International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Stock Market Prediction Using Sentiment Analysis

Mayukh Mitra[1], Jagannath Adhikary[1], Indrajit Nayek[1], Bitan Baidya[1], Kankana Ganguly[1], Dipanjan Saha[1]

[1]Department of CSE; JIS College of Engineering; Kalyani; West Bengal

ABSTRACT –

In today's financial realm, the stock exchange has become a pivotal event, significantly impacting the world economy. As a result, stock market research has gained prominence as a crucial and trending topic, attracting individuals from diverse educational and business backgrounds. However, traditional methodologies such as fundamental and technical analysis fail to ensure consistent and accurate stock price predictions. To address this, machine learning technologies, specifically Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), have emerged as promising approaches for stock market trend prediction. By leveraging the non-linear nature of RNN and LSTM, these techniques utilize historical stock market values for training and generate predictions that minimize risks and maximize profits. Additionally, sentiment analysis plays a vital role in capturing user opinions and thoughts on microblogging platforms like Twitter. To enhance sentiment analysis accuracy, this study proposes text classification using Bidirectional Encoder Representations from Transformers (BERT) and its variants for natural language processing. Experimental results demonstrate the effectiveness of combining BERT with Convolutional Neural Networks (CNN), RNN, and Bidirectional LSTM (BiLSTM) in terms of accuracy, precision, recall rates, and F1-scores compared to other approaches such as Word2Vec or no variant. Ultimately, these machine learning techniques aim to provide investors with more accurate insights for making informed investment decisions in the stock market.

Keywords – Stock market prediction, RNN, LSTM, Sentiment analysis, BERT

Introduction:

The stock market, a public marketplace for buying and selling shares of publicly listed companies, plays a crucial role in the world of marketization. Stocks, also known as equities, represent ownership in these companies and are often seen as long-term investments that provide financial security during retirement. However, the stock market is inherently unpredictable, driven by a multitude of factors and resources that constantly fluctuate. Despite efforts to analyze and predict market trends, the true nature of the stock market remains elusive and unpredictable.

Stock market prediction and analysis pose significant challenges due to market volatility and the complex interplay of dependent and independent variables that influence stock values. Even seasoned experts find it difficult to accurately anticipate market fluctuations. However, the emergence of Machine Learning and its powerful algorithms have brought new advancements to stock market research and prediction by enabling the analysis of vast amounts of market data.

In stock market prediction, the target can be the future stock price, price volatility, or overall market trends. Prediction methods can be categorized into two types: dummy prediction and real-time prediction. Dummy prediction involves defining a set of rules to calculate average prices and make future price projections. Real-time prediction, on the other hand, relies on internet connectivity to gather current price information and make predictions accordingly.

Before investing in stocks, investors typically perform two types of analysis: fundamental analysis and technical analysis. Fundamental analysis focuses on intrinsic stock value, industry performance, economic factors, and the political climate to determine whether an investment is viable. In contrast, technical analysis involves studying statistical data derived from market activity, such as past prices and trading volumes, to evaluate stock trends. Advancements in computational capabilities have led to the application of machine learning techniques in predictive systems for financial markets. In this paper, we employ various machine learning techniques, including Linear Regression, Moving Average, K-Nearest Neighbors, Auto ARIMA, Prophet, and LSTM (Long Short-Term Memory), to predict stock values. These techniques leverage the programming language Python to facilitate the analysis and prediction process. Figure (i) depicts the flow of shares and funds with respect to stock market.

