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News Based Analysis For Stock Market Trends

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Abstract : In today's fast-paced financial markets, news plays a major role in shaping stock prices and influencing investment decisions. From financial publications to social media, the constant influx of information can be overwhelming, making it difficult for investors to extract actionable insights. This research introduces a novel framework that integrates news sentiment analysis with stock market prediction, leveraging advanced natural language processing (NLP) and machine learning (ML) techniques to uncover sentiment patterns that may indicate market trends. The study examines the influence of both general financial news and company-specific news on stock prices, providing a comprehensive view of how sentiment impacts market behavior. Additionally, the framework explores the timing, frequency, and context of news events to enhance predictive accuracy. By systematically analyzing news sentiment alongside historical stock data, this research equips investors with deeper insights into market dynamics, improving decision-making and risk assessment. The proposed framework has the potential to transform traditional stock analysis by incorporating real-time sentiment-driven insights, offering a data-driven approach to navigating financial markets with greater confidence and precision.

Keywords - Sentiment analysis, Natural language processing (NLP), Machine learning (ML), Text classification

I. INTRODUCTION

The stock market is notoriously unpredictable, and investors and analysts continually strive to identify patterns that might predict price movements. Traditional stock analysis methods, such as technical and fundamental analysis, often fail to capture the rapid impact of news events [1]. In today's digital age, news spreads quickly through social media and online platforms, significantly influencing public opinion and investment decisions [2]. This research introduces a novel approach that combines sentiment analysis of news headlines with traditional stock market analysis to better understand how news events influence stock performance.

Recent studies have demonstrated the potential of sentiment analysis in predicting stock market trends. For instance, Jariwala et al. [1] compared machine learning models like Support Vector Machine (SVM) and Naïve Bayes for sentiment analysis of news headlines, finding that these models outperform traditional methods in capturing the influence of news on stock prices. Similarly, Liu et al. [2] explored deep learning models such as GRU and LSTM, highlighting their effectiveness in incorporating temporal context from news headlines for accurate market predictions. These findings underscore the importance of leveraging advanced natural language processing (NLP) and machine learning (ML) techniques to analyze news sentiment and its correlation with stock price movements.

Despite these advancements, several research gaps remain. For example, while many studies focus on sentiment analysis of news headlines, there is a need to analyze entire news articles to capture more nuanced sentiment and context [1]. Additionally, the integration of alternative data sources, such as social media and macroeconomic indicators, could enhance prediction accuracy [12]. Furthermore, the application of advanced techniques like ensemble learning, reinforcement learning, and transformer models has shown promise but requires further exploration [3], [8].

This study aims to address these gaps by developing a robust model that integrates sentiment analysis of news headlines with traditional stock analysis methods. By utilizing NLP and ML techniques, including word embeddings and real-time data integration, the research evaluates how both general financial news and company-specific news affect stock prices. As illustrated in **Fig. 1**, stock price reactions to news events can be classified into two categories:

- **Sector-wide news**, which affects multiple companies within the same sector, leading to correlated stock movements.
- **Company-specific news**, which impacts only an individual stock while the broader sector remains unaffected.



Figure 1 Stocks following its sector

Understanding this distinction is crucial for improving sentiment-based stock prediction models. The primary objectives of this research include:

- Investigating the correlation between news sentiment and stock price movements, with a focus on both general (sector-wide) and company-specific news.
- Enhancing sentiment analysis accuracy through advanced NLP techniques and real-time data integration.
- Exploring the potential of ensemble models and alternative data sources to improve prediction accuracy.

The scope of this project involves creating a comprehensive framework for news-driven stock sentiment analysis, enabling predictive capabilities for stock price trends and providing actionable insights for investors. By addressing the limitations of existing methods and incorporating insights from recent studies, this research aims to equip investors with more effective tools for analyzing the impact of news on the stock market and making informed investment decisions.

II. RELATED WORKS

The relationship between news headlines and stock market movements has been widely explored in sentiment analysis studies. Various approaches, including traditional machine learning models, deep learning techniques, and hybrid models, have been investigated for their ability to predict stock market trends using financial news. These studies highlight the influence of sentiment in news articles and demonstrate how different methodologies can enhance predictive accuracy.

