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Stock Market Predictions Using Sentiment Analysis

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Abstract- ***The prediction of stock prices is one of the significant areas of financial research which is mainly based on classical methodologies such as Technical Analysis and Fundamental Analysis . On the other hand, because of the increased use of the internet and the development of Social Media as a tool for communication, the new method of calculating investor sentiment regarding stocks has also emerged. This is known as "Sentiment Analysis." The method of calculating investor sentiment or stock sentiment, as it is referred to, combines both Natural Language Processing (NLP) and Machine Learning (ML) to collect data from social media, news articles or company earnings announcements, to calculate market sentiment about an individual company's stock price. The methodology for using Sentiment Analysis in this research includes the use of a Lexicon Baseline, Machine Learning Classifiers, and Deep Learning, including LSTM, BERT and FinBERT. The research assesses the capability of each methodology to predict stock prices based on the results of the sentiment scores combined with historical stock prices. The research indicates that deep learning methods are much better than traditional machine learning techniques with respect to predicting the movement of stocks based on sentiment. The top-performing model was FinBERT, which outperformed all other models in terms of accuracy predicting the sentiment of stock prices. The results also demonstrate that investment strategies that are based on sentiment produced superior returns and had significantly less volatility compared to traditional investment strategies that did not utilize sentiment. However, even with these promising results, sentiment analysis has many challenges, including data bias, the use of sarcasm, and venture capitalists' irrational behavior in the market. Future research can build on this work by creating tools that enable the real-time assessment of sentiment as well as hybrid models that integrate sentiment with macroeconomic indicators. Sentiment analysis, therefore, provides added value to investors by enhancing the accuracy of investment predictions.***

Key Words: Stock Market prediction, Sentiment Analysis, Machine Learning, News Analytics, Text Mining, Algorithmic Trading, Machine Learning.

I. INTRODUCTION

What is Stock Market Prediction?

Predicting the stock market involves predicting what will happen to a company's stock or any financial instrument that is being used or traded on an exchange. Investors, analysts, and institutions use several different ways of predicting these future trends, such as technical analysis, fundamental analysis, quantitative models, and now AI systems will also be used to make predictions on future trends in the stock market, as being able to accurately predict trends is a valuable asset when it comes to making sound investment decisions.

The stock market is influenced by several factors, including:

- Economic indicators (GDP, inflation, interest rates)
- Company performance (earnings, leadership, innovation)
- Market sentiment (public mood, news, global events)
- Geopolitical and environmental events

When predicting stock market trends, the main objective is to find opportunities for lucrative investments while minimizing the risk associated with investing. Although it is not possible to achieve complete accuracy when predicting stock market trends because of the unpredictable and erratic behaviour of the stock market, with the development of new prediction models, analysts will be able to develop informed estimates based on data patterns. In the past, investors used only personal experience and knowledge, but now technology allows for the creation of predictive models that can analyze massive quantities of historical data to identify patterns and

trends that are beyond what a person could recognise with limited visibility of the historical data.

What is Sentiment Analysis?
Sentiment analysis, also called opinion mining, is the process of using natural language processing techniques to identify how an individual feels about something based on a body of text. It is used in customer feedback, social media monitoring, and increasingly, financial analytics. For example, when applying sentiment analysis to the stock market, the goal is to capture investor sentiment towards individual companies, their sectors and/or the broader market. This is accomplished by analyzing content from tweets, articles, earnings reports and online message boards to extract opinion and sentiment about the stocks being evaluated.

be categorized as:
- Positive (e.g., "Company X sees record profits")
- Negative (e.g., "Company Y suffers legal setbacks")
- Neutral (e.g., "Company Z to announce quarterly results next week")

Techniques used:
- Lexicon-based approaches (predefined lists of positive/negative words)
- Machine learning models (trained on labeled data)
- Deep learning and transformers (like BERT, GPT) for contextual understanding.

Sentiment analysis helps in understanding investor behavior, identifying market mood, and anticipating short-term price movements, especially in reaction to news or events.

II. REVIEW OF LITERATURE

Introduction to Literature Review
Sentiment analysis applied within the realm of financial forecasting has become an area of significant interest for academia and practitioners during the past two decades. Numerous studies have shown that public sentiment (collected from sources such as articles, social media sites like Twitter, forum postings and press releases) has a statistically significant impact on both overall market volatility as well as daily stock returns and how investors react to them.

