Impact of Twitter Sentiment Based Retweet on Financial Decision using Big Data Analytics, AI Machine Learning

Hassaan Daoud

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Diagram

Description automatically generated with medium confidence

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Supervisor: Kislay Raj

# Declaration

I hereby certify that the material, which l now submit for assessment on the programme of study leading to the award of Master of Science in Computing in Data Analytics, is entirely my own work and has not been taken from the work of others except to the extent that such work has been cited and acknowledged within the text of my own work. No portion of the work contained in this thesis has been submitted in support of an application for another degree or qualification to this or any other institution. I understand that it is my responsibility to ensure that I have adhered to CCT rules and regulations. I hereby certify that the material on which I have relied on for the purpose of my assessment is not deemed as personal data under the GDPR Regulations. I ensured that the dataset was anonymised from the source before using it in line with the Data Protection Commissioners Guidelines on Anonymisation.

#### **Ethics statement disclaimer**

The findings and outcomes of this research are purely an academic exercise and are intended solely for use within this research thesis, not for public decision-making or enterprise use. The results demonstrated a correlation between sentiment analysis and stock behavior, offering insights into the potential applications of sentiment analysis in financial contexts, but not for public or commercial stock-related decisions. Furthermore, sentiment analysis in this study was conducted using anonymised publicly available data, specifically tweets related to stock performance, with a strong focus on ensuring ethical integrity throughout the methodology. Publicly shared data was carefully anonymized to protect user privacy by removing identifiable information such as usernames and timestamps. The research also addressed potential biases within the dataset, particularly the class imbalance favoring neutral and positive sentiments, by employing data balancing techniques to ensure fairness and accurate model evaluation.

Signature of Candidate Date

Hassaan Daoud September 2024

# Acknowledgements

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Gratitude is also expressed to my spouse for her understanding of my limited availability and for caring for our baby, Noah, during this research.

Additionally, heartfelt thanks are extended to my friends at TU Berlin. Their support on this finance topic provided me with the additional necessary tools when required, playing a crucial role in enabling the completion of this work.

# Acronyms

|  |  |  |
| --- | --- | --- |
| Acronym | Definition | Page |
| EDA  GCP  VM  BDA  AI  EDA  GAN  ELM  NLP  SVM  RNN  ML  GPU  Twitter  TLBO  LSTM  ARIMA  VADER  ELM  MSE  . | Exploratory data analysis  Google cloud platform  Virtual machine  Big data analytics  Artificial intelligence  Exploratory data analysis  Generative adversarial networks  Elaboration likelihood model  Natural language processing  Support vector machines  Recurrent neural networks  Machine learning  Graphics processing unit  X  Teaching and Learning Based Optimization  Long Short-Term Memory  AutoRegressive integrated moving average.  Valence aware dictionary sentiment reasoner  Elaboration likelihood model  Mean squared error  Squared metrics | 25  31  31  2  3  4  7  11  11  11  11  12  50  8  8  8  8  8  9  19  19 |

# Abstract

This study critically analyses the influence of Twitter sentiment on financial decision-making and stock market movements. The study claims to demonstrate the significant impact of social media sentiment, particularly on investor decisions and financial market forecasting. The analysis evaluates the use of qualitative (primary research) and quantitative (second research) methods, identifying flaws and assessing the representative of focus group with primary and secondary research (dataset). Furthermore, the study delves into the implications of social media sentiment analysis for financial analysts**.** By demonstration the relationship between Twitter sentiment and market movements, it offers evaluation into the potential use of sentiment-based strategies for optimizing investment decisions and managing market risk. Moreover, the research highlights the importance of transparency in data collection and analysis methodologies, the importance of using the practices such as retweets and hashtags in collecting data from social media for financial purposes. Through examination of Twitter sentiment's impact on financial markets, this study contributes to understanding of the evolving landscape of digital information and its influence on economic decision-making processes. The research introduces a comprehensive dataset comprising labelled instances extracted from Twitter in English, allowing for company-level analysis of tweet-based impact on stock returns periods. According to eMarketer's study, over fifty percent of the US population regularly engages with social networks (Rimma Kats, 2018). The study baselines are established using standard EDA, AI, and machine learning algorithms and a multi-view learning-based approach, leveraging diverse feature sets to enhance predictive accuracy. This dataset facilitates in-depth exploration of public opinion dynamics on financial markets, enabling researchers to develop AI machine learning model for sentiment-based investment strategies and market forecasting only for research purposes. The outcomes offer practical applications in initial monitoring, crisis response, promotions, predictive information spread, associated ranking and pricing activities.

**Keywords:** Twitter sentiment analysis, social media and financial decisions, stock market prediction using Twitter, Data analytics, Sentiment-based investment strategies, social media influence on financial markets, AI Machine learning for financial decision-making.

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**Published content and** **contributions**

**[1] GitHub:** Hassaan Daoud

* **Published**: GitHub repository documentation by Hassaan Daoud.  
  **URL:** [GitHub Repository](https://github.com/sbs23096/capstone-sbs23096).
* **Description**: This document provides a comprehensive guide to deploying and visualizing sentiment analysis dataset using GCP, python notebook, readme overview, and architecture diagram.
* **Contribution**: The documentation provided detailed and implemented the pipeline's visualization components.

**[2] Tools and Technologies**

* **Tools used:** Google cloud platform Toolkit URL: [Google Developer Tutorials](https://developer.x.com/en/docs/tutorials/developer-guide--twitter-api-toolkit-for-google-cloud1).
* **Usage in the Project:**
  + GCP was employed as the primary data warehouse for storing in VM, querying, and analyzing processed dataset.
  + A GCP Linux VM was configured to host data cleaning and preprocessing pipelines.
* **Acknowledgment**: Services utilized under GCP’s licensing terms.

**[3] GCP colab python notebook**:

* **Tools used:** Jupyter notebook and google colab.

**URL:** [Part 1 colab jupyter notebook](https://colab.research.google.com/drive/1Sa0fJQnCekt1a6C7NDTb_sPiz8az7UDE#scrollTo=0u9uOWWhQeHO)

**URL:** [Part 2 colab jupyter notebook](https://colab.research.google.com/drive/1b64QLpGapU7OEJSdE8j2t5pW7rP1HC_c)

* **Usage in the project**:
  + Jupyter notebook was employed for prototyping and testing data cleaning pipelines, sentiment analysis models, and exploratory data analysis.
  + Google Colab was leveraged for GPU-powered sentiment analysis using pre-trained BERT-based models.
* **Acknowledgment**: Tools used as per their open-source and SaaS licensing agreements.

**[4] Data Source**

**Kaggle Datasets**:

* [**Source**](https://www.kaggle.com/api/v1/datasets/download/zzishan/tesla-stocks-with-tweets-from-x?dataset_version_number=3): Anonyme public datasets available on Kaggle for academic purpose research, including historical social media sentiment datasets.
* **Usage in the Project**: Dataset was used to train and test spam detection, bot filtering, and sentiment analysis algorithms and building AI model.
* **Acknowledgment**: Data used under Kaggle's terms of use and specific dataset licensing conditions.

**[5] Third-Party Materials**

1. **Pre-trained Language Models:**
   * **Source:** OpenAI (e.g., BERT via [Hugging Face](https://huggingface.co/daoud0205)).

**Usage in the Project**

* + BERTweet from Huggingface API token AI automated tool was utilized pre-trained language model to filter out sentiment analysis, such as spam, sarcasm, irony detection, noise, bias, bot-generated content, irrelevant tweets, remove bot-like accounts, eliminate noisy and unrelated content.
  + finBERT from Huggingface API token AI automated tool was utilized for fine-tuning, building AI model, analyse sentiments, having better performance and accurate results.
  + **Acknowledgment:** Model usage complied with OpenAI’s opensource licensing and research use guidelines.

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**Appendix A: Timeframe and Supervisory Meetings**

The activities associated with this research were planned and executed within the designated timeframe, commencing on the 19th of September and concluding on the 4th of December. To ensure the project remained on track, tasks were systematically distributed over the 13-week period. This distribution was guided by the capstone research objectives and conclusions drawn from the literature review. The timeline chart below outlines the chronological sequence in which each task was undertaken, aligning with the supervisor’s recommendations and the project's overall objectives, thereby ensuring a structured approach to the research process.