Jariwala et al. (2020) conducted sentiment analysis on stock market-related news headlines, comparing models like K-Means clustering, Naïve Bayes, and Support Vector Machine (SVM). Their results showed that supervised models, particularly Naïve Bayes, outperformed K-Means clustering. The study emphasized the importance of sentiment analysis in stock price prediction, suggesting that future research could explore analyzing entire news articles for more nuanced insights, as well as the application of advanced machine learning techniques [1]. Similarly, Liu et al. (2020) explored deep learning models such as CNN, LSTM, and GRU, using news headlines to forecast stock market trends, particularly during the COVID-19 pandemic. They found that GRU performed best, demonstrating the importance of incorporating temporal context from news for accurate market predictions. The study proposed future improvements by incorporating deep transformer models and advanced word embeddings to refine prediction accuracy [2].

In a similar vein, Li and Pan (2021) introduced an ensemble deep learning model combining multiple recurrent neural networks (RNNs) like LSTM and GRU for stock price prediction, achieving notable improvements over traditional methods. They suggested that future work could focus on hyperparameter tuning, incorporating reinforcement learning models, and expanding the dataset to include diverse financial data [3]. Furthermore, Nemes and Kiss (2021) employed sentiment analysis using algorithms like TextBlob, NLTK-Vader, and RNN to correlate economic news headlines with stock market fluctuations. Their study revealed the importance of selecting the right algorithm, with RNN showing more significant influence on volume values. They also highlighted the potential of developing user-friendly platforms that integrate advanced sentiment analysis algorithms [4].

Gu et al. (2021) investigated the use of the Investor Sentiment Index (SI) in stock return forecasting, comparing traditional GARCH models with LSTM-based models, including LSTM-SI. Their findings indicated that LSTM models, particularly LSTM-CSI, outperformed traditional approaches, offering valuable insights into improving sentiment analysis techniques. Future work was recommended to refine sentiment analysis and incorporate macroeconomic factors to enhance prediction accuracy [5]. Similarly, Zhang and Cai (2021) proposed an N-CNN model for stock price forecasting, addressing challenges related to limited sample sizes by aggregating financial news from multiple sources. The N-CNN model achieved a remarkable accuracy rate, and the authors suggested future research to refine the model by standardizing news headline time formats and considering stock sensitivity to news [6].

Kamal et al. (2022) explored the impact of sentiment analysis on stock market values by analyzing financial news using deep learning models such as CNN, LSTM, and BERT. Their study revealed that BERT and RoBERTa models achieved exceptional accuracy, reinforcing the significance of sentiment analysis in stock market prediction. They emphasized future research in enhancing word embedding methods and exploring reinforcement learning algorithms to improve forecasting capabilities [8]. Similarly, Sharma and Bhalla (2022) proposed a hybrid machine learning model (DSM) based on SVM and Decision Trees for stock price forecasting using financial news headlines. The model outperformed other sentiment analysis techniques, including BERT and TextBlob, demonstrating the potential of hybrid approaches for improving stock market prediction accuracy [9].

Marshan et al. (2023) delved into the correlation between sentiments extracted from news articles and stock market movements, employing ARIMA models for time series forecasting. Despite identifying a weak correlation between sentiment and stock prices, their study demonstrated the potential utility of sentiment analysis models for traders. They proposed future directions such as analyzing time lags between news release and market response and incorporating additional data sources like social media and financial reports to improve model predictions [10]. Biswas et al. (2023) provided a comprehensive study on stock market prediction through sentiment analysis, underscoring the challenges and opportunities in leveraging news sentiment for market forecasts [11].

These studies collectively underscore the importance of sentiment analysis in stock market prediction. While deep learning models like LSTM, GRU, and CNN have shown promising results, the integration of advanced techniques such as transformers, reinforcement learning, and hybrid models remains a significant area for further research. Furthermore, refining data preprocessing methods and incorporating diverse data sources are essential for improving prediction accuracy and making models more robust to market dynamics.