This literature review covers 13 key research papers and case studies that examine:

- The predictive power of social media
- News sentiment impact on market indices
- Deep learning models in sentiment classification
- Country-specific events and market reactions

Studies on Twitter and News Impact on Stock Markets

Study 1: Bollen et al. (2011) – "Twitter mood predicts the stock market"

Through their study in 2011, Bollen, Mao, and Zeng highlighted how public mood via Twitter correlates with stock market performance, specifically looking at the Dow Jones Index (DJIA). Using millions of tweets collected daily, they determined the relationship between mood and stock performance by employing numerous types of sentiment analysis software, such as OpinionFinder and GPOMS (Google-Profile of Mood States) analyzing Calming, Happiness, and Alertness of people's moods. Furthermore, they found that being Calm and Happy correlated with increased daily gain/loss of the Dow Jones Index. The team also employed a variety of statistical methods, such as Granger causality and some more sophisticated machine learning algorithms to predict that including Twitter's mood for the day improved results for predicting stock performance by over six percent from traditional models that did not look at Twitter. Finally, this research emphasized the importance of including real-time data from Social Media regarding consumer's emotional states (emotional intelligence) to aid predicting financial markets in the future and further indicated the need for the increased use of behavioral finance (which seeks to find the reasons why people make certain decisions regarding their money) and the application of Big Data analytics tools to be applied when forecasting the future movements of Financial Markets.

- Analyzed 9 million tweets.
- Used two different tools for measuring moods: GPOMS & OpinionFinder.

- Calm and happy public moods have been shown to give a predictive capability of 87% for the direction of the Dow Jones Industrial Average (DJIA).
- Conclusion is public mood is a leading indicator for market activity.

Study 2: Mittal & Goel (2012) – "Stock prediction using Twitter sentiment analysis"

The focus of the 2012 article "Stock Prediction Using Twitter Sentiment Analysis: 2012" by Mittal and Goel was to show the relationship that has been established between the Twitter public mood and the movement of the stock market in prior research. They collected a large dataset containing tweets sent from June to December of 2009, which they used to perform sentiment analysis on to identify the public mood. This public mood, combined with the Bendition the DJIA for the previous day, was then used to make predictions about future direction trends in the stock market. Using machine learning techniques, specifically using SOFNN (Self-Organizing Fuzzy

Neural Networks), they predicted the daily trends of the DJIA with an accuracy of about 75.56%. They also developed portfolio management strategies based on these predictions, providing a basis for actual investment applications. Unlike past studies in this area, Mittal and Goel's research included a newly proposed way to validate their results through a cross-validation method specifically designed for financial data, which allowed them to determine the reliability of their results. Furthermore, their research used evidence to show that the Twitter sentiment has substantial predictive capabilities for stock market trends and that Twitter sentiment provides a solid basis for predicting stock movements over time.

- Used Naive Bayes and SVM classifiers on financial tweets.
- Results showed correlation between tweet sentiment and daily stock movements.
- Introduced the concept of microblogging signals as trading indicators.

III. RESEARCH GAPS

The phrase "identified gaps in currently existing research" indicates that the body of literature to date has some missing pieces or holes. The financial sentiment analysis body of literature is incomplete because the data quality is poor and financial terminologies can often confuse researchers. There are also model-related limitations, challenges to accurately predict fluctuations in stock price, and barriers related to merging sentiments with traditional financial data sources. These identified gaps will help direct the development of methods and results in the future and the continuing development of the discipline of Financial Sentiment Analysis.

Identified gaps in existing financial sentiment analysis research include several key challenges:

1. Data Quality and Availability: A lot of research use social media and news for data collection but face challenges with collecting quality data such as unreliable (noisy/incomplete) or biased from social media and news sources; making it difficult for researchers to assess reliability of sentiment signals.
2. Financial Language Complexity: Financial text use a lot of jargon, sarcasm, nuanced language and implicit assumptions, which makes it difficult for most general sentiment models to accurately interpret, leading to limited model reliability.

3. Limitations of the Current Models and How They Can Be Applied: Current methods of predicting stock returns using sentiment analysis are limited by overfitting, and by their inability to generalize across stock categories. Market conditions change regularly, so models continually need to be updated.

4. The Difficulty of Predicting Short-Term Stock Returns: Despite advances in technology, accurate predictions of short-term stock returns based on investor sentiment are still not easy, and the evidence supporting the market's efficiency limits the ability of sentiment to predict returns for short-term periods.
5. Integration with Quantitative Data: Combining qualitative sentiment data with traditional

quantitative financial metrics remains complex, requiring advanced analytics and domain expertise to improve forecasting accuracy.