Appendix A capstone timeline

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Capstone Project Timeline: Week 1 (Starting 19/09/2024) to Week 13 (Ending 13/12/2024) | | | | | | | | | | | | | | | |
| Meeting Agenda | | Deliverables / Milestones | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| Discuss capstone proposal & LR scope confirmation | | Initial Overleaf draft of literature review |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Primary Research Discussion | | Final reflections on research |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Methodology discussion | | Outline of methodology GCP architecture, GitHub, AI tools |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Implementation | | Final artifact & Complete documentation on GitHub |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Review findings & insights | | Detailed findings, results and evaluation report |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Feedback on results section | | Review full draft |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Paper final edits & references Refinements | | Finalized capstone project paper |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Presentation preparation | | Final presentation slides & practices |  |  |  |  |  |  |  |  |  |  |  |  |  |

# Introduction chapter

## 1.1. Background and Context

Social media platforms, particularly Twitter, have become essential channels for information spreading, opinion sharing, and engagement. A significant research challenge has been raised to understand and predict the factors driving tweet popularity to specific directions. This exploration delves into the domain of social media analytics, specifically focusing on why big data analytics, with help of machine learning, can offer valuable insights into the impact of tweet sentiment on the spreading of specific retweets. By developing predictive models, this research aims to clarify the complexities of sentiment-driven retweet patterns, providing a deeper understanding of the dynamics that drive some content to become trending.

Why the research aims to investigate the following key points and aspects?

**Domain Area Overview:** The domain area under consideration is social media analytics, with a particular emphasis on Twitter dynamics. Social media platforms generate large amounts of data, creating a rich landscape for exploration. In this context, the research demonstrates the analysis of tweet/ retweet sentiments and their correlation with finance markets activity. The goal is not concerning only to the reengagements but also to forecast potentials based on the sentiment expressed in the original tweet. Study proves, sharing information is an age-old human practice, now facilitated seamlessly in the online environment (Z. Wang, S. -B. Ho and Z. Lin 2018) such as social influence comes into play when one person's behavior, opinions, or emotions impact others through social networks.

**Role of Big Data Analytics**: Big data analytics serves as the backbone of this research, enabling the processing and analysis of large datasets generated by Twitter (V, Harika and R, Jeberson 2023). This large amount and different types of social media data need advanced analysis methods. Through these modern BDA, we can uncover patterns, trends, and correlations within the data, offering a comprehensive view of tweet sentiments and their subsequent impact on retweet behavior.

**Integration of AI and Machine Learning training models:** A subset of artificial intelligence (Wang, L., Zhang, Y., Yuan, J. 2024), is instrumental in constructing predictive models. By leveraging AI and machine learning algorithms, the research aims to develop a model capable of forecasting retweet activity based on the sentiment of the original tweet based only for academic research. The AI machine learning component allows for the identification of complex patterns within the data, enabling the model to learn and adapt as it processes more information.

## 1.2. Problem Statement

Understanding the factors that contribute to the popularity of tweets holds substantial implications for diverse sectors. For example, stakeholders can refine their short-term business strategies; it can guide effective communication strategies; provides a lens into the evolving dynamics of online conversations. The significance of this problem area lies in its potential to uncover patterns that can be leveraged for strategic decision-making across various aspects.

## 1.3. Research Objectives Hypotheses

**Primary Objective**: The primary objective of this study is to investigate whether the sentiment of retweeted tweets on social media can influence decision-making processes. This will be achieved by analyzing the results of primary research conducted among finance specialist active on social media platforms. The study aims to determine whether the sentiments expressed in retweeted tweets have an impact on decisions, particularly regarding stock diagram.

**Expected Outcome:** The primary research objective aims to provide a comprehensive understanding of the quantitative relationship between tweet sentiment and the spread of Twitter content. This involves investigating the dynamics of Twitter tweets, and evaluating it by developing predictive AI machine learning model to forecast retweet activity based on sentiment. By combining these approaches, the study seeks to advance knowledge in the field of social media analytics and provide valuable insights into the role of sentiment in shaping information and user interactions on Twitter.

**Secondary Objectives:**

**Hypotheses:** The secondary objective of this study is to develop an AI machine learning model to analyze tweet sentiments and predict whether they are genuine expressions of public opinion or strategically crafted for targeted advertising purposes. This model will be trained using historical publicly anonym tweet dataset and validated against the findings of the primary research. Through this secondary objective, the study seeks to provide insights into the authenticity of tweet sentiments and their potential influence on decision-making processes in the context of social media.

**Expected Outcome:** By developing an AI machine learning model capable of analyzing tweet sentiments, the study aims to provide understanding of the authenticity and impact of sentiments expressed on social media platform. Through evaluation and validation, the research seeks to enhance the reliability of tweet sentiment analysis and provide valuable evaluation into the role of sentiment in shaping user behavior and decision-making processes in social media environments.

## 1.4. Research Key Questions

* The research provides academic evaluation into the role of social sentiment in financial decision-making and lays a foundation for optimizing predictive accuracy in high-dimensional datasets.
* This research investigates whether sentiments in retweeted tweets, analyzed through automated AI machine learning model like BERT, influence individuals' financial decisions, particularly in investment behavior.
* By integrating these advanced AI machine learning model with modern Big Data Analytics (BDA) tools, the study aims to improve the accuracy and reliability of sentiment-based predictions.

## 1.5. Significance of the Study

The anticipated outcomes of this research are two directions. First, a refined understanding of how sentiment influences retweet behavior on Twitter. Second, the development of a predictive model that, based on sentiment analysis, can predict the chances of tweets gaining widespread attention.

This research embarks on a journey to explore the complexities of Twitter popularity by employing BDA and AI machine learning. By focusing on the impact of tweet sentiment, the study not only contributes to the academic understanding of social media dynamics but also offers academic evaluation that can inform strategies across various aspects. The combine of BDA and AI machine learning represents a powerful approach to decode the complexities of sentiment-driven retweet patterns. In recent years, social media has evolved into a powerful communication medium and a tool for observing user preferences, offering predictive insights in various contexts, with their rapid information distribution capabilities, serve purposes such as early warning, and emergency response. As of (Statista April 2024), X (formerly Twitter) had an estimated 421 million monthly active users worldwide. While specific data on the total number of tweets posted in 2023 is not readily available, historical estimates suggest that users generate over 500 million tweets daily, which would amount to approximately 15 billion tweets per month. However, these figures can vary over time due to changes in user engagement and platform policies. These allowing users to share content, communicate rapidly, and contribute to the circulation and resonance of tweets through retweets.

The impact of a tweet is often measured by its retweet count, providing a metric for engagement and outreach (Nesi et al., 2018), this content, expressing emotional states, judgments, or commonly retweet sentiments.

## 1.6. Ethics Differences for Public Data

When working with **public data**, the ethical considerations differ significantly from private or consent-based data due to its availability. Below is a detailed clarification of these differences:

**Availability public data:** Data that is publicly available, such as this study X dataset, does not require explicit consent for collection under most legal frameworks. However, the ethical issues have been consideration and explained in each chapter.

**Consent public data:**

While explicit consent may not be required, ethical research practices suggest respecting user rights.

Platforms often state in their terms of service that user content is public, but this doesn’t absolve researchers of ethical responsibility and must be solved during research. In chapter three the study will offer different techniques to cover this ethic point e.g thorugh and BERTweet filter.

**Anonymity and privacy public data:**

Ethical concerns focus on de-identifying public data, even though it is public. Data anonymization, encryption, and secure storage are mandatory to comply with ethical and legal standards (e.g., GDPR) this point will cover together with CGP terms and conditions.

**Purpose of use public data:**

The ethical use of public data depends on how the data is used. If used in ways inconsistent with user expectations (e.g., data mining for commercial profit), ethical issues arise. Researchers must clarify the academic purpose of using public data and ensure it aligns with its context of creation this point will cover through clear disclaimer in Declaration section.

**Bias and representation public data:**

Public datasets often reflect biased populations (e.g. more technologically than the general population). This can lead to skewed research findings. Researcher must filter such bias address and limitations to avoid misrepresentation or misleading conclusions. This study will use two steps, EDA and AI automated tool BERTweet filter techniques.

**Harm and impact public data:**

Public data use can lead to unforeseen harm, such as opinions are highlighted without anonymization or market manipulation in cases of financial sentiment analysis. Here the ethical research will ensure dataset during data explorations does not have adverse effects on individuals or society.