2.1 RESEARCH GAPS IDENTIFIED

While these studies collectively underscore the importance of sentiment analysis in stock market prediction, several research gaps remain:

- **Analysis of Entire Articles:** Existing studies primarily focus on news headlines. Incorporating entire articles could enhance model performance by capturing contextual details and deeper sentiment nuances [1].
- **Improved Word Embeddings:** Utilizing advanced word embedding methods such as Word2Vec and BERT can better address word order issues and improve sentiment classification accuracy [8].
- **Integration of Real-Time Data:** Incorporating real-time news and market data could enhance the predictive power of models, allowing for more dynamic and responsive forecasts [10].
- **Prediction of Sentiment Strength Levels:** Developing models that predict sentiment intensity could improve stock trend forecasting [9].
- **Handling Numerical Data More Effectively:** Many sentiment analysis models struggle with incorporating numerical and financial indicators. Integrating structured financial data with sentiment analysis could lead to more robust market predictions [5].

Addressing these gaps could lead to more comprehensive and accurate stock prediction models, ultimately benefiting traders and investors by providing more reliable market insights.

III. METHODOLOGY

This study proposes a robust framework for stock sentiment analysis, leveraging advanced Natural Language Processing (NLP) techniques and deep learning models to predict stock price movements based on news headlines. The approach integrates financial data from multiple sources, including stock price datasets and news articles, with feature engineering and sentiment analysis to provide valuable insights into the stock market. The system's primary objective is to enhance decision-making by combining sentiment-driven news analysis with historical stock data, using machine learning models such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost).

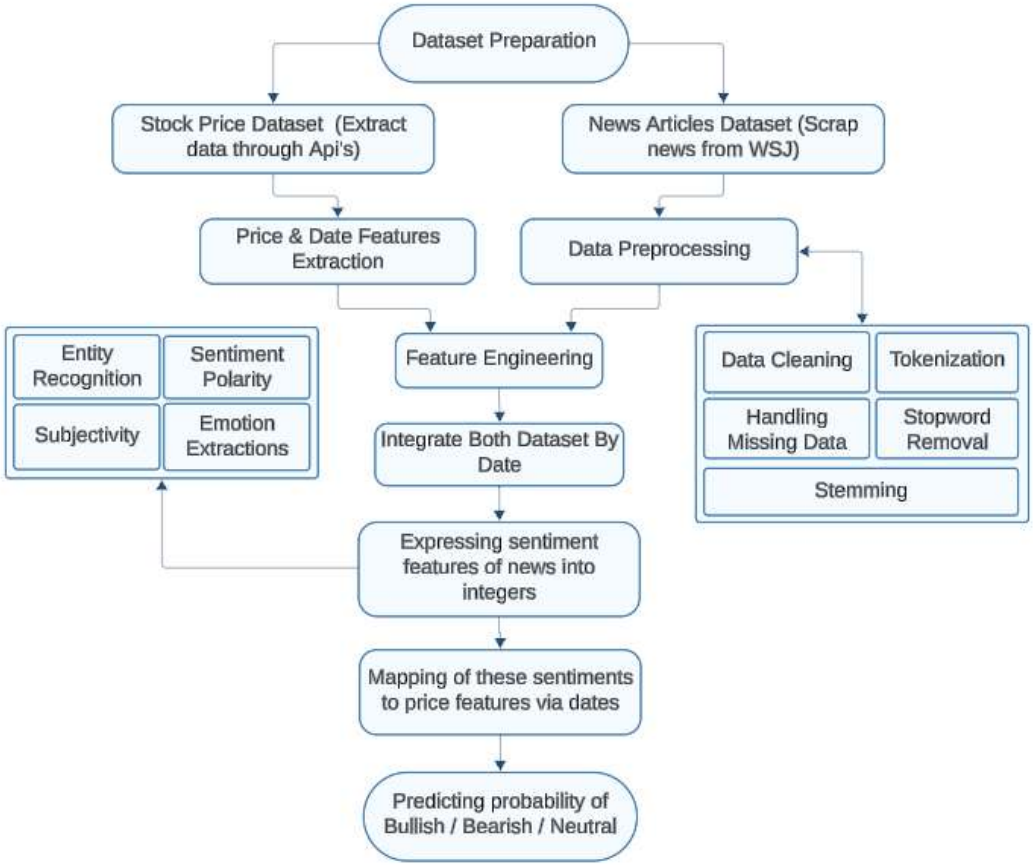


Fig.2. Proposed system architecture

3.1 DATA COLLECTION

The first step of the proposed methodology involves collecting two crucial datasets for predicting stock price movements: Stock Price Dataset and News Articles Dataset.