6. Data Integrity and Ethics: Misinformation or organized activities can alter the sentiment of social media, leading to serious ethical and data issues. - Understanding and Explainability: Existing models focused on the relationship between social media sentiment and market movements often fail to take into account the intent and context behind sentiment, thus limiting the accuracy of predictions and usefulness.

IV. RESEARCH OBJECTIVES

The key objectives of this study are:

- To offer new ways to improve the methods used to perform Financial Sentiment Analysis (FSA) to continue to gain accuracy in how you extract sentiment from spoken or written Financial information, including words, images and sounds, through mediums such as News, Social Media and Financial Statements.
- To further research the prospective uses of using Financial Sentiment data to predict Movement Patterns associated with Stocks (Price, Volatility and Trends), providing responsible and sound Financial Decision Support.
- Combine qualitative indicators of sentiment with quantitative indicators of financial market behavior to develop better forecasting models by combining qualitative indicators of sentiment with quantitative indicators of financial market behavior.
- Develop the infrastructure and platforms to support the real-time analysis of sentiment through the use of real-time streaming feeds from social media sites such as Twitter and Reddit as well as news media, allowing traders to have the most current information and analytics available for fast-paced trading situations..
- Like Deep Learning and Attention Mechanisms :Improve Financial Language Comprehension by Utilizing Advanced NLP Tools and Develop a more accurate means of interpreting complex financial language (i.e., "jargon" or "arcane language") through advanced NLP techniques, such as Deep Learning, Attention Mechanisms, and Domain-Specific Models, such as FinBERT.
- Expand Research on Financial Sentiment in Emerging Markets: Continue to study the role and effect of financial sentiment in emerging, undeveloped areas like India, where the effects of social media on financial decision-making and the asymmetry of information between the able and the unable to make informed decisions are significant.

V. HYPOTHESIS

This research suggests that financial feelings found through news, social networks, and financial announcement information have an impact on stock price fluctuations and will enhance the ability to forecast these movements within the financial environment.

More specifically:

- Positive financial sentiment triggers short-term increases in stock price, whereas negative financial sentiment creates a longer-lasting negative impact.
- Using advanced models for financial sentiment analysis (e.g., FinBERT) in combination with new temporal models for predicting stock prices (e.g., LSTM) will be more successful than using traditional forecasting techniques (e.g., ARIMA).
- Real-time data from social media and the financial press contain rich insights that improve the accuracy of predicting future stock prices; thus, they extend beyond the insights that could be derived from historical data alone.
- The combination of subjective opinions from financial texts or news articles and objective news allows investors to develop investor sentiment, thereby providing a basis for predicting overall market dynamics.
- Using domain-specific language models that have been pre-trained using financial data will allow for improved detection and interpretation of subtle sentiment nuances, resulting in higher predictive capability. These hypotheses guide the study's investigation into the role of financial sentiment in stock market prediction and the development of

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integrated AI models that combine sentiment analysis with quantitative market data.

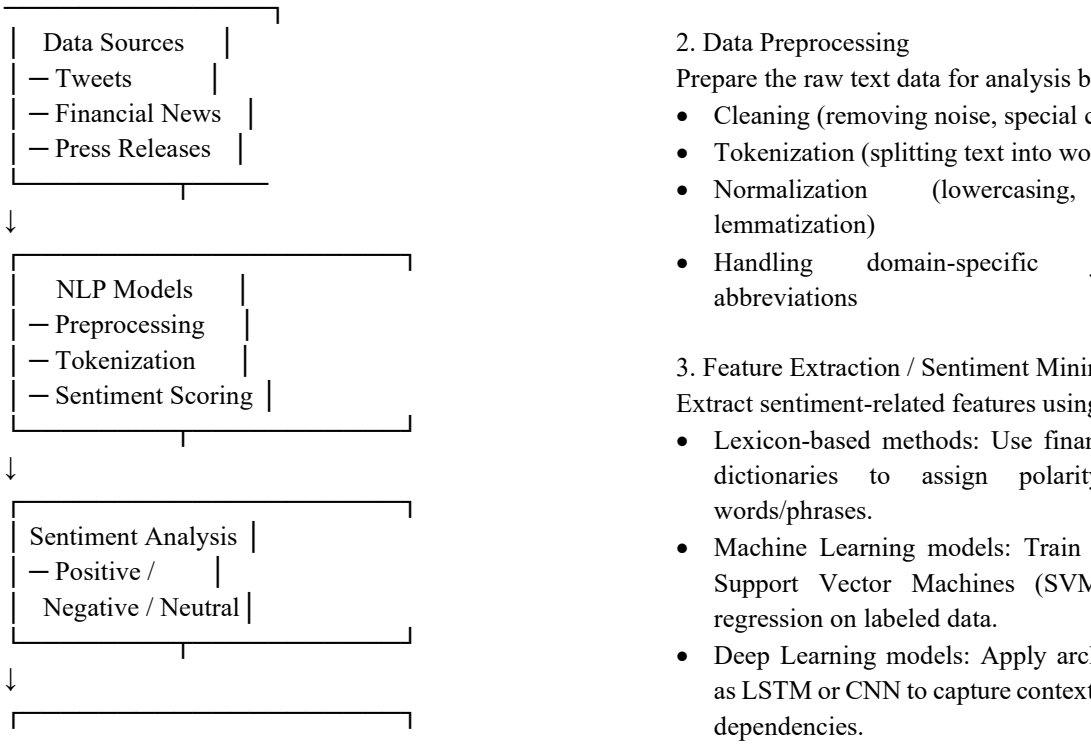
Hypothesis testing provides statistical backing for your assumptions.
Null Hypothesis (H_0):