**Legal and ethical compliance public data:**

Public data use may not require legal compliance with frameworks like GDPR unless identifiable information is retained. However, ethical best practices should always be followed and adhering to platform terms of service and ensuring transparency in reporting how data was used.

**Transparency public data:**

Research will represent transparently document about methodology, dataset source, and how the data was processed. This ensures ethical accountability even in the absence of direct consent.

In above introduction ethics section, ethics issues has been raised and explained how the public dataset ethical challenges will be approached and how this study will cover and solve each ethic challenge. While public data allows for broader access, research will ensure mindful of privacy, anonymization, potential biases, fairness, accountability, and academic benefit through different techniques.

# 2. Literature review chapter

## 2.1 Introduction to the literature

The integration of Twitter sentiment analysis with advanced technologies such as Big Data Analytics (BDA) and Artificial Intelligence (AI) is revolutionizing financial forecasting, particularly in stock movements predictions and market sentiment analysis. This chapter reviews the extensive body of literature on Twitter sentiment analysis, financial forecasting, AI machine learning models, and the impact of social sentiment on stock market behavior. Sentiment analysis, also known as a natural language processing (NLP) technique aimed at understanding and extracting the emotional sentiment from textual data (Liu, Bing, 2012). This field has gained significant attention in recent years due to its widespread applications across domains such as marketing, politics, and finance. In finance, sentiment analysis provides insights into how public emotions influence market behavior, enabling better decision-making for investors and financial institutions (Mitra, Sandipan, 2020). With the rise of social media platforms like Twitter, sentiment analysis has emerged as a powerful tool for predicting stock price movements and financial market trends (Bollen, Johan, Mao, Huina, & Zeng, Xiaojun, 2011). Tweets and other social media posts serve as rich data sources, capturing public opinions on companies, products, and broader market sentiments (Zhang, Wei, Skiena, Steven, & Andersen, John, 2018). This data-driven approach allows researchers and analysts to understand how external factors such as news, public sentiment, and geopolitical events impact finance markets. Financial sentiment analysis has become increasingly important as it bridges the gap between qualitative public opinion and quantitative market analysis (Loughran, Tim, & McDonald, Bill, 2011). By integrating EDA techniques, AI advanced tools (BERT), and machine learning algorithms with sentiment analysis, researchers have been able to achieve predictive evaluation into stock trends, enhancing the decision-making capabilities of financial market participants (Swathi, T., Kasiviswanath, N., & Rao, A. Ananda, 2022). To provide a comprehensive and structured overview, this literature review is organized thematically. Each section addresses a key theme relevant to this research, including the use of Twitter sentiment in financial forecasting, the challenges and methodologies of processing social media data, the applications of Big Data Analytics in finance, and the effectiveness of machine learning models such as BERT in sentiment classification. This thematic approach allows this study a detailed exploration of each component, demonstrating how they collectively contribute to the goal of improving prediction accuracy through sentiment analysis.

#### **Thematic Approach**

The literature review is organized around key themes and topics relevant to this research, rather than following a chronological order or specific theories. Each section explores a particular aspect of the research topic, such as " What researchers regarding this topic twitter sentiment analysis for financial forecasting have done before," "how researchers in BDA finance approached it," ”how these previous studies helped this research,” "and how these studies helped this research to choose the suitable modern and accurate AI ML tools and models". These themes are essential components of this research and are examined in depth, supported by relevant studies and findings.

**Why thematic approach:** The thematic approach was chosen as it allows for a comprehensive exploration of each critical component of this research topic. This structure enables a focused discussion on how different aspects of Twitter sentiment analysis, Big Data, and machine learning intersect to address the research objectives. The thematic organization ensures that the literature review is logically structured and easy to follow, making it suitable for a complex, multi-dimensional research topic that combines elements of social media analytics, financial forecasting, and advanced AI machine learning techniques.

Prior research has extensively explored sentiment analysis, particularly its applications in financial markets and stock prediction. However, sentiment analysis involves extracting and quantifying emotions or opinions from textual data, such as financial news or social media posts, to assess public sentiment toward financial assets (Jiang, Tingsong, & Zeng, Andy, 2023). So in modern BDA permanently different techniques have become increasingly significant in finance, the study will help the finance stakeholders such as investor to demonstrate the recent techqniques (Zhu, Enmin, & Yen, Jerome, 2024). Studies have demonstrated that integrating sentiment analysis with financial models enhances the accuracy of predictions. Recent study, (Gu et al. 2024) developed a FinBERT-LSTM model that combines financial news sentiment with historical stock movements, resulting in improved predictive performance. Similarly, (Deveikyte et al. 2020) found that sentiment extracted from news headlines could be used as a signal to predict market returns, indicating a correlation between sentiment and stock market movements. The advent of advanced natural language processing models, such as FinBERT and OpenAI, has further refined sentiment analysis in financial contexts. These models are adept at capturing the financial language, thereby providing more accurate sentiment assessments (Jiang, Tingsong, & Zeng, Andy, 2023). Consequently, sentiment analysis has become a vital tool for investors and analysts aiming to understand and predict stock market trends. With the increasing of social media discussions around financial markets and investment strategies, analyzing tweet sentiment has become crucial in explaining public sentiment and its potential influence on stock market dynamics. The phenomenon of retweets, where users share content by reposting others' tweets, adds another layer of complexity to tweet sentiment analysis. Retweets serve as indicators of engagement and interest, reflecting the degree to which specific content potentially influences their actions. This literature review focuses on summarizing key advancements in sentiment analysis within financial markets and stock prediction, highlighting how these studies have informed the methodological choices of this research. Recent developments in natural language processing (NLP) and machine learning have significantly enhanced the ability to analyze and interpret financial sentiments from diverse data sources, such as news articles and social media platforms (Bayer, Constanze, 2019). For example, the integration of Generative Adversarial Networks (GANs) with transformer-based attention mechanisms has improved the accuracy of stock price forecasts by effectively capturing complex market sentiments (Zhu, Enmin, & Yen, Jerome, 2024). Moreover, comparative analyses of various machine learning algorithms have provided professional comparison insights into the most effective models for financial sentiment analysis, guiding the selection of appropriate techniques for this study (Renault, Thomas, 2019). Additionally, the application of AI advanced tools and machine learning in finance has expanded, with sentiment analysis being utilized to predict market developments and inform investment decisions (Bayer, Constanze, 2019). These advancements have collectively supported to choose the suitable methodological framework of this research, enabling a more nuanced and accurate analysis of financial sentiments and their impact on stock market behavior.

By examining above existing researchers on tweet sentiment analysis and its implications for financial markets, this literature review seeks to provide insights into the dynamics of social media-driven investment decisions and the potential implications for investors, financial professionals, and market regulators. Through a comprehensive analysis of relevant literature, this review aims to contribute to a deeper understanding of the interplay between tweet sentiment, retweets, and stock market outcomes, and demonstrate the latest modern BDA techniques. This academic objective will be explored through thematic lenses, including Theoretical Framework, Historical Overview of each chapter “Methodologies and Approaches, Applications, Challenges, Limitations, Evaluation, Results, Discusion and Future Directions and Emerging Trends”. The Theoretical Framework theme will provide insights into theoretical foundations relevant to these chapters and help to find the suitable approach for each one. The Historical Overview theme will offer a historical perspective on research in tweet sentiment analysis and its evolution over time. Methodologies and Approaches will explore

different methodologies and implementations used in sentiment analysis and decision-making studies. Applications will discuss the practical applications of tweet sentiment analysis in financial decision-making contexts. Evaluation will talk about the methodologies experiments in depth and address comparison between different implementations and how results mirror the research objectives. Ethics section will close how the ethics challenges and implications in each stage and chapter have been solved, discuss how the study avoided the related ethics consequences and how the research mitigated those risks to affect any partner. Challenges and Limitations will address the technical and theory challenges associated with tweet sentiment analysis and its implications for decision-making. Lastly, Discussion, conclusion will explore the prove/disprove the hypothesis and if the problem statement has been solved. Future directions and emerging trends will discuss highlight potential avenues for future research and developments in the field.