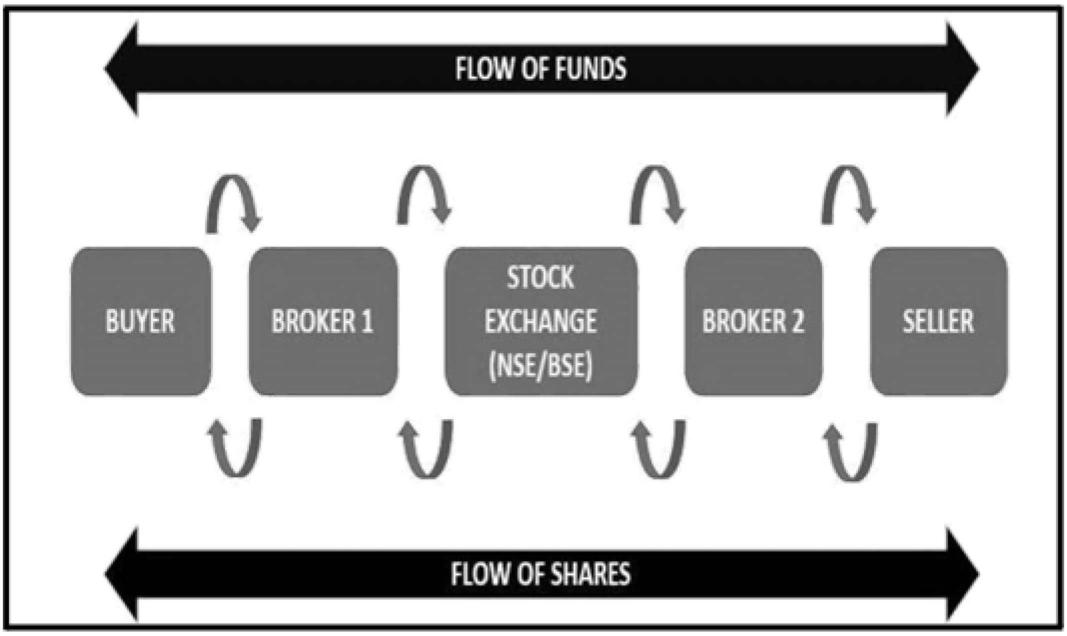

Figure (i) – Flow of stocks and shares in a common stock market

The evolutionary impact of social media on human communication has been extensively explored in this paper, shedding light on the growing dependence on user-generated content and the significant amount of time spent on social platforms. Additionally, the integration of Artificial Intelligence, particularly in the form of Natural Language Processing (NLP) and neural networks, has revolutionized language processing capabilities, enabling advanced applications across diverse domains. The intricate relationship between social media, AI, and deep learning underscores their transformative potential in shaping communication dynamics and knowledge acquisition in the future.

By integrating machine learning methodologies into stock market prediction, this research aims to enhance the understanding and forecasting of stock market behavior, providing investors with valuable insights for making informed investment decisions.

Literature Survey:

Sayavong Lounnapha et al. [1] proposes a prediction model based on Convolutional Neural Networks (CNNs) applied to the Thai stock market. The model demonstrates exceptional capability in learning the market behavior and accurately predicting stock price trends. The study reports elevated prediction accuracy, highlighting the potential of CNNs in the field of finance.

Soheila Abrishami et al. [2], proposed a deep learning system is presented for stock price prediction on the NASDAQ exchange. The model utilizes an autoencoder to remove noise and incorporates time series data engineering techniques to combine advanced features with the original features. The proposed framework outperforms state-of-the-art forecasting methodologies, demonstrating superior analytical accuracy and effectiveness.

Ferdiansyah et al. [3] focused on predicting Bitcoin prices in the stock market using LSTM. Bitcoin, as a cryptocurrency, experiences significant fluctuations that can influence the stock market. The study measures the prediction results using the Root Mean Square Error (RMSE) and shows that the LSTM-based approach can forecast Bitcoin prices with reasonable accuracy.

Jeevan B et al. [4] discussed stock price prediction on the National Stock Exchange using Recurrent Neural Networks (RNNs) and LSTM. The models incorporate various factors, including current market prices and anonymous events. Additionally, the paper introduces a recommendation system for selecting suitable companies for investment purposes.

Naadun Sirimevan et al. [5] addressed the impact of social media platforms, such as Twitter and web news, on stock market decision-making. By incorporating behavioral reflexes towards web news, the prediction accuracy is improved for different time horizons.

The advent of the internet has revolutionized the way people express ideas and thoughts, with a significant portion of the global population actively engaging in social media platforms. Statistics from Kepios indicate that approximately 4.74 billion individuals, accounting for 59.3 percent of the world's population, use social media [6]. This widespread usage underscores the profound influence of social media on human communication, with users spending an average of 2.5 hours per day on various platforms [6]. Moreover, businesses recognize social media as a valuable advertising platform and rely on user-generated content for decision-making [7]. Microblogging platforms like Twitter serve as important sources of information, enabling users to stay informed about events and sentiments in specific geographic areas [7, 8].

Artificial Intelligence (AI) has emerged as a field encompassing the development of intelligent machines and computer programs capable of reasoning and acting similarly to humans. AI finds applications across various industries, including communication, IT, healthcare, agriculture, logistics, education, and aviation. In recent years, there has been a significant surge in interest surrounding natural language processing (NLP) due to its remarkable ability to computationally analyze and represent human language. NLP has expanded its reach across various industries, including machine translation, email spam detection, information extraction, summarization, and even medicine [9]. By leveraging computational linguistics and machine learning techniques, NLP enables simple and effective interactions between humans and computers. NLP systems have the capability to generate written texts or processed speech based on inputs such as text, images, or speech [10].

Neural networks, a subset of machine learning, find applications in diverse domains such as compressed image reconstruction, asset allocation, non-negative matrix factorization, and model predictive control [11-16]. The concept of deep learning, introduced by G.E. Hinton with the advent of transfer learning, involves extracting meaningful features from raw data through the utilization of layered architectures [17]. Neural networks are inspired by the intricate networks of neurons in the human brain and exhibit remarkable capabilities. Deep learning networks can be applied to both supervised and unsupervised learning tasks [18-21]. Deep learning approaches, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and other multi-layered architectures, have proved highly effective in various tasks such as text generation, vector representation, word estimation, sentence classification, phrase modeling, feature presentation, and emotion recognition [22, 23].