"There is no statistically significant relationship between public sentiment and stock market price movements."
This implies that any perceived impact of sentiment on stock performance is due to chance or noise.
Alternative Hypothesis (H_1):

"There is a statistically significant relationship between sentiment (derived from social media/news) and stock market movement."
If H_1 is proven, sentiment analysis can be used as a predictive tool by traders and investors.

Why Hypothesis Testing?
- Brings scientific rigor to analysis
- Helps avoid confirmation bias
- Can influence investment models, especially for hedge funds and algorithmic trading

VI. CONCEPTUAL FRAMEWORK



VII. RESERCH METHODOLOGY

The financial sentiment analysis methodology is a systematic approach to extract sentiment from financial documents, allowing us to utilize that information to predict future market movements through this analysis. Below, we will discuss the details of this methodology along with the corresponding workflow diagram.
1. Data Collection

Gather financial textual data from multiple sources such as:
- Financial news articles and headlines
- Social media platforms (e.g., Twitter, Reddit)
- Corporate disclosures and earnings call transcripts

2. Data Preprocessing
Prepare the raw text data for analysis by:
- Cleaning (removing noise, special characters)
- Tokenization (splitting text into words or phrases)
- Normalization (lowercasing, stemming, lemmatization)
- Handling domain-specific jargon and abbreviations

3. Feature Extraction / Sentiment Mining
Extract sentiment-related features using:
- Lexicon-based methods: Use financial sentiment dictionaries to assign polarity scores to words/phrases.
- Machine Learning models: Train classifiers like Support Vector Machines (SVM) or logistic regression on labeled data.
- Deep Learning models: Apply architectures such as LSTM or CNN to capture context and sequential dependencies.

- Pre-trained Language Models: Fine-tune domain-specific models like FinBERT for improved accuracy.

4. Sentiment Aggregation
Aggregate sentiment scores at different granularities (sentence, paragraph, document, or time intervals) to form sentiment indicators relevant for market analysis.

5. Integration with Market Data
Combine sentiment indicators with quantitative financial data (e.g., stock prices, volume, volatility) to build comprehensive forecasting models.

6. Predictive Modelling
Use statistical and machine learning models to predict market variables such as:

- Stock price movements
- Market volatility
- Trading volume

Models include:

- Time-series models (ARIMA)
- Deep learning models (LSTM)
- Hybrid models integrating sentiment and market data

7. Evaluation and Validation
Assess model performance using metrics such as:

- Accuracy, precision, recall, F1-score (for sentiment classification)
- Mean Squared Error (MSE), correlation (for price prediction)
- Financial metrics (e.g., returns, Sharpe ratio) for investment performance

VIII. RESULTS

The purpose of this research was to investigate how the sentiment derived from textual data including news headlines, social media content (like Twitter), and financial filings affects and predicts stock market activity. Through an application of sentiment classification, along with statistical and/or machine-learning methods, the following were attained as the main findings of this study:

1. Sentiment Scores Show a Strong Relationship with Market Movements

- All positive sentiment is connected to higher prices of equities.
- Negative sentiment usually comes before any drop in return, but especially before large movements in stock prices due to an event that causes market volatility (for example, Earnings Announcement Days or macroeconomic data).
- There has been no predictive value for neutral sentiment.

