (ML), Long ShortTerm Memory (LSTM).

I. INTRODUCTION

Financial markets are most unpredictable in predicting the process of changing the statistical analysis based on the stock prices]. Early prediction of financial market prices is a tedious task because of the fluctuations in the market. Generally, financial markets are based on the decisions taken by the central government. These decisions may significantly impact market prices, which may increase or decrease. Every country and organization relies heavily on stock markets to boost their economies. Many researchers are working to construct accurate financial market prediction models. Many companies are listed on stock exchanges to boost their business and stock prices. For many years, people have been trading in the financial market. This study discusses the performance of various sentiment analyses in Deep Learning (ML) techniques, as well as the performance of prediction-based algorithms. Many countries are interlinked with the financial markets because these stock prices significantly impact investment decisions globally. The prediction of stock prices is more complex for normal persons and is also a manual process. The inherent complexity, non-linear relationship, and high volatility of stock price movements are better captured by advanced data-driven methods than traditional forecasting models such as the statistical/econometrics models. However, all this was fundamental and furthers the implementation of deep learning that uses big data, relies on complex and adaptive algorithms, and creates highly accurate real-time forecasts.



II. LITERATURE REVIEW

For ML based approaches for stock price prediction has found its application in the financial markets because of its capability to handle non-linear data. This is because there are many shifting factors that affect the stock prices and these are very volatile markets; simple techniques like linear regression or even ARIMA can do more harm than good in stock market predictions. LSTM, SVM, and Gradient Boosting Regressor are some of the most common machine learning techniques currently used for stock prediction as its improves accuracy significantly due to improved feature identification with higher sophistication and data processing. This literature review considers such algorithms, with respect to their advantages, some drawbacks, and utilization in predicting stock prices.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 4, April 2025

DOI: 10.17148/IARJSET.2025.12426

This chapter presents a literature review in hopes of finding what works and what does not for the purpose of accurately predicting stock prices. In the same review, the efficiency of these models will also be determined by such factors such as Mean Square Error (MSE).

recently devised a new way for predicting stock market indices by combining PFTD on top of several state-of-the-art TSDL techniques. First, theoretically, the proposed method is performing Fourier Transform (FT) on the stock price time series to decompose the stock price time series and compensate for the noise in the high-frequency section, and the optimized padded technique is introduced to eliminate this high-frequency noise. The next step follows the denoised data sent to the proposed LSTM, GRU, and other transform-based systems. Finally, the filter-based model hit ratio obtained an accuracy of 45.43%. The proposed approach P-FTD_LSTM obtained an accuracy of 75.81%, which is high compared with other models. Li et al. proposed a Multimodal Event-Driven model (MED_LSTM) that combines historical stock data and online news sentiment to improve the result of prediction. The NLP techniques combine sentiment scores and key financial news events from online news articles with MED_LSTM. The textual components are subsequently combined with the numerical stock features employing a multimodal LSTM model, allowing the model to capture complex correlations between market movements and external factors. Using an event-driven component allows for major news to be given corresponding weight in regard to stock price trends. Experiments are conducted on China markets and obtain better results than existing models. Nabipour et al.discusses the ML and DL methods can be effective in forecasting stock market movements for continuous and binary representations of data. Inherent to stock price movement is a dynamic aspect, exhibiting various market volatilities and fluctuating due to external economic conditions, making it difficult for traditional models to capture correctly. The experimental results suggest that LSTM-based deep learning models yield better performance on continuous time-series data compared to traditional machine learning methods, while tree-based models show competitive results on binary classification tasks. The prediction rate of proposed approach is 86% which is high compare with other models.

III. DATASET DESCRIPTION

The National Financial Exchange of India updates the data for each listed stock daily. This data can be opening and closing prices, high and low, trading volumes, and other relevant metrics. This data is available via the NSE's official website, which has daily and historical reports. The NSE data is downloaded programmatically and can be used in the OpenChart Python library. It streamlines the downloading of intraday and end-of-day historical data from the NSE for different intervals, making it easy to analyze your study and forecasts. The dataset contains 1.5 Lakhs of data belonging to stocks of various companies. The training data includes 100k, and the testing data contains 50k stock data.