Moreover, the term "deep learning" has gained prominence in the field of computer science, denoting pattern-recognition algorithms that enable computers to learn autonomously. This has led to advancements in speech and image recognition, as well as more accurate translation software. Deep learning also encompasses a focus on context, thought, and abstraction, enabling knowledge acquisition at a deeper and more contemplative level [24].

Natural language processing has emerged as a prominent field due to its ability to computationally analyze human language. Neural networks, as a subset of machine learning, have found widespread use in various domains, including image reconstruction, asset allocation, and model predictive control. Deep learning techniques, with their layered architectures, have further enhanced the capabilities of neural networks in both supervised and unsupervised learning tasks, enabling tasks such as text generation, vector representation, sentence classification, and emotion recognition. The combination of social media, AI, and deep learning presents an exciting prospect for the future of communication and knowledge acquisition.

Furthermore, this comparative analysis delves into the application of deep learning techniques for stock price prediction. The selected research papers showcase the effectiveness of Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNNs) in accurately forecasting stock prices, optimizing profit, and considering external factors such as web news and social media platforms. These studies provide valuable insights and lay the foundation for further advancements in prediction models, emphasizing the need for improved accuracy and real-world applicability in investment scenarios

Suhasini et al. [25] conducted a study focused on emotion identification in Twitter data using supervised learning techniques. They compared the performance of two algorithms, namely K-nearest neighbor (KNN) and naive Bayes (NB), in this task. The results of their research revealed that naive Bayes outperformed the K-nearest neighbor algorithm in accurately identifying emotions in Twitter data. In another study by Jayakody et al. [26], Twitter data based on product reviews was collected and analyzed using various machine learning algorithms, including support vector machine (SVM), logistic regression, and K-nearest neighbor. To convert the textual data into numerical vectors for inputting into the machine learning models, count vectorizer and term frequency-inverse document frequency mechanisms were employed. The highest accuracy score of 88.26% was achieved by logistic regression in combination with a count vectorizer. Bhagat et al. [27] adopted a hybrid approach utilizing naive Bayes and K-nearest neighbor algorithms to categorize tweets into three classes: positive, negative, and neutral. Their research demonstrated that the proposed hybrid approach yielded better accuracy results compared to the random forest algorithm.

These studies highlight the effectiveness of different supervised learning algorithms, such as naive Bayes, logistic regression, and support vector machine, in analyzing Twitter data for tasks such as emotion identification and sentiment classification. The findings contribute to the development of more accurate and reliable methods for understanding and interpreting social media content.

Chiorrini et al. [28] proposed two BERT-based approaches, namely BERT-base and cased BERT-base, for text classification tasks. Their research focused on utilizing microblogging sites, specifically Twitter, as a source of information. The experiment involved two separate datasets, which were employed for sentiment analysis and emotion recognition. The proposed models achieved an impressive accuracy rate of 92%. The researchers emphasized the positive outcomes obtained through the use of BERT in text classification tasks. In the study conducted by Huang et al. [29], a model for text classification was presented, leveraging a deep convolutional neural network with bidirectional gated recurrent units. The foundation of this model was built upon BERT. Two distinct datasets, namely CCERT email and movie comments, were utilized for evaluation. The results demonstrated high accuracy scores of 92.66% on the CCERT dataset and 91.89% on the movie dataset, showcasing the effectiveness of the proposed approach.

The researchers in [30] introduced a comprehensive seven-layer framework for analyzing the sentiments expressed in sentences. This framework incorporated convolutional neural networks (CNN) and Word2vec to calculate vector representations and perform sentiment analysis, respectively. The utilization of Word2vec, a method proposed by Google, aimed to enhance the accuracy and generalizability of the model. Various techniques, including dropout, normalization, and parametric rectified linear unit (PReLU), were employed to further refine the model [31 -32]. The researchers validated their framework using a dataset extracted from rottentomatoes.com, consisting of movie review excerpts classified into five labels: positive, slightly positive, neutral, negative, and somewhat negative [33]. Compared to previous models such as matrix-vector recursive neural network (MV-RNN) and recursive neural network, the proposed model outperformed them with an accuracy of 45.4% [34].

These studies showcase the utilization of advanced techniques such as BERT, deep convolutional neural networks, and Word2vec in text classification tasks. The achieved accuracy rates and the improvement over previous models highlight the potential of these sophisticated approaches in effectively analyzing and understanding textual data.

Methodology:

The basic flow of work is shown in figure (ii).