1. ***Stock Price Dataset***

Sourced from RapidAPI, this dataset includes 12,500 records spanning the past 10 years, covering five major companies: Google, Microsoft, Amazon, Tesla, and Apple. Each record contains 25 key variables, including the trading date, stock symbol, opening price, closing price, highest and lowest prices of the day, and trade volume. This data allows for comprehensive analysis of financial behavior and market trends.

Table.1. Outlines the attributes of the stock market indices:

Attributes	Details
Date	The specific date on which the stock was traded.
Open	The initial price of the stock when the market opened.
Close	The final price of the stock when the market closed.
High	The maximum price the stock reached during the trading session.
Low	The minimum price the stock fell to during the trading session.
Volume	The total number of shares exchanged during the day.
Name	The name of the stock or the company being traded.

2. ***News Articles Dataset***

The second component of data collection is a dual-source news dataset. The Wall Street Journal (WSJ) dataset, collected through WebHarvy, contains headlines and abstracts from news articles related to Google, Microsoft, Amazon, Tesla, and Apple over the past seven years. The New York Times (NYT) dataset includes 2.1 million articles published from 2000 to the present, covering a wide range of financial news. These datasets help examine the influence of both company-specific and general news on stock performance.

Table.2. Summarizes the attributes of the news dataset

Attributes	Details
Date	The publication date of the news article.
Headline	The main title summarizes the news story.
Abstract	A brief summary providing key details of the news article.
Division	The section or category of the news (e.g., business, technology).

Table.3. Provides specifications of the datasets

Dataset	Source	Dimensions	Period
Stock	Google Finance	12500 x 25	10 Years
NYT Articles (General)	NYT	2.1M x 20	24 Years
WSJ Stock Sentiment News (Relevant)	WSJ	26000 x 4	7 Years

3.2 DATA PREPROCESSING

Data preprocessing involves several critical steps to ensure the data is ready for analysis and machine learning. For text preprocessing, the first step is data cleaning, which removes unwanted characters such as special symbols, punctuation, and irrelevant text. Next, handling missing data addresses any null values in the dataset, either by filling them with appropriate values or removing the corresponding records. Tokenization follows, splitting the text into individual words or tokens, which allows the text to be analyzed at a granular level. Stopword removal eliminates common, non-informative words such as "the," "is," or "and," which do not contribute to the sentiment or meaning of the text. Lastly, lemmatization is applied to reduce words to their root form, ensuring consistency by transforming variations of words (e.g., "running" to "run"). These preprocessing steps ensure that the text data is clean, structured, and ready for sentiment analysis and further machine learning tasks. Fig. 3 and Fig. 4 compare the distribution of positive and negative words in the General News Dataset and the Relevant News Dataset. In the General News Dataset, which has an average

word count of 355.37 per article, each abstract contains approximately 16.92 positive words and 12.52 negative words. This indicates a relatively balanced sentiment, with a slight inclination towards positive words. In contrast, the Relevant News Dataset, which consists of stock-specific news articles with an average of 24.04 words per article, contains 1.21 positive words and 0.86 negative words per abstract.

The significantly lower word count in relevant news articles suggests a more concise and focused reporting style, likely tailored for quick financial insights. The comparison between the two datasets highlights key differences in sentiment distribution and article structure. The General News Dataset contains a more extensive vocabulary, which may capture broader economic sentiments but could introduce noise when analyzing stock-specific sentiment. On the other hand, the Relevant News Dataset has fewer sentiment words, but they may carry stronger, more direct implications for stock movements.