#### **Ethical considerations in sentiment analysis research**

Literature review studies adhere ethical principles to take in consideration, particularly in the context of using publicly available data and addressing potential biases in sentiment analysis methodologies. This ensured compliance with ethical research standards and demonstrated a commitment to protecting individual privacy (Kumar, 2022). Key measures implement to mitigate the potential biases in sentiment analysis models, such as EDA and BERTweet. This approach will ensure fairness in training and evaluation, enhancing the reliability of the findings (Renault, 2019). Also, transparency was integral to the research process. The methodology was documented in GitHub, and open-source tools were employed to facilitate replicability under its terms. Additionally, the principles of the General Data Protection Regulation (GDPR) were reflected in the research methodology e.g.

* **Data Minimization and Purpose Limitation (Article 5):** Only the data necessary for the specific research objectives was collected, and it was used solely for sentiment analysis in the context of stock price movements (Kumar, 2022).
* **Anonymization and Pseudonymization (Recital 26, Article 32):** Identifiable information was removed, aligning with GDPR’s requirements for protecting individuals’ privacy (Zhu & Yen, 2024).
* **Transparency (Article 12):** Although direct transparency to data subjects was not issue, the research maintained academic transparency by explicitly GitHub documenting data handling and methodologies (Renault, 2019).

By adhering to these principles, this research balances methodological aligned with ethical responsibility in each stage and overall the limitation in 6th ethics section, study ensuring that the findings contribute to academic discourse while respecting public dataset privacy and minimizing risks associated with (Bayer, 2019).

## 2.2 Literature main body

**Theoretical Framework:** Tweet sentiment analysis is grounded in various theoretical frameworks and concepts from disciplines such as communication studies, psychology, sociology, and computer science. Understanding these theoretical foundations is crucial for contextualizing and interpreting the dynamics of sentiment expression on social media platforms like Twitter. Recent studies from 2019 to 2024 have significantly advanced the understanding of sentiment analysis in financial markets, particularly concerning the impact of social media sentiment on stock movements. These studies have employed various methodologies, including AI model and natural language processing techniques, to analyze data from platforms like Twitter. (Swathi et al. 2022) approach, developed a Teaching and Learning Based Optimization (TLBO) model combined with Long Short-Term Memory (LSTM) networks to predict stock movements using Twitter sentiment analysis. The model involved pre-processing tweets, classifying sentiment using LSTM, and optimizing the output with the TLBO algorithm. Findings of this study, the TLBO-LSTM model achieved a precision of 95.33%, recall of 85.28%, and F1-score of 90%, outperforming other techniques in stock prediction. This study

highlights the effectiveness of combining optimization algorithms with deep learning for sentiment analysis, informing the methodology of integrating advanced models like FinBERT for financial sentiment analysis. Another approach (Zaichenko et al. 2023) compared sentiment features and semantic features derived from Twitter data to forecast market trends, utilizing the Temporal Fusion Transformer model for prediction. The findings of sentiment features led to higher predictive accuracy in most cases, indicating the importance of sentiment analysis in financial forecasting. This influence on current study by showing the value of sentiment features over raw text embeddings, supporting the focus on sentiment analysis in this research (Avila 2024).

investigated the relationship between tweet sentiment and stock market behavior in the biotechnology sector, employing RondomForest sentiment analysis models to forecast stock performance. The findings identified a complex interplay between tweet sentiment and stock performance, emphasizing the role of social media in financial markets. This importance of considering social media sentiment in stock analysis, informing the reason and inclusion of using Twitter dataset in this research. To support the choice of methodology of analyzing Twitter sentiment in this research (Milikich and Johnson 2023) study proposed framework leveraging Twitter sentiment analysis for predicting stock market movements, using TextBlob for sentiment assessment and correlating sentiment scores with stock prices. This predicts stock price movements, aligning with the objectives of this research. Findings of (Milikich and Johnson 2023) study demonstrated a correlation between public sentiment on Twitter and stock movements, suggesting the viability of using social media sentiment for market predictions. Also (Matthies et al. 2023) research

analyzed the impact of collective trading events organized on social media platforms like Reddit and Twitter, examining the correlation between social media activity, sentiment, and stock volatility. The findings found a significant relationship between social media activity and stock volatility, though the link between sentiment and stock performance was weaker. These raises up more the importance of social media activity in stock market dynamics, informing the analysis of Twitter data in this research.

All these studies collectively inform the current research by demonstrating the effectiveness of advanced sentiment analysis models and the importance of social media data in predicting stock movements. They provide a foundation for selecting methodologies that integrate deep learning and natural language processing techniques tailored to financial sentiment analysis. Another central theoretical framework in tweet sentiment analysis is the concept of social influence theory, rooted in sociology and psychology, posts that individuals' behaviors, attitudes, and decisions are influenced by the actions and opinions of others within their social networks. On Twitter, this theory manifests through the mechanism of retweets, where users retweet content they find relevant or compelling, thereby influencing the perceptions and actions of their followers. Another common theoretical perspective relevant to tweet sentiment analysis is Model (ELM) from communication studies. ELM suggests that individuals process messages through two distinct routes (central and peripheral).

In the context of tweet sentiment analysis, the sentiment expressed in a tweet may influence individuals' attitudes and behaviors through either route, depending on factors such as message content, source credibility, and audience receptivity. Understanding the interplay between these routes is essential for predicting the impact of sentiment on user engagement and decision-making processes. Additionally, theories from computational linguistics and natural language processing (NLP) provide valuable insights into the technical aspects of tweet sentiment analysis. The Bag-of-Words model, for example, treats each tweet as a collection of words or tokens, disregarding grammar and word order but capturing the overall sentiment expressed. This model forms the basis for many lexicon-based sentiment analysis approaches, where sentiment scores are assigned to individual words or phrases based on pre-defined dictionaries or corpora. Furthermore, machine learning algorithms, such as Support Vector Machines (SVM) and Recurrent Neural Networks (RNN), draw on concepts from statistical learning theory and artificial intelligence to analyze and classify tweet sentiments automatically. These algorithms learn from labeled data to identify patterns and relationships between tweet content and sentiment labels, enabling more sophisticated and scalable sentiment analysis approaches. By explaining these theoretical frameworks, research can gain deeper insights into the mechanisms underlying sentiment expression on Twitter and its implications for user behavior and decision-making processes to choose the suitable technique. The theoretical framework for understanding the impact of retweets on financial decision-making processes, particularly in stock markets, encompasses insights from communication studies, psychology, and machine learning.

* + - 1. Communication Studies

Communication theories such as agenda-setting theory and social influence theory provide a foundation for understanding how information disseminated through retweets can shape perceptions and decision-making behaviors in financial markets. Agenda-setting theory suggests that the prominence and frequency of topics in media, including social media, influence the public's perception of their importance. In the context of retweets, this theory helps explain how certain stock-related information amplified through retweets can influence investors' attention and decision-making. Social influence theory explores how individuals' decisions are influenced by the actions and opinions of others within their social networks. Retweets serve as social cues that can affect investors' perceptions of market sentiment and investment opportunities.

* + - 1. Psychology:

Psychological theories such as behavioral finance and sentiment analysis shed light on the cognitive and emotional factors driving financial decision-making in response to retweeted information. Behavioral finance theory suggests that investors' decisions are influenced by psychological biases and heuristics, rather than purely rational calculations. Retweets may trigger emotional responses or cognitive biases that impact investors' perceptions of stock market trends and investment opportunities. Sentiment analysis techniques from psychology help analyze the emotional tone and sentiment conveyed in retweeted content, providing insights into investors' collective mood and sentiment towards specific stocks or market conditions.

* + - 1. Machine Learning

Machine learning models offer predictive capabilities to analyze patterns and trends in retweeted content and its impact on financial decision-making. Natural language processing (NLP) techniques within machine learning enable sentiment analysis of retweeted content, allowing for the classification of tweets as positive, negative, or

neutral. These sentiment labels can then be used to predict investors' reactions and

stock market movements. Supervised learning algorithms, such as classification and

regression models, can be trained on historical retweet data and corresponding market outcomes to predict the impact of retweets on stock prices or trading volumes.

By taking in consideration these framework insights from communication studies, psychology, and machine learning, research can develop a comprehensive theoretical framework for understanding how retweets influence financial decision-making in stock markets. This framework provides a basis comparison between retweeted content, investor behavior, and stock market dynamics.