	A	B	C	D	E	F	G	H
1	Date	Stock	Open	High	Low	Close	Volume	Change Pct
2	########	20MICRON	80.35	80.55	77.5	77.8	1088880	-3.23
3	########	20MICRON	78.58	79.78	76	76.4	590180	-1.8
4	########	20MICRON	76.5	77.25	75.5	75.83	380850	-0.75
5	########	20MICRON	76.88	78	74	74.9	1144204	-1.23
6	########	20MICRON	74.97	75.97	74.25	75.28	605020	0.51
7	########	20MICRON	75.9	77.5	74.4	74.72	393190	-0.74
8	########	20MICRON	75.03	75.5	74	74.33	362922	-0.52
9	########	20MICRON	74.55	75.75	73.7	74	451474	-0.44
10	########	20MICRON	74.15	74.42	73	73.08	333356	-1.24
11	########	20MICRON	74.4	76.75	72.53	76.05	1198216	4.06
12	########	20MICRON	72.78	77.2	72.78	75.17	463044	-1.16
13	########	20MICRON	75.5	77	74.58	75.2	269720	0.04
14	########	20MICRON	75.5	78.42	74.65	76.08	2354266	1.17
15	########	20MICRON	75.95	77.7	75.05	75.55	755778	-0.7
16	########	20MICRON	75.75	76.97	74.97	75.17	475772	-0.5
17	########	20MICRON	75.47	80.38	75	78.1	1602058	3.9
18	########	20MICRON	79.45	79.45	72.05	74.25	845836	-4.93
19	########	20MICRON	74.5	75.25	62.5	68.17	2921352	-8.19
20	########	20MICRON	67.9	80.7	67.9	71.75	2661516	5.25
21	########	20MICRON	72.4	72.5	68	68.85	492543	-4.04
22	########	20MICRON	68.65	68.8	67.6	68.1	377153	-1.09
23	########	20MICRON	68.1	70.15	68	68.8	345591	1.03
24	########	20MICRON	69.85	70.5	68.5	68.65	264315	-0.22

Figure : Indian Stock Market Dataset

IV. METHODOLOGY

This chapter provides an account of the studies' approach to the development of a machine learning model for the provision of company stock prices forecasts. The approach uses LSTM as a model that captures temporal dependence

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⫹ Peer-reviewed & Refereed journal ⫹ Vol. 12, Issue 4, April 2025

DOI: 10.17148/IARJSET.2025.12426

within the data, SVM for classification of stock data, and Gradient Boosting for model updates. The methodology involves several stages: by stages of data gathering, data cleaning, data transformation, feature extraction and selection model calibration, model assessment and evaluation of all the algorithms regarding the criteria such as Mean Square Error (MSE) and R-squared.

These techniques were chosen to be able to learn from data flow in financial trading environments and to be able to process financial datasets. The systematic approach pronounced ensures the findings present the right templates, to enable accurate predictions of stock prices. These points of the chosen methodology are designed to enhance the performance of the models and be useful to provide suggestions for stock forecasting in the ever-shifting scenario of the financial market.

DATA PREPROCESSING

It is a very important step to make the data more eligible for model building. Preprocessing encompasses data washing, the management of missing values, scaling the data and making new feature vectors which enhance the predictive ability of the model (Bhandari *et al*. 2022).

Handling Missing Values

This is because missing values if not dealt with correctly can lead to a skewed model. Various strategies for handling missing data include:

Removal: When the proportion of missing values is relatively low or widespread only in separate rows or columns, intact data can be excluded without undermining the general matrix.

Imputation: In order to enhance the given approach, the missing values can be filled in by statistical measures like mean, median, or mode or by the advanced technique like K- Nearest Neighbors (KNN) imputation, whose approach is based on the similarity of data points.