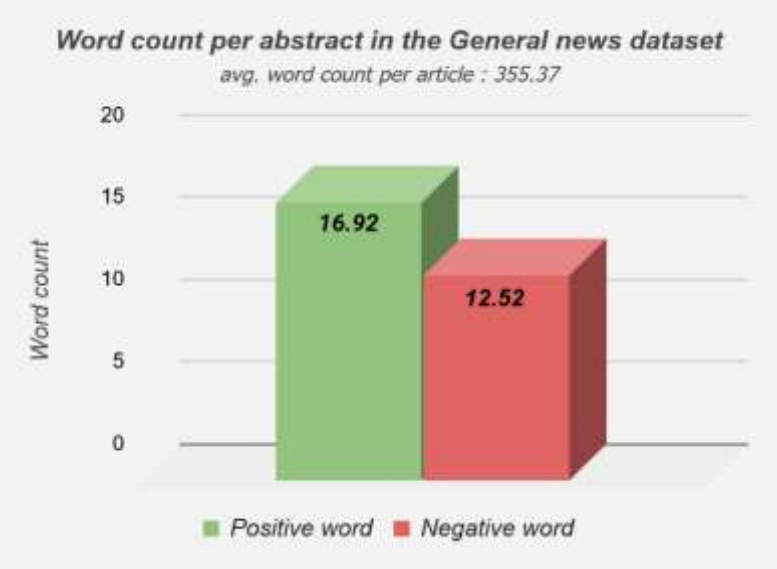


Fig.3. Word count NYT Article

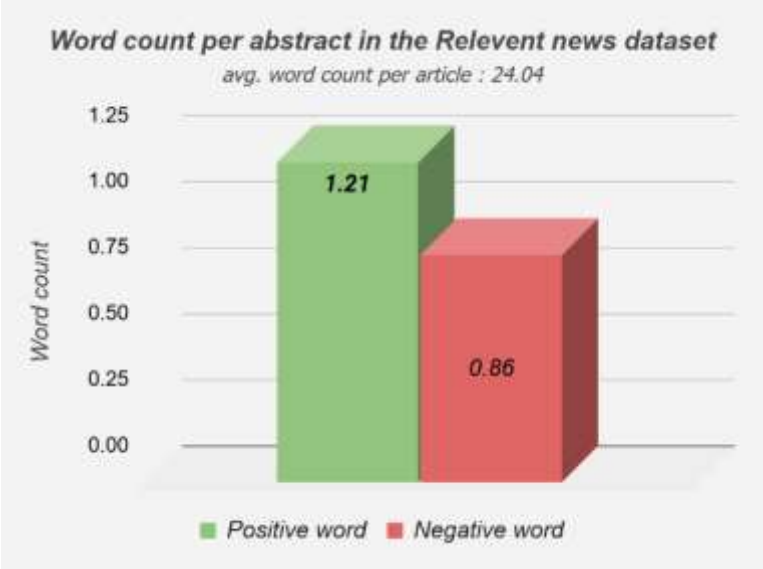


Fig.4. Word count WSJ Stock Sentiment News Dataset

3.3 FEATURE ENGINEERING

Feature engineering is a critical component of the project, as it involves extracting essential characteristics from both the stock price and news article datasets to enhance predictive capabilities. For the Stock Price Dataset, several key features are identified. The closing price movement serves as a primary indicator, showing whether the stock's closing price is higher than its opening price. Additionally, trading volume reflects the total number of shares traded during a given session, providing insight into market activity. The percent change in closing price measures the daily percentage difference in closing prices compared to the previous day, while the percent change in trading volume captures the daily percentage variation in trading activity, which can indicate market interest or sentiment. In terms of the News Articles Dataset, various Natural Language Processing (NLP) techniques are employed for sentiment feature extraction. Entity recognition is utilized to identify relevant entities such as companies or individuals mentioned in the headlines, helping to contextualize the news in relation to specific stocks. The VADER (Valence Aware Dictionary and sEntiment Reasoner) technique is applied for sentiment polarity, allowing for a nuanced classification of the expressed sentiment as positive, negative, or neutral. VADER is particularly effective for analyzing social media and news text due to its ability to consider the context of words and their sentiments, making it ideal for understanding how news sentiment may influence stock prices. Furthermore, the NRC Lexicon is employed for emotion extraction, identifying specific emotions such as joy, anger, or fear conveyed in the news articles. This lexicon allows for a deeper understanding of the emotional context surrounding news events, which can significantly impact market sentiment and investor behavior. Additionally, TextBlob is used to assess the subjectivity of the text, classifying it as either factual or opinion-based. This differentiation is crucial, as factual news may have a more stable impact on stock prices, whereas