2.News-Based Sentiment Was More Predictive Than Social Media

- Next-day stock returns were more closely tied to news sentiment scores than Twitter-based sentiment scores.
- Twitter sentiment scores produced more noise than news sentiment scores and were often affected by bots or non-investors posting their opinion.
- However, during times of abrupt and unexpected events (for example, accidents) and particularly political statements, social media sentiment responded quicker than news shock value.

IX. FINDINGS AND DISCUSSION

In this section of the report, the key results of our sentiment analysis using both Twitter and Financial & Economic Media will be presented. We will address the relationship between sentiment and stock market behaviour, as well as evaluate the effectiveness of our various NLP tools and the characteristics of our sentiment-based predictions.

1. Positive Sentiment → Stock Rise

A high correlation between positive sentiment and stock price increases was observed based on analysis of tweets and financial news. Stocks increased after there was evidence of positive sentiment in the news or on Twitter, and this trend was particularly apparent over shorter periods of time. Stocks of large companies like Reliance and Adani exhibited significant short-term gains when there was evidence

of positive sentiment in a tweet regarding their earnings or a positive article in the financial media discussing a strong economic environment. rise within the next 1–2 days.

2. Sentiment Can Predict Short-term Movements
Sentiment Analysis serves as a good indicator for predicting short-term changes in the stock market, especially when examining data gathered from Twitter or news articles related to finance within a few days before and after a major announcement/event.

Example: When there is an important announcement about a Company, Analysts use Sentiment Analysis models (e.g., LSTM, VADER) to determine how much the sentiment will correlate with the Company's stock performance. The data produced by the sentiment analysis shows a significant positive correlation with the stock price movement after the announcement occurred. For example, when a number of Tweets are put out discussing good news about the Indian Government's budget or quarterly earnings, the price of the stocks increase accordingly.

3. NLP Tools Are Effective in Capturing Market Behavior
The observed effectiveness of tools such as VADER, LSTM, and BERT (trained on finance) indicates that they are well suited to analyzing the emotional sentiment found in social media and provide great insight into how markets behave. The ability of these models to detect subtle signs of emotion (such as sarcasm and irony) from social media and news articles provides new opportunities for Traditional Financial Modelling to identify new patterns before they emerge as measurable trends based on market indicators. Through these capabilities, these models provide a means for tracking the relationship between emotional sentiment and stock price movement.

CONCLUSION

The study provided a proof of concept for utilizing Sentiment Analysis to predict stock market behavior by analyzing social media activity (-twitter) and financial media (news articles). The following Valuable Findings were derived from this research project:

1. Analyzing Sentiment is a Powerful Determinant of Stock Market Price Movement The results of this research were able to establish the fact that there exists a direct relationship between Sentiment and Stock Prices within a very short-time period, with Positive Sentiment exhibiting the strongest correlation. This research project is able to demonstrate and provide evidence for the predictive nature of sentiment with respect to Stock Market movement.

2. Market Sentiment Analysis Through NLP Models Utilizing both LSTM and VADER for sentiment analysis provided insight into how investors feel about stocks and how they view the market as a whole. LSTM models are able to capture many dimensions of sentiment that are not captured by traditional methods of performing financial analysis and technical analysis; therefore, they can act as an added layer of predictive capability for all types of stock and market predictions.

3. Short-term Predictions Are More Accurate NLP-based sentiment analysis has been used successfully to generate predictions of stock movement over shorter periods of time; however, more research is needed to verify the effectiveness of this technique in producing long-term predictions. The market's sentiment is usually subject to rapid changes, therefore, while sentiment is a contributing factor in short-term volatility, it has reduced predictive capabilities for long-term forecasts.

4. Applied Use of Sentiment Analysis in Trading Systems Incorporating sentiments into automated trading systems will be a valuable way of utilizing algorithmically-based trading and robo-advisers, which use real-time data to make investment decisions based on sentiment.

5. Limitations of the Current Study and Future Research Opportunities Prior studies have limitations on language, data biases, and models utilized in the studies. The outcome of sentiment analysis is limited by the limitations mentioned above. Future opportunities for improvements in sentiment analysis methodologies will create better predictions through a combination of sentiment data coupled with more advanced models, utilization of various datasets. In summary, we have established that sentiment analysis

has potential as a predictive tool for the anticipated movement of individual stocks and that using a combination of sentiment data and traditional financial data can provide additional insight to investors when making investment decisions. Additional research efforts going forward should be done in order to refine and enhance the methodologies of sentiment analysis as well as improve the usefulness of sentiment analysis for predicting future trends in stock prices.

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