Normalization

To improve efficiency of the model, normalization is conducted to make all the data scores to be of similar range. Therefore, normalization of the features was done using Min-Max scaling as a common technique of scaling the features to the range 0 – 1. This process is imperative when using feature scaling algorithms that are sensitive to scale of an input data as seen with the implementation of a SVM.

The normalization process follows the formula:

$$X_{scaled}=(X- X_{min})-(X_{max}-X_{min})$$

where X is the original data.

Xmin the minimum value

and Xmax is the maximum value of the data.

Feature Engineering

Feature engineering is used for improving the model's predictive power since the new variables are engineered out of the available data. Some of the engineered features include:

Lagged Features: This approach brings into focus predictors based on the previous stock prices like the weekly closing price, timing patterns.

Technical Indicators: Analyzing such financial parameters, as MA, MACD, RSI, Bollinger Bands; used to prompt trends and possible prices change.

Volatility Measures: Using additional parameters such as Average True Range (ATR) in order to consider volatility in stock prices.

SEQUENCE DIAGRAM:

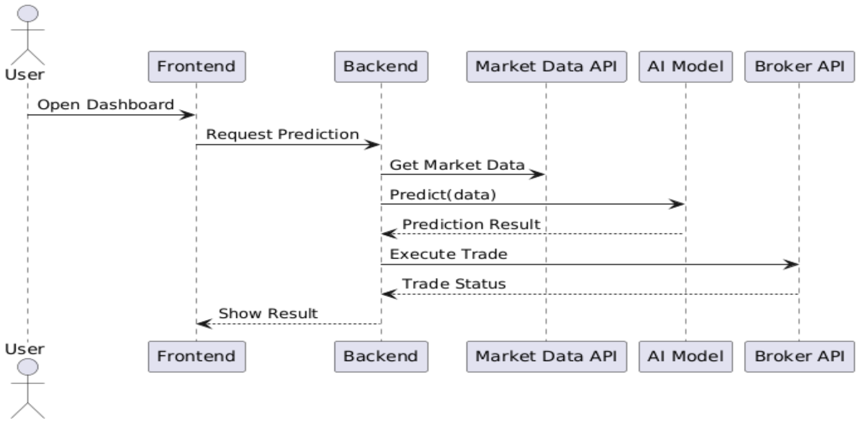
A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

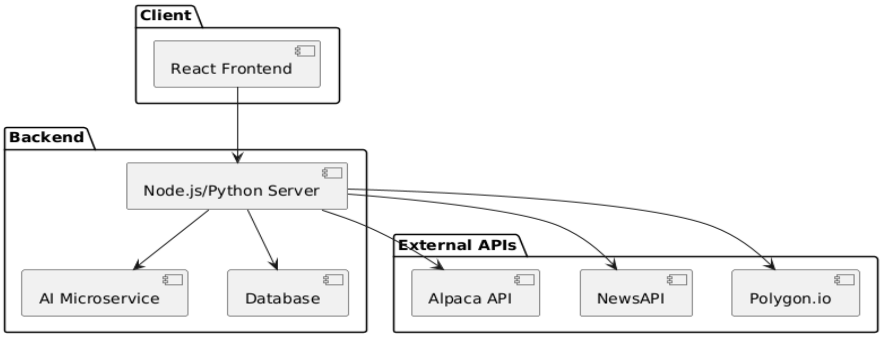
International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⧓ Peer-reviewed & Refereed journal ⧓ Vol. 12, Issue 4, April 2025

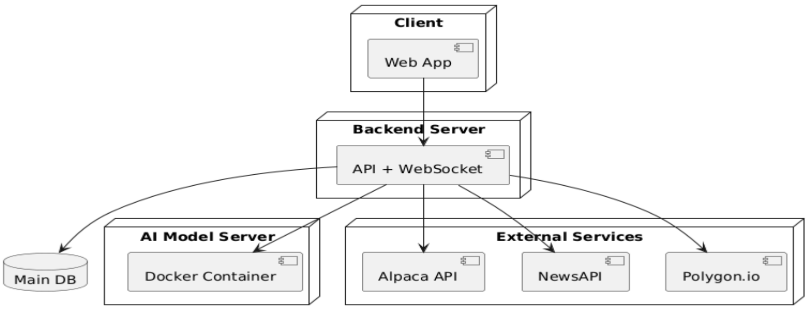
DOI: 10.17148/IARJSET.2025.12426



COMPONENT:



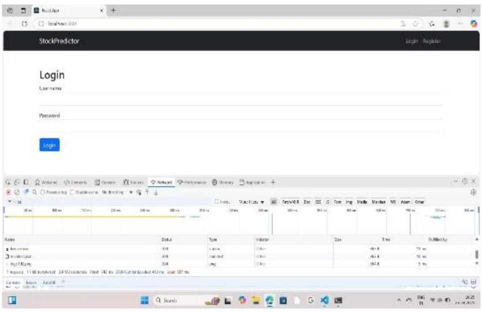
DEPLOYMENT:

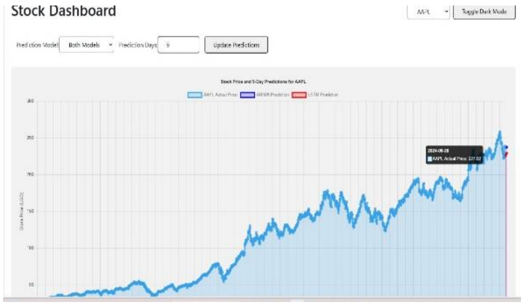


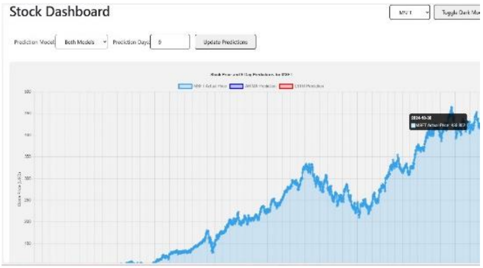
V. RESULTS AND ANALYSIS

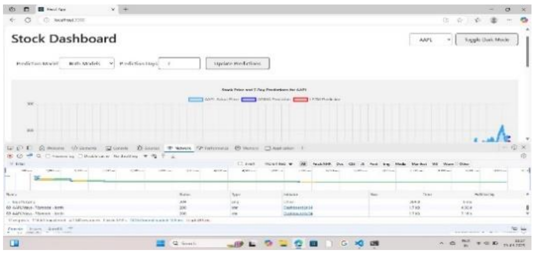
The algorithms are implemented by suing the LSTM&ARIMA mechanisms using python programming language. This section shows the classification of high stock prices that are analyzed by the proposed algorithm and compared with other existing models.

IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 4, April 2025
DOI: 10.17148/IARJSET.2025.12426









VI. CONCLUSION

The development of an AI-driven, real-time trading platform integrating financial data APIs, sentiment analysis tools, and brokerage APIs marks a significant step toward the future of automated trading systems. By leveraging both REST and WebSocket technologies, the system ensures low-latency data access and real-time responsiveness—critical requirements for financial applications.

This platform not only enables intelligent decision-making through the use of machine learning models but also streamlines the entire trading lifecycle—from market data acquisition and sentiment analysis to strategy execution and trade monitoring. It addresses key limitations of existing systems by offering a unified, modular, and scalable architecture, with high transparency and minimal manual intervention.

Overall, the proposed solution offers a robust foundation for building next-generation financial applications that are not only automated and intelligent but also flexible enough to adapt to rapidly changing market dynamics.

REFERENCES

[1] S. K. Shukla, K. Joshi, G. D. Singh and A. Dumka, "Stock Market Prediction Using Deep Learning," 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP), Uttarakhand, India, 2022, pp. 91-95, doi: 10.1109/ICFIRTP56122.2022.10059433.

[2] G. Sismanoglu, M. A. Onde, F. Kocer and O. K. Sahingoz, "Deep Learning Based Forecasting in Stock Market with Big Data Analytics," 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), Istanbul, Turkey, 2019, pp. 1-4, doi: 10.1109/EBBT.2019.8741818.