opinion-based articles can introduce volatility and uncertainty. By effectively utilizing these techniques in feature engineering, the project aims to establish a comprehensive understanding of how stock price movements and news sentiment interact to influence market trends. This, in turn, enhances the tools available for informed investment decision-making.

3.4 INTEGRATION OF BOTH DATASETS

After extracting features from the stock price data and news articles, the integration process maps sentiment features from the news to stock price data based on the date. This alignment allows for a direct connection between sentiment analysis and stock price fluctuations. Additionally, the integration addresses potential time lags and correlations, acknowledging that market reactions to news may not always be immediate.

3.5 MACHINE LEARNING MODELS

After integrating the datasets, the next step is to train models to predict stock price movements using features extracted from both the general and relevant datasets. Advanced machine learning techniques, such as Random Forest and XGBoost, are employed to analyze the relationship between news sentiment and stock prices. The models are trained on historical data, utilizing features like sentiment polarity, trading volume, and price changes. Through iterative training, the models are fine-tuned to enhance their accuracy and predictive capabilities. Ultimately, the goal is to create robust models that provide actionable insights for investors based on the combined influence of news sentiment and stock performance.

1. ***Random Forest***

   Random Forest is an ensemble learning method that constructs multiple decision trees during training and merges their outputs to improve prediction accuracy. This technique is particularly useful in this project because it effectively handles large datasets and can manage both numerical and categorical variables, making it ideal for integrating diverse features such as sentiment polarity, trading volume, and stock prices. Additionally, Random Forest is robust against overfitting, which is crucial given the complex nature of financial data that can be influenced by numerous factors.

2. ***XGBoost***

   XGBoost (Extreme Gradient Boosting) is another powerful ensemble algorithm that uses a gradient boosting framework. XGBoost is favored in this project for its high performance and efficiency in handling large datasets. It optimizes the loss function by focusing on the mistakes made by previous models, leading to a faster convergence and improved accuracy in predictions. Its ability to incorporate regularization helps prevent overfitting, which is essential in financial applications where the model needs to generalize well to unseen data.

3.6 EXPERIMENTAL STUDIES

To evaluate the efficacy of our stock sentiment analysis framework, we conducted experiments focusing on Nvidia's news data for the month of August 2024. The aim was to assess the correlation between news sentiment and stock market movements, using our model to predict stock performance based on real-world news headlines.

The dataset used for this experiment was curated from various financial news sources, focusing on Nvidia-related headlines published during August 2024. For each article, the sentiment score, true label (actual market movement), and predicted label (model's output) were recorded. The model's performance was evaluated by comparing the predicted labels with the true labels, calculating the accuracy, and analyzing cases where discrepancies occurred. The experiment yielded promising results, achieving an overall accuracy of 80% in predicting stock movements based on news sentiment.

The model demonstrated notable success in predicting stock movements based on the sentiment of news articles. For example, it accurately identified downward trends in Nvidia's stock performance following news of challenges like production delays and geopolitical issues. However, the model faced difficulties in cases involving nuanced or mixed sentiments. Articles that combined optimism, such as Nvidia's stock surge due to AI demand, with cautionary tones were often misclassified, underscoring the challenge of interpreting complex narratives.