**Historical overview of manual ML social media sentiment analysis:**

Provide a historical overview of research on tweet sentiment analysis traces the evolution of methodologies and approaches employed to understand the role of sentiment in shaping user behavior on social media platforms, particularly in the context of financial decision-making. Initially, studies in this domain focused on manual content analysis, where researchers **manually** annotated tweets todetermine their sentiment polarity:

**1. (Swathi et al. 2022):**

* **Approach:** Developed a Teaching and Learning Based Optimization (TLBO) model combined with Long Short-Term Memory (LSTM) networks to predict stock prices using Twitter sentiment analysis. The model involved pre-processing tweets, classifying sentiment using LSTM, and optimizing the output with the TLBO algorithm.
* **Findings:** The TLBO-LSTM model achieved a precision of 95.33%, recall of 85.28%, and F1-score of 90%, outperforming other techniques in stock prediction.
* **Influence on Current Study:** This research highlights the effectiveness of combining optimization algorithms with deep learning for sentiment analysis, informing the methodology of integrating advanced models like FinBERT for financial sentiment analysis.

**2. (Zaichenko et al. 2023):**

* **Approach:** Compared sentiment features and semantic features derived from Twitter data to forecast market trends, utilizing the Temporal Fusion Transformer model for prediction.
* **Findings:** Sentiment features led to higher predictive accuracy in most cases, indicating the importance of sentiment analysis in financial forecasting.
* **Influence on Current Study:** This study underscores the value of sentiment features over raw text embeddings, supporting the focus on sentiment analysis in this research.

**3. (Milikich and Johnson 2023):**

* **Approach:** Proposed "Taureau," a framework leveraging Twitter sentiment analysis for predicting stock market movements, using TextBlob for sentiment assessment and correlating sentiment scores with stock prices.
* **Findings:** Demonstrated a correlation between public sentiment on Twitter and stock price movements, suggesting the viability of using social media sentiment for market predictions.
* **Influence on Current Study:** Supports the methodology of analyzing Twitter sentiment to predict movements, aligning with the objectives of this research.

**4. (Asgarov 2023):**

* **Approach:** Assessed the viability of Twitter sentiments as a tool for predicting stock prices of major corporations like Tesla and Apple, utilizing Long Short-Term Memory (LSTM) neural networks.
* **Findings:** Identified a robust association between the emotions conveyed in tweets and fluctuations in stock prices, with positivity, negativity, and subjectivity being primary determinants.
* **Influence on Current Study:** Highlights the significance of incorporating public opinions into stock price prediction models, informing the use of sentiment analysis in this research.

**5. (Mumtaz and Mumtaz 2023):**

* **Approach:** Investigated BERT capacity to predict stock market movements using social media tweets and sentiment analysis, focusing on the effect of tweets on stock values of Microsoft and Google.
* **Findings:** Found a positive link between BERT’s evaluations and subsequent stock results, emphasizing the growing importance of AI in financial market forecasts.
* **Influence on Current Study:** Demonstrates the potential of AI models in analyzing social media sentiment for stock prediction, supporting the integration of advanced AI techniques in this research.

Above studies collectively inform the current research by demonstrating and metrics the effectiveness of previous manual sentiment analysis models to support more the accurate choice of selected methodology in chapter three.

**Challenges and limitations in tweet sentiment analysis for financial decision-making.**

1. Data Quality Concerns: One of the primary challenges in tweet sentiment analysis for financial decision-making is ensuring the quality and reliability of the tweet data. Tweets may vary widely in terms of relevance, accuracy, and credibility, posing challenges in selecting and filtering relevant tweets for sentiment analysis (Gupta, Rajesh, 2021). Additionally, the presence of noise, spam, and bot-generated content in tweet streams can introduce biases and distortions in sentiment analysis results, potentially leading to conclusions about sentiment market trends.
2. Sentiment Ambiguity: Another challenge is the inherent ambiguity and subjectivity in sentiment interpretation wrote by (Chen, Michael, 2022), particularly in the context of financial tweets. Financial discussions often involve complex language, sarcasm, irony, and domain-specific terminology, making it challenging to accurately determine the sentiment polarity of tweets. Ambiguous or context-dependent sentiments may lead to misclassification errors in sentiment analysis, impacting the reliability of sentiment-driven insights for financial decision-making.
3. Ethical Considerations:Ethical considerations are paramount in tweet sentiment analysis for financial decision-making, particularly concerning user privacy, data consent, and algorithmic fairness. Researchers must adhere as discussed in introduction chapter to ethical guidelines and data privacy regulations when collecting, analyzing, and sharing tweet data for sentiment analysis purposes and adhere findings ethics. (Lee, Michael, 2020) mentioned in his article, the use of sentiment analysis algorithms should be transparent, accountable, and unbiased to avoid unintended consequences or ethical dilemmas in financial decision-making contexts.

Addressing these challenges and limitations requires a multidisciplinary approach that integrates expertise in data science, computational linguistics, finance, and ethics. Researchers must employ methodologies, leverage advanced sentiment analysis techniques, and consider contextual factors to mitigate biases and ensure the validity and reliability of sentiment analysis results for informing financial decision-making processes. By acknowledging and addressing these challenges, researchers can enhance the effectiveness and utility of tweet sentiment analysis in facilitating informed and ethically sound financial decisions.

## 2.3 Conclusion

The literature reviewed the relationship between social media, particularly Twitter, and financial decision-making processes, with a specific focus on the impact of retweets. The collective insights from the reviewed studies underscore the significant role of sentiment analysis in financial markets, particularly in predicting movements. Advancements in natural language processing (NLP) and machine learning have enabled more accurate extraction of sentiments from diverse data sources, such as financial news and social media platforms (Bayer, Constanze, 2019). For instance, integrating Generative Adversarial Networks (GANs) with transformer-based attention mechanisms has enhanced the precision of stock price forecasts by effectively capturing complex market sentiments (Zhu, Enmin, & Yen, Jerome, 2024). However, several gaps and limitations exist in prior research. Many existing studies focus on coarse-grained sentiment analysis, often overlooking the nuanced sentiments associated with specific entities within financial texts (Kumar, Rishu, 2022). Additionally, the scarcity of large, labeled datasets tailored for financial sentiment analysis poses challenges to the development of robust models (Renault, Thomas, 2019). Moreover, the dynamic nature of financial markets necessitates sentiment analysis, a requirement that many traditional models fail to meet (Bayer, Constanze, 2019). To address these limitations, this study employs a fine-grained, entity-aware sentiment analysis approach, utilizing advanced NLP models such as FinBERT, which are specifically trained on financial corpora to capture the subtleties of financial language (Kumar, Rishu, 2022). By leveraging a comprehensive, annotated dataset of financial news headlines, this research aims to enhance the accuracy of sentiment classification and its correlation. Furthermore, the study incorporates in future work data processing capabilities can be implemented to ensure timely analysis, thereby aligning with the dynamic nature of financial markets. The findings from the reviewed studies have significantly guided the methodological decisions of this research. The demonstrated efficacy of domain-specific NLP models in financial sentiment analysis informed the selection of FinBERT as the primary model for this study (Kumar, Rishu, 2022). Additionally, recognizing the importance of entity-level sentiment extraction led to the adoption of an entity-aware analysis framework. After demonstrating these above studies and together with following key findings from the literature review. The methodology has been selected in the next

chapter 3 with these techniques (AI advanced tools BERTweet to filter, finBERt to analyse and build model designed from 3 stages, EDA for preparations/exploration stage, manual ML RondomForest stage to evaluate its metrics with stage AI BERT models metrics)

**Key findings:**

**A**. Role of Retweets in Financial Decision Making:

Retweets play a pivotal role in shaping financial decision-making, acting as catalysts for information dissemination and influencing investor sentiment in stock markets. Studies have demonstrated a strong correlation between tweet sentiment and subsequent market movements, highlighting the importance of understanding the dynamics of sentiment expression on social media platforms.

**B**. Applications of Sentiment Analysis in Finance:

Sentiment analysis has found diverse applications in finance, ranging from predicting market trends to assessing investor sentiment and sentiment-aware trading strategies.The use of social media sentiment data, particularly from platforms like Twitter, has become increasingly prevalent in informing investment decisions, risk management practices, and regulatory compliance efforts in financial markets.

**C**. Challenges and Limitations:

Despite advancements, challenges such as data quality issues, sentiment ambiguity, and ethical considerations persist in sentiment analysis. Addressing these challenges is imperative to enhance the reliability and accuracy of sentiment analysis in finance and to ensure informed decision-making processes.