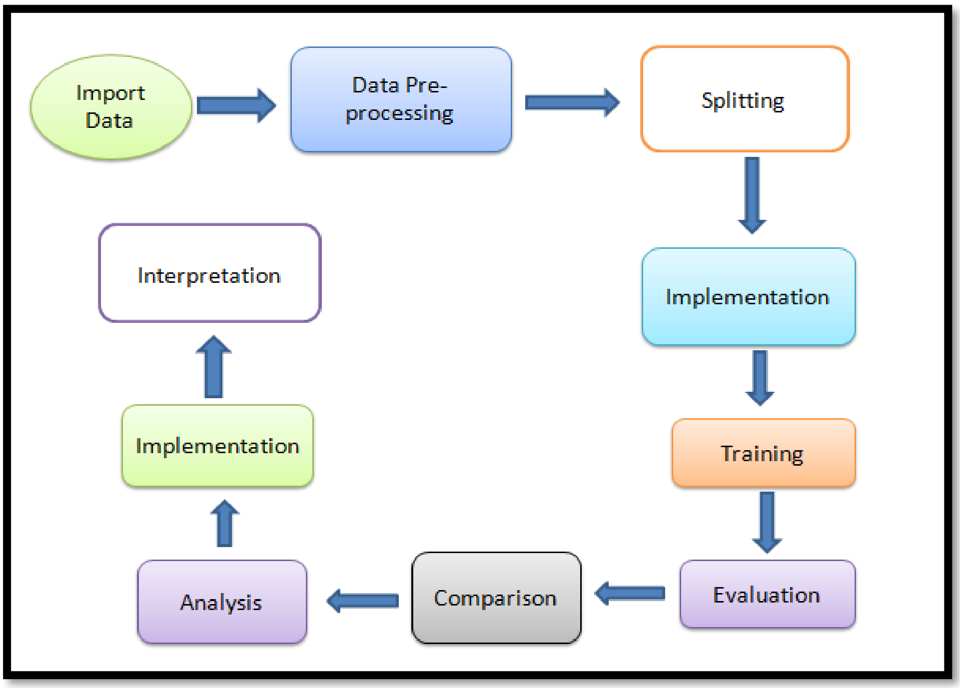

Figure (ii) Methodology

Explanation of methodology is as follows:-

- Historical stock market data is collected and preprocessed for analysis.
- The dataset is divided into training and testing subsets for model evaluation.
- Machine learning techniques, including Linear Regression, Moving Average, K-Nearest Neighbors, Auto ARIMA, Prophet, and LSTM, are implemented.
- The models are trained on the training data, and hyperparameters are adjusted as necessary.
- Model performance is evaluated using metrics such as MSE, MAE, and accuracy.
- The performance of different models is compared to identify the most effective technique.
- Feature importance is analyzed, and trends are identified using the selected model.
- Models are implemented using Python and relevant libraries, such as TensorFlow and Keras.
- Results are interpreted, and conclusions are drawn regarding the feasibility of machine learning in stock market prediction.
- Limitations are discussed, and future research directions for improvement are suggested.

The focus lies on examining the effectiveness of these methods in enhancing stock market predictions. Initially, we establish a baseline model using time series data from the Dow Jones Index. Subsequently, we employ an n-gram model on daily news data and extract additional features through sentiment analysis, which are comprehensively described and analyzed. Furthermore, we investigate the notions of objectivity and subjectivity. Two features are derived: the average subjectivity and objectivity scores of news articles for each day, ranging from 0 to 100. Notably, these two scores tend to complement each other, with higher subjectivity corresponding to lower objectivity and vice versa. In the final preprocessing step, we perform opinion finding (mood mining) by assigning sentiment polarity values to tokens in the headline text. The average sentiment value for each day is then normalized to obtain a value between 0 and 100, reflecting the positive, negative, or neutral sentiment associated with the daily news. Figure (iii) reveals the flow in a classical paradigm.

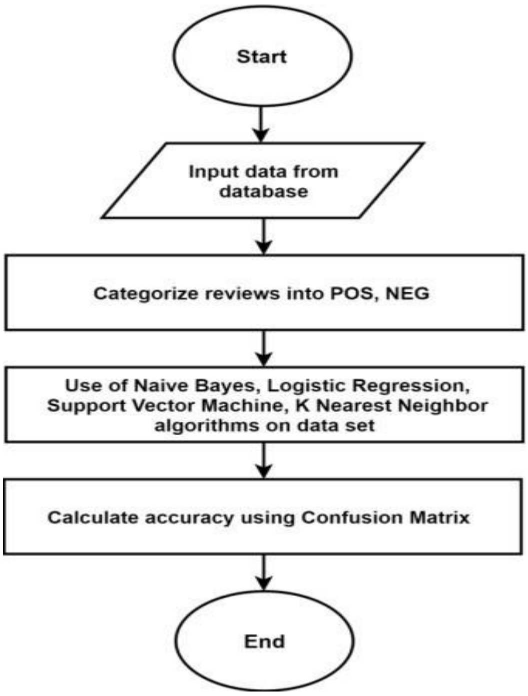

Figure (iii) – Classical paradigm flow of work

Results and Discussions:

publish_date	headline_text
2009-02-14	How Treasuries and ETFs Work
2009-04-27	Update on the Luxury Sector: 2nd Quarter 2009,...
2009-04-29	Going Against the Herd
2009-05-22	Charles Sizemore Radio Interview Saturday Morning
2009-05-27	MRM a $15-$20+ stock - FIT new information - J...
...	...
2020-06-07	Apple's Top Supplier Foxconn Launched New Recr...
2020-06-08	Shares of several retail and apparel companies...
2020-06-09	Why Apple's Stock Is Trading Higher Today,Appl...
2020-06-10	Shares of retail & apparel companies are tradi...
2020-06-11	Johnson & Johnson To Start Coronavirus Vaccine...

3957 rows × 1 columns

Figure (iv) – Headline Text extraction from dataset

	headline_text	negative	neutral	positive
publish_date				
2009-02-14	How Treasuries and ETFs Work	0.102426	0.828853	0.068721
2009-04-27	Update on the Luxury Sector: 2nd Quarter 2009,...	0.094900	0.870135	0.034965
2009-04-29	Going Against the Herd	0.165430	0.805855	0.028715
2009-05-22	Charles Sizemore Radio Interview Saturday Morning	0.017397	0.943096	0.039507
2009-05-27	MRM a $15-$20+ stock - FIT new information - J...	0.009468	0.678259	0.312273
...	...	...	...	...
2020-06-07	Apple's Top Supplier Foxconn Launched New Recr...	0.015591	0.732633	0.251776
2020-06-08	Shares of several retail and apparel companies...	0.001716	0.287165	0.711119
2020-06-09	Why Apple's Stock Is Trading Higher Today,Appl...	0.004181	0.138877	0.856942
2020-06-10	Shares of retail & apparel companies are tradi...	0.201864	0.701867	0.096269
2020-06-11	Johnson & Johnson To Start Coronavirus Vaccine...	0.019349	0.849489	0.131162

3957 rows × 4 columns

Figure (v) – Headline Text

	Close	Open	High	Low	Volume	headline_text	negative	neutral	positive
2009-04-27	11371.849609	11237.419922	11492.099609	11176.549805	52400.0	Update on the Luxury Sector: 2nd Quarter 2009,...	0.094900	0.870135	0.034965
2009-04-29	11403.250000	11091.559570	11430.250000	11091.559570	40400.0	Going Against the Herd	0.165430	0.805855	0.028715
2009-05-22	13887.150391	13663.540039	13936.929688	13611.299805	39400.0	Charles Sizemore Radio Interview Saturday Morning	0.017397	0.943096	0.039507
2009-05-27	14109.639648	13851.849609	14122.780273	13848.150391	47000.0	MRM a $15-$20+ stock - FIT new information - J...	0.009468	0.678259	0.312273
2009-05-29	14625.250000	14384.759766	14726.599609	14384.759766	45200.0	In $7.60 UTA - New Chinese Listing - Travel St...	0.061584	0.903710	0.034706
...	...	...	...	...	...	...	...	...	...
2020-06-05	34287.238281	34198.550781	34405.429688	33958.019531	24600.0	Stocks That Hit 52-Week Highs On Friday,Shares...	0.001390	0.120022	0.878588
2020-06-08	34370.578125	34841.171875	34927.800781	34211.828125	25700.0	Shares of several retail and apparel companies...	0.001716	0.287165	0.711119
2020-06-09	33956.691406	34520.789063	34811.289063	33881.191406	19200.0	Why Apple's Stock Is Trading Higher Today,Appl...	0.004181	0.138877	0.856942
2020-06-10	34247.050781	34029.140625	34350.171875	33949.460938	15500.0	Shares of retail & apparel companies are tradi...	0.201864	0.701867	0.096269
2020-06-11	33538.371094	34214.691406	34219.390625	33480.421875	20900.0	Johnson & Johnson To Start Coronavirus Vaccine...	0.019349	0.849489	0.131162