Table. 4 Experiment Results

Article	Date	True Label	Predicted Label
Intel Will Cut Over 15,000 Jobs Amid Struggles to Turn Itself Around	Aug 1, 2024	Down	Down
The chips are an American innovation powering self-driving cars, chatbots and medical research.	Aug 4, 2024	Up	Up
Nvidia's second-quarter revenue saw a notable rise amidst high investor expectations.	Aug 27, 2024	Up	Down

These results showcase the framework's practical potential in real-world financial scenarios. With an accuracy rate of 80%, the model can provide valuable insights for investors and analysts by identifying sentiment-driven market trends. This tool can support informed trading decisions, enhance algorithmic trading strategies by integrating sentiment analysis, and serve as a decision-support system for financial advisors, contributing to more effective and data-driven decision-making processes.

IV. RESULTS

The training accuracy results for the Random Forest (RF) and XGBoost models are illustrated in Figures 5 and 6, showcasing the performance across two distinct datasets: the general dataset sourced from Kaggle (New York Times) and the relevant dataset obtained through web scraping.

In the **NYT Articles** XGBoost demonstrates superior performance compared to Random Forest, achieving an accuracy of **73.21%** for predicting when the closing price will rise, compared to **65.7%** for Random Forest. For the prediction of trade movements, Random Forest achieves **62.66%**, while XGBoost stands at **65.56%**. These results indicate that both models perform

reasonably well, but XGBoost consistently outperforms Random Forest in both tasks, highlighting its effectiveness in handling the complexities of stock price movements influenced by news sent.