**D**. Integration of Multi-Modal Data: Investigate the integration of multi-modal data sources, including text, images, and videos, to provide a more comprehensive understanding of sentiment dynamics in finance.

**F**. Development of Context-Aware Sentiment Analysis Techniques: Explore the development of context-aware sentiment analysis techniques that consider the unique characteristics of market conditions.

# 3. Methodology chapter

## Primary research report

**Appendix B primary research result is attached on GitHub repository**

**Sampling strategy**

**Population**:The population for this research consists of individual expert who have expressed interest in financial news, investment strategies, or stock market trends on social media.

**Type:** This study adopted a qualitative research design to gather in-depth perspectives and experiences from finance expert regarding the impact of social media sentiment on their decision-making processes.

**Method:** Purposive sampling was employed to intentionally select participants with relevant expertise in finance and active engagement with social media platforms. This method ensured that the sample included individual who could provide valuable insights based on their practical experience and domain-specific knowledge.

**Justification:** Purposive sampling was critical for this research due to its focus on participants with expertise in analyzing market trends influenced by social media sentiment. This approach allowed the study to capture informed perspectives that are highly relevant to understanding the relationship between social media content and financial decision-making.

**Purpose of the primary research**

Primary research defined the objectives and formulated the research questions with input from advisors and stakeholders. Objectives will encompass methodology, structure, and desired outcomes. This report summarizes the qualitative research process undertaken to explore the impact of social media sentiment-based retweets on financial decision-making. By leveraging interview with finance professional actively engaging with social media, the report aims to outline the sampling strategy, methodology, key findings, and how these findings support the broader research objectives.

**Link to research objectives**  
The qualitative approach aligns with the study’s primary objective of understanding whether sentiment in retweeted tweets influences financial decisions. It also supports the secondary objective of providing insights into the authenticity of tweet sentiments, which serve as a qualitative foundation for evaluating quantitative models like auto AI tool FinBERT and manual ML RandomForest.

**Data collection method**  
The study utilized interview as the primary data collection method. The semi-structured format facilitated open-ended questions, enabling participant to share detailed responses while allowing the interviewer to probe further into specific topics as needed.

**Duration and structure**: Average interview duration 30-45 minutes.

**Key Areas Covered**:

**A**. Impact of social media sentiment on financial decision-making

* Social media platforms like Twitter play a significant role in shaping short-term financial decisions, especially during events like earnings announcements or major market shifts.
* Sentiment-based retweets often show emotional reactions, leading to different behavior and overreactions in financial markets.

**B**. Role of Sentiment Polarity

* Positive sentiments in retweets create optimism and often decision positive behavior among investors.
* Negative sentiments, while less frequent. However, their influence heavily depends on the credibility of the tweet source.

**C**. Ethical and Analytical Challenges

* Identifying authentic sentiment remains a challenge due to the bias of bot-generated or manipulative content.
* Financial tweets often include complex language, sarcasm, making sentiment interpretation and classification difficult.

**Validation with second research method**  
The qualitative findings of primary research provide a foundational understanding that informs the second research method quantitative analysis using AI automated tool FinBERT and manual ML RandomForest models. Insights from the interview support the development of more targeted preprocessing steps and evaluation criteria for choosing the suitable strategy in methodology chapter.

**Qualitative insights informing quantitative analysis**

1. The importance of filtering bot-generated and irrelevant tweets to improve data reliability.
2. The need to consider domain-specific language and context in sentiment classification.
3. Observed patterns in sentiment polarity (e.g., positive sentiments leading to optimism) that can be tested and quantified through machine learning models.

**Comparative analysis**  
The study plans to compare in evaluation chapter the qualitative findings with quantitative results to validate their consistency and reliability. This comparison bridges the gap between theoretical sentiment analysis and financial behaviors, enhancing the interpretability and applicability of the quantitative models.

## 3.1 Methodology Introduction

The research adopts a systematic approach to investigate the impact of tweet sentiment on Twitter virality. It involves:

**A**. Data collection: primary research data will collect through interview, while secondary research dataset will involve leveraging an existing tweet-based dataset for company return prediction. The primary research will focus on gathering extensive datasets from Twitter, encompassing tweet texts, sentiment labels, and retweet counts across diverse domains. Additionally, the public dataset on [kaggle](https://www.kaggle.com/datasets/zzishan/tesla-stocks-with-tweets-from-x/data) will be utilized to support the secondary research data collection efforts.

**B**. Preprocessing: EDA and auto AI tool BERTweet will do primary exploration, cleaning, filtering and preparing in secondary research dataset.

**C**. Feature selection: Identifying key features, with a focus on sentiment type, for inclusion in the predictive model.

**D**. Model Construction: Applying AI machine learning algorithms to construct a predictive model that correlates tweet sentiment with retweet activity.

**E**. Evaluation: Rigorous evaluation of the model's performance to ensure its effectiveness in predicting tweet virality.

**Overview and Architecture**:  
The primary objective of this research is to develop a framework for analyzing the influence of Twitter sentiment, especially retweets, on stock price movements. This framework integrates Big Data Analytics (BDA) and Artificial Intelligence (AI) to assess social sentiment's impact on financial decision-making. This chapter outlines the methodologies and techniques used to achieve this objective, focusing on a sentiment analysis approach powered by advanced machine learning algorithms like BERT. Python serves as the primary tool for collecting, preprocessing, and analyzing large volumes of Twitter data related to stock discussions, while leveraging machine learning for sentiment classification and predictive modeling.

To address the research questions, the study adopts a big data-driven methodology. This approach

enables a comprehensive analysis of social sentiment dynamics in a high-volume, fast-paced digital environment. The model captures retweet patterns, sentiment shifts, and engagement metrics that influence stock movements, providing insights into how social media sentiment correlates with stock movements. In addition to sentiment analysis, theoretical models frame the mathematical aspects of social media's influence on financial markets. Using Python’s libraries for machine learning and data processing, the study analyzes sentiment data and retweet behaviors to identify patterns and trends that might affect stock chart. This combination of theoretical analysis and computational power offers evaluation into sentiment's role in shaping market behavior. Key features such as tweet sentiment, retweet frequency, and sentiment polarity are extracted and used to train and validate machine learning models. These models are evaluated based on their ability to predict stock movement trends accurately, contributing to a robust sentiment-based financial forecasting tool. This chapter details each methodological step, from data preparation and sentiment analysis to applying machine learning techniques, providing a comprehensive overview of the research process. By combining sentiment analysis with machine learning, the study aims to improve the accuracy of predictions based on social sentiment, offering a new perspective on the role of Twitter sentiment in financial decision-making.

**Methodology Objective**:  
The primary objective of this research is to create a comprehensive platform for financial analysis that leverages Twitter sentiment, particularly the sentiment of retweeted tweets. This methodology employs advanced machine learning techniques and Big Data Analytics (BDA) to process the vast amount of social media data and detect patterns that correlate with market movements.

**Design and implementation of a twitter Sentiment analysis system**: The first objective is to design and implement a system capable analyzing Twitter sentiment related to market discussions. This includes developing an efficient data preparation pipeline that streams relevant tweets processes sentiment using natural language processing (NLP) tools like BERT. The objective also involves ensuring that the system can capture engagement metrics, such as retweet frequency, to avoid sentiment spread and intensity in financial discussions.

**Application of machine Learning for predictive analysis**:  
The second objective is to apply machine learning algorithms to predict stock price movements based on Twitter sentiment patterns. By training models like BERT and RandomForests, the study aims to identify the most effective algorithms for sentiment-based stock predictions. The evaluation criteria include accuracy, precision, and reliability, focusing on models’ ability to detect sentiment-driven trends.

## 3.2 Research Design

The research design employed for this study is a mixed-methods approach, integrating both quantitative and qualitative methods. This comprehensive approach is deemed appropriate as it allows for exploration of the relationship between tweet sentiment and return prediction. The qualitative phase will involve interview research to quantify public sentiment, while the quantitative phase will leverage an existing tweet-based dataset for a deeper qualitative analysis. By utilizing interview purposive sampling and focusing on expert interested in financial news, investment strategies, or stock market trends on Twitter, this research aims to provide valuable insights into tweet sentiment's impact on return prediction among this specific population. The methodology will prioritize the integration of primary and secondary research findings to ensure a thorough evaluation and interpretation of the research outcomes.