[3] N. Smith, R. Wilkinson, D. Y. Kim and M. Lech, "Stock Market Crash Forecasting Using an Assembly of Deep Learning Classifiers," 2024 17th International Conference on Signal Processing and Communication System (ICSPCS), Surfers Paradise, Australia, 2024, pp. 1-10, doi: 10.1109/ICSPCS63175.2024.10815809.

[4] X. Ji, J. Wang and Z. Yan, "A stock price prediction method based on deep learning technology", International Journal of Crowd Science, vol. 5, no. 1, pp. 55-72, April 2021.

[5] S. Goswami and S. Yadav, "Stock Market Prediction Using Deep Learning LSTM Model", 2021 International Conference on Smart Generation Computing Communication and Networking (SMART GENCON), pp. 1-5, 2021.

[6] P. S. Sisodia, A. Gupta, Y. Kumar and G. K. Ameta, "Stock Market Analysis and Prediction for Nifty50 using LSTM Deep Learning Approach", 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), pp. 156-161, 2022.

[7] T. Kabbani and E. Duman, "Deep Reinforcement Learning Approach for Trading Automation in the Stock Market", IEEE Access, vol. 10, pp. 93564-93574, 2022.

[8] C. Zhang, N. N. A. Sjarif and R. B. Ibrahim, "Decision Fusion for Stock Market Prediction: A Systematic Review", IEEE Access, vol. 10, pp. 81364-81379, 2022.

[9] D. Song, A. M. Chung Baek and N. Kim, "Forecasting Stock Market Indices Using Padding-Based Fourier Transform Denoising and Time Series Deep Learning Models", IEEE Access, vol. 9, pp. 83786-83796, 2021.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 12, Issue 4, April 2025

DOI: 10.17148/IARJSET.2025.12426

[10] D. Song, A. M. Chung Baek and N. Kim, "Forecasting Stock Market Indices Using Padding-Based Fourier Transform Denoising and Time Series Deep Learning Models", IEEE Access, vol. 9, pp. 83786-83796, 2021.

[11] Q. Li, J. Tan, J. Wang and H. Chen, "A Multimodal Event-Driven LSTM Model for Stock Prediction Using Online News", IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 10, pp. 3323-3337, Oct. 2021.

[12] M. Nabipour, P. Nayyeri, H. Jabani, S. S. and A. Mosavi, "Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis," in IEEE Access, vol. 8, pp. 150199-150212, 2020, doi: 10.1109/ACCESS.2020.3015966.

[13] K. Alam, M. H. Bhuiyan, I. U. Haque, M. F. Monir and T. Ahmed, "Enhancing Stock Market Prediction: A Robust LSTM-DNN Model Analysis on 26 Real-Life Datasets," in IEEE Access, vol. 12, pp. 122757-122768, 2024, doi: 10.1109/ACCESS.2024.3434524.

[14] Z. H. Kilimci and R. Duvar, "An Efficient Word Embedding and Deep Learning Based Model to Forecast the Direction of Stock Exchange Market Using Twitter and Financial News Sites: A Case of Istanbul Stock Exchange (BIST 100)," in IEEE Access, vol. 8, pp. 188186-188198, 2020, doi: 10.1109/ACCESS.2020.3029860.

[15] Y. Li, L. Chen, C. Sun, G. Liu, C. Chen and Y. Zhang, "Accurate stock price forecasting based on deep learning and hierarchical frequency decomposition", IEEE Access, vol. 12, pp. 49878-49894, 2024.

[16] P. Singh, M. Jha, M. Sharaf, M. A. El-Meligy and T. R. Gadekallu, "Harnessing a hybrid CNN-LSTM model for portfolio performance: A case study on stock selection and optimization", IEEE Access, vol. 11, pp. 104000-104015, 2023.