2684 rows × 9 columns

Figure (vi) – Combined Stock Data

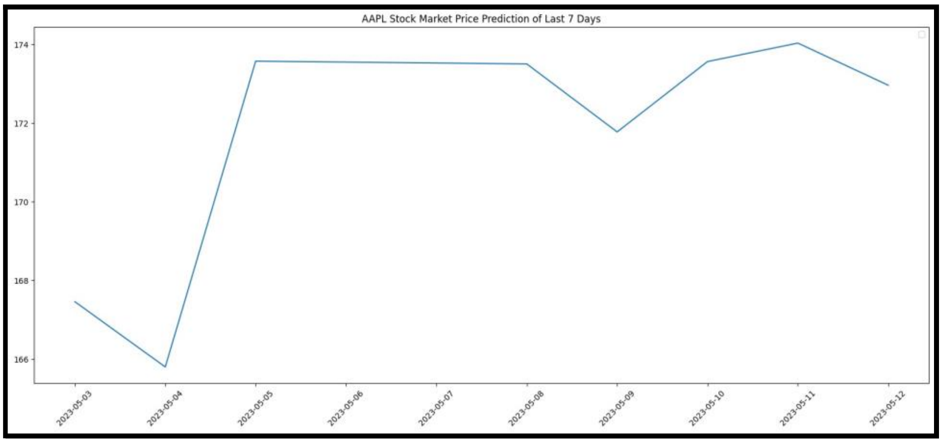

Figure (vii) – Analysis and prediction of Stock Data of Apple Inc.

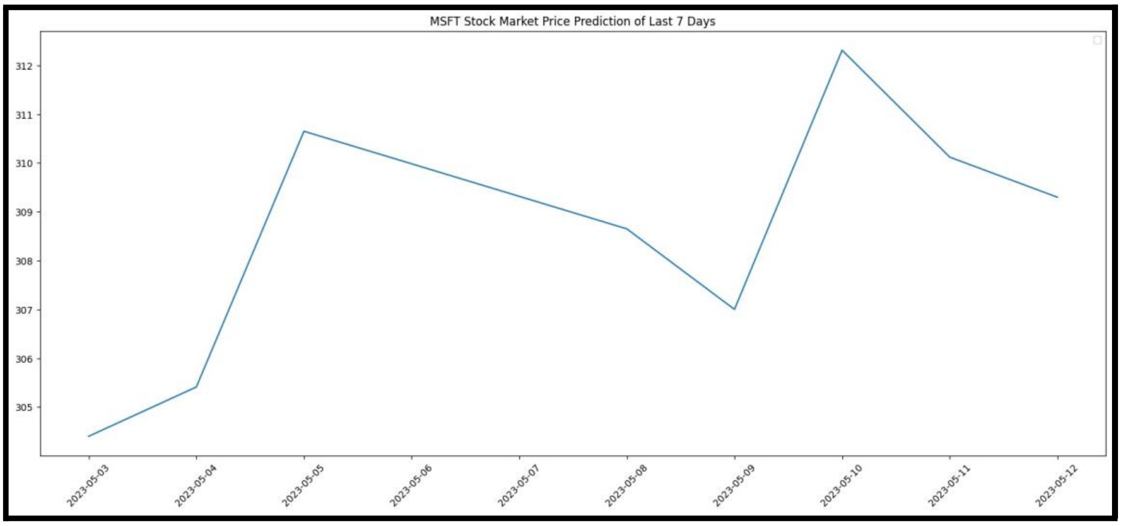

Figure (viii) – Analysis and prediction of Stock Data of Microsoft Corporation

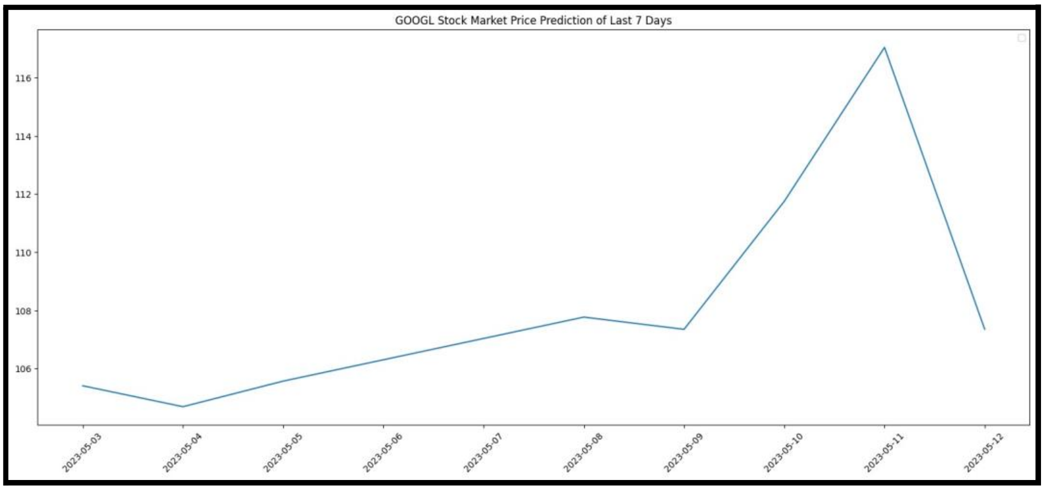

Figure (ix) – Analysis and prediction of Stock Data of Alphabet Inc.