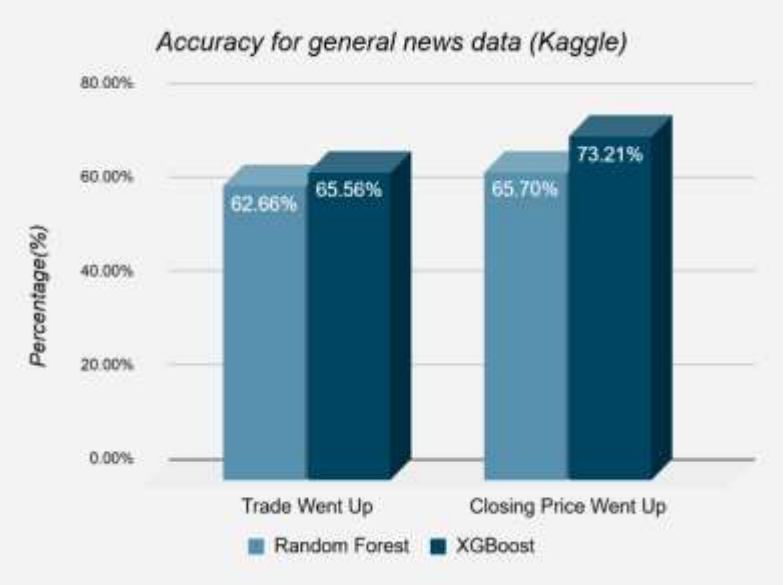


Fig.5. Accuracy for NYT Articles

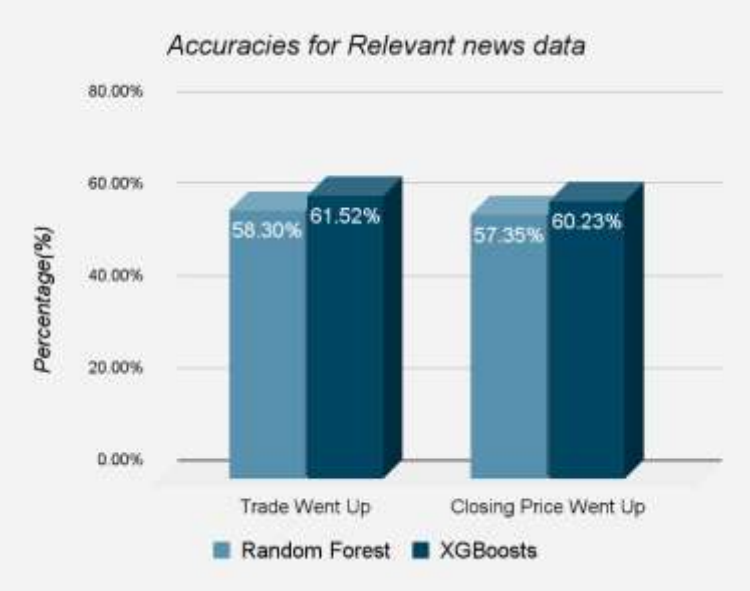


Fig.6. Accuracy for WSJ Stock Sentiment News

Conversely, in the **WSJ Stock Sentiment News Dataset**, the performance of both models is comparatively lower. Random Forest achieves an accuracy of **61.52%** for predicting trade movements and **57.35%** for closing price movements. In contrast, XGBoost achieves **60.23%** for closing prices and **58.3%** for trade movements. While the differences in accuracy between the two models are not as pronounced in this dataset, XGBoost still maintains a slight edge over Random Forest, underscoring its resilience across different datasets.

The performance metrics for predicting closing prices using both Random Forest (RF) and XGBoost (XGB) algorithms are presented in the table 5, outlining key evaluation criteria such as accuracy, precision, recall, and F1 score across two datasets: the scraped dataset and the Kaggle dataset.

Table.5. Performance Metrics (Close Went Up)

Dataset	Algorithm	Accuracy	Precision	Recall	F1 Score
Scraped	RF	57.35%	0.56	0.86	0.68
Scraped	XGB	60.23%	0.59	0.75	0.66
Kaggle	RF	65.70%	0.62	0.89	0.73
Kaggle	XGB	73.21%	0.71	0.81	0.76

Table.6. Performance Metrics (Trade Went Up)

Dataset	Algorithm	Accuracy	Precision	Recall	F1 Score

Scraped	RF	58.03%	0.59	0.52	0.55
Scraped	XGB	61.52%	0.63	0.57	0.60
Kaggle	RF	62.66%	0.66	0.38	0.49
Kaggle	XGB	65.66%	0.64	0.58	0.61

The charts (Figures 7, 8, 9 and 10) provide a detailed and comprehensive comparative analysis of the performance of the Random Forest and XGBoost models across two distinct datasets: the General Dataset and the Relevant Dataset. These charts focus on evaluating the models' ability to predict two crucial stock behaviors, which are essential for understanding market dynamics. The first behavior is predicting whether the closing price of a stock increased, which is a key indicator of the stock's performance. The second behavior is identifying changes in trade volume, which is an important signal of market activity and investor sentiment.



Fig.7. Accuracy Measure (Close & Trade)



Fig.8. Precision Measure (Close & Trade)



Fig.9. Recall Measure (Close & Trade)



Fig.10. F1 Score Measure (Close & Trade)

V. CONCLUSION

This research presents a framework for integrating sentiment analysis from news headlines into traditional stock analysis methods. By utilizing two key datasets—the stock price dataset from RapidAPI and news articles from the Wall Street Journal and The New York Times—we investigated the relationship between news sentiment and stock price movements. Our findings demonstrate that sentiment analysis significantly enhances stock price prediction accuracy, with XGBoost outperforming Random Forest in various evaluation metrics. The study highlights the importance of feature engineering, where we extracted essential features to establish meaningful correlations and accounted for time lags in market reactions. In conclusion, this research underscores the significance of real-time news sentiment in stock market forecasting and risk assessment. Incorporating sentiment analysis into financial forecasting can lead to more informed investment decisions. Future work may expand this framework to include a wider range of financial instruments and news sources, further improving predictive capabilities in stock analysis. Additionally, refining feature extraction methods and incorporating real-time news analysis could enhance the effectiveness of sentiment-based stock predictions, offering valuable insights for investors, analysts, and financial institutions seeking a data-driven approach to market analysis.

V. FUTURE SCOPE

The dataset can be expanded to include inputs like social media sentiment and economic indicators, enhancing predictive accuracy by capturing diverse dimensions of market sentiment. Additionally, employing advanced architectures such as transformers or RNNs will improve the model's ability to interpret sentiment by better capturing contextual nuances in language. A real-time system that continuously processes news articles and stock data can provide timely insights, helping investors react promptly to market movements.

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