[17] Fraz, T.R., Fatima, S. and Uddin, M., 2022. Modeling and forecasting stock market volatility of CPEC founding countries: using nonlinear time series and machine learning models. *JISR management and social sciences & economics*, *20*(1), pp.1-20.

[18] Wang, Y. and Guo, Y., 2020. Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost. *China Communications*, *17*(3), pp.205-221.

[19] Lu, H., Ma, X., Huang, K. and Azimi, M., 2020. Carbon trading volume and price forecasting in China using multiple machine learning models. *Journal of Cleaner Production*, *249*, p.119386.

[20] Shapi, M.K.M., Ramli, N.A. and Awalin, L.J., 2021. Energy consumption prediction by using machine learning for smart building: Case study in Malaysia. *Developments in the Built Environment*, *5*, p.100037.

[21] Machireddy, J.R., Rachakatla, S.K. and Ravichandran, P., 2021. AI-Driven Business Analytics for Financial Forecasting: Integrating Data Warehousing with Predictive Models. *Journal of Machine Learning in Pharmaceutical Research*, *1*(2), pp.1-24.

[22] Liu, Y., Chen, H., Zhang, L., Wu, X. and Wang, X.J., 2020. Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: A case study in China. *Journal of Cleaner Production*, *272*, p.122542.

[23] Ozbayoglu, A.M., Gudelek, M.U. and Sezer, O.B., 2020. Deep learning for financial applications: A survey. *Applied soft computing*, *93*, p.106384.

[24] Cao, S., Jiang, W., Wang, J. and Yang, B., 2024. From man vs. machine to man+ machine: The art and AI of stock analyses. *Journal of Financial Economics*, *160*, p.103910.

[25] Birim, S., Kazancoglu, I., Mangla, S.K., Kahraman, A. and Kazancoglu, Y., 2024. The derived demand for advertising expenses and implications on sustainability: a comparative study using deep learning and traditional machine learning methods. *Annals of Operations Research*, *339*(1), pp.131-161.

[26] Chen, W., Xu, H., Jia, L. and Gao, Y., 2021. Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants. *International Journal of Forecasting*, *37*(1), pp.28-43.

[27] Bharadiya, J.P., 2023. Machine learning and AI in business intelligence: Trends and opportunities. *International Journal of Computer (IJC)*, *48*(1), pp.123-134.

[28] Jensen, T.I., Kelly, B.T., Malamud, S. and Pedersen, L.H., 2024. Machine learning and the implementable efficient frontier. *Swiss Finance Institute Research Paper*, (22-63).

[29] Ensafi, Y., Amin, S.H., Zhang, G. and Shah, B., 2022. Time-series forecasting of seasonal items sales using machine learning–A comparative analysis. *International Journal of Information Management Data Insights*, *2*(1), p.100058.

[30] Lu, W., Li, J., Wang, J. and Qin, L., 2021. A CNN-BiLSTM-AM method for stock price prediction. *Neural Computing and Applications*, *33*(10), pp.4741-4753.

[31] Yang, H., Liu, X.Y., Zhong, S. and Walid, A., 2020, October. Deep reinforcement learning for automated stock trading: An ensemble strategy. In *Proceedings of the first ACM international conference on AI in finance* (pp. 1-8).

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁎ Peer-reviewed & Refereed journal ⁎ Vol. 12, Issue 4, April 2025

DOI: 10.17148/IARJSET.2025.12426

BIOGRAPHY

N.Bhagya Lakshmi,M.Tech, Asst.professor,
Dept of Computer Science & Engineering,
BWEC, Andhra Pradesh,India

K.Venisha,B.Tech, Student,
Dept of Computer Science & Engineering,
BWEC, Andhra Pradesh,India.

M.Amitha,B.Tech, Student,
Dept of Computer Science & Engineering,
BWEC, Andhra Pradesh,India

G.Sri Lakshmi,B.Tech, Student,
Dept of Computer Science & Engineering,
BWEC,Andhra Pradesh,India

B.Nirmala Kuari,B.Tech, Student,
Dept of Computer Science & Engineering,
BWEC, Andhra Pradesh, India