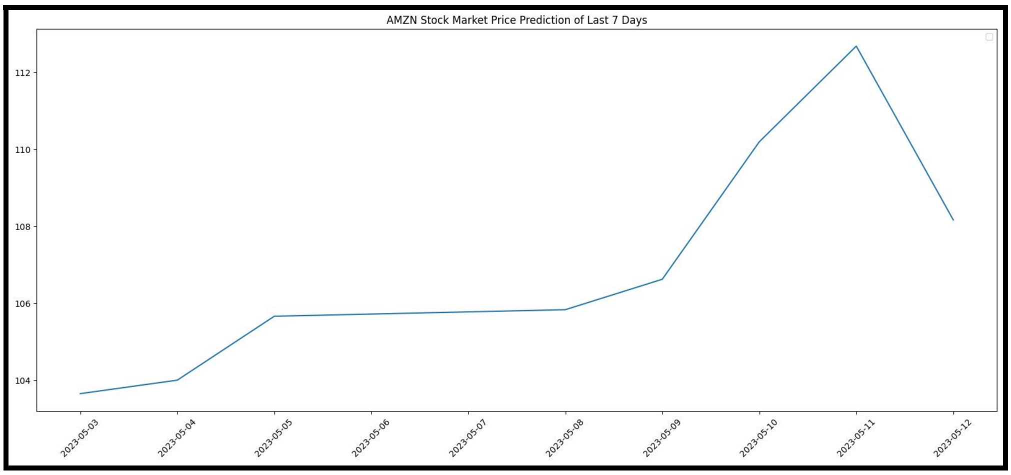

Figure (x) – Analysis and prediction of Stock Data of Amazon.com

In this study, we investigated the relationship between news articles and stock trends to predict future stock trends using sentiment analysis. By automating sentiment detection and analyzing the words in news articles, we determined the overall news polarity, which indicates the impact on stock prices. We employed a polarity detection algorithm and implemented three classification models. Our findings demonstrated that the Random Forest model performed well, achieving accuracy rates ranging from 88% to 92%. These results highlight the potential of utilizing news sentiment for predicting stock trends and offer opportunities for further research in this field.

Conclusion:

The study focused on the relationship between news articles and stock trends, aiming to predict future stock trends using sentiment analysis. By automating sentiment detection and analyzing news article content, an overall news polarity was determined, indicating the impact on stock prices. The findings highlighted the potential of utilizing news sentiment for stock trend prediction. However, the study faced limitations, such as challenges in data quality due to filtering issues and the potential distortion of unrelated news sentiment. The computation of daily sentiment was also noted as a limitation, as the approach used might temper down strong sentiments due to neutral news items. Furthermore, the choice of using Random Forest Regressor for sentiment analysis faced limitations compared to LSTM models. Future improvements could involve manual annotation and word vector techniques for data quality and exploring alternative sentiment aggregation methods. Overall, this research provides valuable insights into the predictive power of news sentiment in stock trends, but further advancements in model implementation and data processing are warranted.

References:

1. Naadun Sirimevan; I.G. U. H. Mamalgaha; Chandira Jayasekara; Y. S. Mayuran;
2. Chandimal Jayawardena (2020). Stock Market Prediction Using Machine Learning
3. Techniques in Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka. DOI: 10.1109/ICAC49085.2019.9103381
4. Sukhman Singh; Tarun Kumar Madan; Jitendra Kumar; Ashutosh Kumar Singh (2020) Stock Market Forecasting using Machine Learning: Today and Tomorrow in
5. National Institute of Technology, Kurukshetra, Haryana, India. DOI: 10.1109/ICICICT46008. 2019. 8993160
6. Ferdiansyah Ferdiansyah; Siti Hajar Othman; Raja Zahilah Raja Md Radzi; Deris Stiawan; Yoppy Sazaki; Usman Ependi(2020). A LSTM-Method for Bitcoin Price Prediction: A Case Study Yahoo Finance Stock Market in School of Computing,
7. Universiti Teknologi Malaysia, Johor Bahru, Johor, Malaysia. DOI : 10.1109/ICECOS47637.2019.8984499
8. Meghna Misra; Ajay Prakash Yadav; Harkiran Kaur (2020). Stock Market Prediction using Machine Learning Algorithms: A Classification Study in Department of Computer Science and Engineering, (Deemed to be University, Patiala). DOI: 10.1109/ICRIEECE44171.2018.9009178
9. Mojtaba Nabipour , Pooyan Nayyeri , Hamed Jabani , Shahab S., (Senior Member, Ieee), and Amir Mosavi (2020). Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; aComparative Analysis. DOI : 10.1109/ACCESS.2020.3015966
10. Kepios. [(accessed on 15 December 2022)]. Available online: https://kepios.com/
11. Comito, C., Falcone, D., & Talia, D. (2017, October). A peak detection method to uncover events from social media. In 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 459-467). IEEE.
12. Comito, C., Pizzuti, C., & Procopio, N. (2016, November). Online clustering for topic detection in social data streams. In 2016 IEEE 28th international conference on tools with artificial intelligence (ICTAI) (pp. 362-369). IEEE.
13. Khurana, D., Koli, A., Khatter, K., & Singh, S. (2023). Natural language processing: State of the art, current trends and challenges. Multimedia tools and applications, 82(3), 3713-3744.
14. Patten, T., & Jacobs, P. (1994). Natural-language processing. IEEE Expert, 9(1), 35.
15. Dai, C., Che, H., & Leung, M. F. (2021). A neurodynamic optimization approach for l 1 minimization with application to compressed image reconstruction.
16. International Journal on Artificial Intelligence Tools, 30(01), 2140007.
17. Leung, M. F., Wang, J., & Che, H. (2022). Cardinality-constrained portfolio selection via two-timescale duplex neurodynamic optimization. Neural Networks, 153, 399-410.
18. Leung, M. F., Wang, J., & Li, D. (2021). Decentralized robust portfolio optimization based on cooperative-competitive multiagent systems. IEEE Transactions on Cybernetics, 52(12), 12785-12794.