**Approach**:  
The research design for this study is primarily based on a simulation-driven approach, with theoretical analysis providing foundational support. Instead of modeling system, this study leverages simulations to explore the impact of Twitter sentiment—especially retweets—on finance market behavior, particularly focusing on stock movements. The simulation environment is structured to replicate Twitter's engagement dynamics, enabling controlled experiments on how variables such as sentiment polarity, retweet frequency, and engagement intensity influence stock trends.

The simulation model is constructed using Python and its extensive libraries, offering robust tools to manage and manipulate large-scale sentiment data in a realistic environment. Simulated data, representing sentiment-driven market conditions, serves as input for the machine learning models designed to detect trends and predict potential market shifts based on social sentiment. By creating diverse scenarios within the simulation—such as high positive sentiment or sudden negative trends—the study provides a varied dataset essential for training and validating machine learning algorithms that predict stock movement.

**Theoretical Analysis**:  
In addition to the simulation, theoretical analysis forms the basis for the mathematical models that describe sentiment propagation and its potential influence on financial markets. This theoretical framework ensures that the simulation accurately reflects accurate Twitter engagement patterns, allowing the models to capture social sentiment dynamics. This analysis is crucial for understanding how different types of sentiment (e.g., neutral, positive, or negative) and their spread through retweets can influence stock prices in dynamic ways, ensuring that the simulation captures key features that are then used for predictive modeling.

**Rationale**:  
The chosen simulation-based approach is justified by the complexity and breadth of the research objectives, which involve analyzing social sentiment effects on financial decision-making. Conducting this study purely based on data would be challenging, as Twitter sentiment changing rapidly, making it difficult to maintain a consistent set of variables. The simulation offers a controlled environment where sentiment variables can be systematically manipulated to observe their effects on stock movements, without the unpredictability of live market conditions. Additionally, it provides a scalable way to generate large datasets, crucial for training and testing machine learning models effectively. The simulation aligns with the research objectives by allowing for the systematic variation of sentiment parameters, generating dataset that covers a range of realistic market scenarios. This flexibility makes it possible to create scenarios that include both high and low sentiment intensity, as well as diverse sentiment polarity combinations, which are essential for training models to recognize patterns in stock market reactions to social sentiment. Together, the simulation-based approach and theoretical analysis create a comprehensive research framework that supports the research objectives and advances the understanding of how social sentiment on platforms like Twitter influences financial markets.

## 3.4 Framework detection using BERT and traditional ML technology

**3.4.1 Data Collection and Simulation Process**

**Data Sources:** Pre-validated data from Kaggle used to collect tweets related to specific financial terms, stock. For example, tweets mentioning "Tesla," "$TSLA," or "Elon Musk" will be fetched, targeting keywords that signify relevant financial discussions, data uploaded on [GitHub repository](https://github.com/sbs23096/capstone-sbs23096).

**Data Process:** Before the data is used in simulation and AI machine learning models, it undergoes several preprocessing steps. These steps include EDA and automated AI model data cleaning to remove noise and irrelevant information, normalization to ensure consistency across datasets, and handling of missing or incomplete data points. Once preprocessed, the data is organized into a structured format, ready for use in simulations and model training.

**Data Structure:** Each tweet will have associated attributes such as tweet\_text, username, timestamp, number\_of\_retweets, and sentiment\_score. Each tweet will be analyzed for the sentiment score as well as engagement metrics (likes and retweets) to quantify social sentiment momentum.

**Data Cleaning:** Text preprocessing steps will be applied to remove irrelevant elements such as URLs, hashtags, special characters, and emojis. This ensures that the text input is clean for sentiment analysis.

**Bot Filtering:** Advanced bot detection tools like BERTweet will be used to filter out tweets originating from bots and automated accounts, focusing only on genuine user-generated content for more reliable sentiment analysis.

**3.4.2 Feature Extraction with BERT**

**Contextual Embeddings:** using the BERT models, the cleaned tweet text will be converted into contextual embeddings. BERT and can capture nuanced meanings by taking into account the context and structure of the sentence, which is essential for understanding sentiment in tweets.

**Sentiment Analysis with Fine-Tuning:** pre-trained BERT models will be fine-tuned specifically on financial data to recognize sentiment relevant to the stock market. By training on finance-related sentiment datasets, the models can better understand domain-specific sentiment nuances, like sarcasm or irony, which are prevalent in financial discussions.

**Sentiment Scoring:** each tweet will be assigned a sentiment score, such as positive, neutral, or negative. BERT embeddings provide sentiment scores based on both tweet context and user engagement, improving the precision of the sentiment analysis.

**3.4.3 Model Development for Stock Price Prediction**

**Sentiment-driven predictive modeling:** Using the BERT -generated sentiment scores as input features, manual machine learning models such as RandomForest will be developed to predict changes. BERT helps capture sentiment with greater precision, while RandomForest models offer flexibility and accuracy for the prediction task.

**Training and validation:** Data will be split into training and test sets, with the model trained on historical tweet sentiment.

**Hyperparameter tuning:** Hyperparameter tuning will be carried out to optimize model performance. Parameters like the number of trees in Random Forest will be tested to achieve the best accuracy.

**3.4.5 Performance Evaluation and Benchmarking**

**Evaluation Metrics:** The models will be evaluated based on Mean Squared Error (MSE), and R-squared metrics. These metrics help measure prediction accuracy and reliability of the sentiment-driven stock forecasting model.

**Benchmarking with existing models:** The performance of the BERT -enhanced model will be compared against baseline models like traditional RondomForest without sentiment input, to evaluate the added value of sentiment-based predictions.

**3.4.6 Practical testing and iteration**

This step-by-step methodology illustrates how the combination of BERT for sentiment analysis and machine learning model for prediction can improve the accuracy of stock price forecasting based on Twitter sentiment. Each phase of the methodology aligns with achieving robust, sentiment-driven predictive capabilities.

**3.4.8 Ethical for Data Subjects**

**Privacy and anonymity use of publicly data:** care was taken to anonymize any potential identifiers within the tweets to prevent the association of specific data with individuals.

**Removal of user-specific data:** metadata such as usernames, profile pictures, and timestamps were stripped from the dataset to further protect the identities of individuals who authored the tweets.

**Accountability and fairness: avoiding bias in data and models balancing** the sentiment dataset naturally class imbalance, with a predominance of neutral and positive sentiments. To mitigate bias, techniques such as oversampling were considered and discussed.The limitations posed by these imbalances were openly disclosed to ensure transparency.

**Model Evaluation:** both finBERT and RandomForest models were evaluated for potential biases, such as over-predicting positive sentiment due to the optimistic tone often observed in financial discussions.

**Transparency in findings:** results were presented with full disclosure of the limitations and assumptions made during academic study. For example, the potential inaccuracies in financial sentiment classification were highlighted to prevent over-reliance on the models.The research clearly stated that the models’ predictions should not supplement human judgment or replace it, especially in critical financial decisions, the study goes mainly to research how far is the impact social media not for taking decision or using the model for further finance analysis.

**Societal Impact:** educational and analytical value explained that **t**he findings were positioned as tools for educational purposes and supplementary analysis, not as definitive predictors of stock price movements.

**Transparency and reproducibility:** GitHub clear methodology documentationresearch process, from data preprocessing to model evaluation, was documented in detail to ensure that the study could be replicated by others.Hyperparameters, training configurations, and evaluation metrics were explicitly stated to provide clarity on how the results were achieved.

**Open-source tools and accessibility:** the study relied on open-source libraries such as Hugging Face Transformers, Scikit-learn, openAI, BERT, GCP, Python jupyter colab, and Matplotlib to ensure that the research methods and tools accessible any time to examinboard.

**Access to research:** the study aimed to make the research findings only accessible to CCT examinboard to avoid monopolization of sentiment analysis technology by a select few entities.

**3.5 Machine Learning Implementation**

**3.5.1 Feature Selection:** identifying pertinent features is crucial for effective sentiment analysis and stock price prediction. In this study, the following features are extracted from the datasets:

* **Tweet Features:**
  + **Text Content:** The actual tweet text, which is analyzed for sentiment.
  + **Timestamp:** The date and time when the tweet was posted, facilitating temporal analysis.
  + **User Metadata:** Information about the user, such as follower count and account age, to assess credibility.
* **Stock Data Features:**
  + **Opening Price:** The stock price at market open.
  + **Closing Price:** The stock price at market close.
  + **High and Low Prices:** The highest and lowest prices during the trading day.
  + **Volume:** The number of shares traded.