19. Chen, K., Che, H., Li, X., & Leung, M. F. (2023). Graph non-negative matrix factorization with alternative smoothed L 0 regularizations. Neural Computing and Applications, 35(14), 9995-10009.
20. Gessler, M., Nägele, C., & Stalder, B. (2021). Scoping review on research at the boundary between learning and working: A bibliometric mapping analysis of the last decade. International Journal for Research in Vocational Education and Training (IJRVET), 8(4), 170-206.
21. Wang, J., Wang, J., & Han, Q. L. (2020). Neurodynamics-based model predictive control of continuous-time under-actuated mechatronic systems. IEEE/ASME Transactions on Mechatronics, 26(1), 311-322.
22. Hinton, O. (2006). Teh, 2006 Hinton GE, Osindero S., Teh Y.-W. A fast learning algorithm for deep belief nets, Neural Computation, 18(7), 1527-1554.
23. Vateekul, P., & Koomsubha, T. (2016, July). A study of sentiment analysis using deep learning techniques on Thai Twitter data. In 2016 13th International joint conference on computer science and software engineering (JCSSE) (pp. 1-6). IEEE.
24. Cao, W., Qian, S., Wu, S., & Wong, H. S. (2019). Unsupervised multi-task learning with hierarchical data structure. Pattern Recognition, 86, 248-264.
25. Cao, W., Zhang, Z., Liu, C., Li, R., Jiao, Q., Yu, Z., & Wong, H. S. (2022). Unsupervised discriminative feature learning via finding a clustering-friendly embedding space. Pattern Recognition, 129, 108768.
26. Duan, Y., Chen, N., Bashir, A. K., Alshehri, M. D., Liu, L., Zhang, P., & Yu, K. (2022). A web knowledge-driven multimodal retrieval method in computational social systems: unsupervised and robust graph convolutional hashing. IEEE Transactions on Computational Social Systems.
27. Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1253.
28. Chakravarthi, B., Ng, S. C., Ezilarasan, M. R., & Leung, M. F. (2022). EEG-based emotion recognition using hybrid CNN and LSTM classification. Frontiers in Computational Neuroscience.
29. Halbert, J., & Kaser, L. (2006). Sustaining Deep Learning–In Inquiring Communities of Practice. Education Canada, 46(3), 43-5.
30. Suhasini, M., & Srinivasu, B. (2020). Emotion detection framework for twitter data using supervised classifiers. In Data Engineering and Communication Technology: Proceedings of 3rd ICDECT-2K19 (pp. 565-576). Springer Singapore.
31. Jayakody, J. P. U. S. D., & Kumara, B. T. G. S. (2021, December). Sentiment analysis on product reviews on twitter using Machine Learning Approaches. In 2021 International Conference on Decision Aid Sciences and Application (DASA) (pp. 1056-1061). IEEE.
32. Bello, A., Ng, S. C., & Leung, M. F. (2023). A BERT Framework to Sentiment Analysis of Tweets. Sensors, 23(1), 506.
33. Huang, H., Jing, X. Y., Wu, F., Yao, Y. F., Zhang, X. Y., & Dong, X. W. (2019, October). DCNN-Bigru text classification model based on BERT embedding. In 2019 IEEE International Conferences on Ubiquitous Computing & Communications (IUCC) and Data Science and Computational Intelligence (DSCI) and Smart Computing, Networking and Services (SmartCNS) (pp. 632-637). IEEE.
34. Ouyang, X., Zhou, P., Li, C. H., & Liu, L. (2015, October). Sentiment analysis using convolutional neural network. In 2015 IEEE international conference on computer and information technology; ubiquitous computing and communications; dependable, autonomic and secure computing; pervasive intelligence and computing (pp. 2359-2364). IEEE.