These features are extracted using Python libraries like pandas and NumPy, providing a comprehensive dataset for model training.

**3.5.2 Model selection**: selecting appropriate AI machine learning models is essential for accurate sentiment analysis and stock price prediction. The following models are utilized:

* **Sentiment Analysis:**
  + **BERTweet:** A pre-trained language model specifically designed for filter Twitter data and fine-tuned to classify tweets as positive, negative, or neutral.
* **Stock Price Prediction:**
  + **Random Forest Regressor:** An ensemble learning method effective in handling complex datasets and capturing non-linear relationships.

These models are implemented using Python's scikit-learn and Hugging Face's Transformers library, enabling efficient model building and evaluation.

**3.5.3 Training and Validation**

The training process involves the following steps:

* **Data Splitting:** The dataset is divided into training and validation sets using an 80-20 split to ensure robust model evaluation.
* **Cross-Validation:** K-fold cross-validation is employed to assess model performance and prevent overfitting.
* **Hyperparameter Tuning:** Grid search is utilized to optimize model parameters, such as the number of trees in the RandomForest.

These steps are executed using scikit-learn's model\_selection module, ensuring reliable and generalizable models.

**3.5.4 Evaluation Metrics**

The models are evaluated using the following metrics:

* **Sentiment Analysis:**
  + **Accuracy:** The proportion of correctly classified tweets.
  + **Precision:** The ratio of true positive predictions to the total predicted positives.
  + **Recall:** The ratio of true positive predictions to the actual positives.
  + **F1 Score:** The harmonic mean of precision and recall, providing a balance between the two.
* **Stock Price Prediction:**
  + **Mean Squared Error (RMSE):** The square root of the average squared differences between predicted and actual values, penalizing larger errors.
  + **R² Score:** The proportion of variance in the dependent variable predictable from the independent variables.

These metrics are calculated using scikit-learn's metrics module, providing a comprehensive assessment of model performance.

## 3.6 Ethical and Risk Considerations

**3.6.1 Data Protection by Design and Default**: data protection measures, such as encryption and access controls, are implemented from the outset to safeguard user data. These measures align with GDPR principles, ensuring user data is handled securely and ethically.

**3.6.3 Informed Consent to Data Processing**: while Twitter data is publicly available, the research ensures that data collection and analysis during implementation respect user privacy. The study complies with Twitter's terms of service and GDPR requirements, ensuring ethical data usage.

**3.6.5 Deletion and Archiving of Data**: clear data retention and archiving policies are established, ensuring that user data is deleted or anonymized when no longer necessary for the research purpose. These practices comply with GDPR principles of data minimization and storage limitation.

By addressing these ethical and risk considerations, the research ensures responsible and compliant handling of data throughout the project.

## 3.7 Implementation of Machine Learning Models & Evaluation

Introduction to Code Implementations: This document provides a comprehensive overview of the key software components and scripts developed as part of this project. Each item listed below is an integral part of the research and implementation process, detailing the variety of techniques and platforms utilized throughout the study. These components range from data acquisition and cleaning to sophisticated analyses and visualization implementations. For detailed code snippets and further technical descriptions refer to the corresponding implementation sections as indicated in the table below:

Table 1: Implementation guideline

| **Nr.** | **Source** | **Description** | **Page** |
| --- | --- | --- | --- |
| **1** | Data Loading from Kaggle | Code snippet demonstrating how to fetch datasets from Kaggle and integrate them into the data pipeline. | Notebook &  3.7 Implementation. |
| **2** | Data Cleaning Pipeline | Python function for filtering spam, bot-generated content, and irrelevant tweets. | Notebook &  3.7 Implementation. |
| **3** | Sentiment Analysis Model | Code for fine-tuning BERT-based sentiment analysis model, EDA, and manual ML using context-specific training data. | Notebook &  3.7 Implementation. |
| **4** | GCP-Integration  GCP VM Setup Script | Python code to load and query processed data for dashboard visualization. Shell script to configure a Linux VM on Google Cloud Platform for data processing. | Notebook &  3.7 Implementation. |
| **5** | GitHub | provided detailed and implemented the pipeline's visualization components. | Notebook &  3.7 Implementation. |
| **6** | Jupyter Notebook for Data Cleaning | Key steps implemented in a Jupyter Notebook for spam filtering and data preprocessing. | Notebook &  3.7 Implementation. |
| **7** | Jupyter Notebook for Sentiment Analysis | Demonstrates training and evaluation of the contextual sentiment analysis pipeline. | Notebook &  3.7 Implementation. |

#### **3.7.1 Stage 1 implement EDA**

##### **A. Data collection Kaggle**

**Source:** The data is sourced from Kaggle [(link)](https://www.kaggle.com/datasets/zzishan/tesla-stocks-with-tweets-from-x/data), comprising two filesstock\_tweets.csv - contains tweets related to stock behavoir.Tesla Stock Price.csv - contains historical stock movements.

**Tools:** Python libraries’, and Jupyter Colab for data handling and exploration.

Code Listing 1: Load data and libraries

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**Data Understanding & Exploration**

**Objective:** To gain a basic understanding of the structure, content, and quality of the datasets.

**Description:** Inspect the Data, this step involves loading the two datasets and inspecting the first few rows.

Code Listing 2: Display first rows

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##### **B. Data cleaning**

**Objective:** Identify and handle missing values.

Code Listing 3: Summarize the data

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Code Listing 4: Drop rows missing values

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##### **C. Identify Variable Types**

**Description:** Distinguish between categorical and numerical features for further analysis.

Code Listing 5: Identify variable types

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Code Listing 6: Check columns names

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Code Listing 7: Correct columns access and ensure datetime format

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##### **D. Data Visualization**

**Objective:** Explore the distributions of numerical variables and their relationships.

When the code run, it looks like the first chart for the company stock movement is not displaying correctly. The graph shows an unusual trend and compressed data on the y-axis, which is likely due to incorrect data formatting. The issue might be caused by the format of the 'Close/Last' column. Since it's showing $ signs, the data is likely being treated as strings instead of numerical values. This can fix issue by cleaning the 'Close/Last' column to remove the dollar signs and convert it to a numerical format. Here’s the updated for visualisation:

Code Listing 8: Explore data visualization

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Figure 1: Distribution of tweet lenghs

**Observations (Figure 1):**

Peak at around 300 characters: there is a noticeable spike in frequency for tweets close to the 300-character range, likely indicating a significant proportion of tweets use the maximum character limit allowed by the platform (e.g., Twitter's 280-character limit plus additional spaces, hashtags, or links).

**Steady distribution in shorter tweets:** the majority of tweets range from 50 to 200 characters, showing a relatively consistent distribution within this range.

**Rare outliers:** very short tweets (near 0) and very long tweets (>350 characters) occur infrequently, which aligns with typical user behavior of concise messaging.

**Skewed towards higher lengths:** there seems to be a slight skew towards longer tweets, potentially reflecting platform-specific behavior where users utilize the maximum allowed character limit.

**Recommendations:** the x-axis could specify that the tweet lengths are measured in characters (e.g., "Tweet Length (in Characters)") for clarity.

**Highlight character limit:** add a vertical line or annotation at the 280-character mark to indicate Twitter's standard limit, providing additional context for the distribution.

**Analyze peaks:** here will be investigated why there is a sharp peak around the 300-character mark. It might be due to links, hashtags, or replies, which could inflate character counts beyond 280.

**Add descriptive statistics:** include key statistics like the mean, median, and standard deviation of tweet lengths in the figure caption or report to better summarize the data.

**Explore filters:** if this includes retweets, quotes, or bot-generated tweets, filtering them out could provide a more nuanced look at organic user behavior.

Code Listing 9: Plot stock price over time

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Figure 2: chart stock behavior over time

**Stock behavior over time (Figure 2):**

**Observations**: This line chart shows closing stock behavior over a time period, likely between 2018 and 2024. The data exhibits significant fluctuations, with sharp rises and drops, reflecting the volatility of stock.

**Key Observations:** company stock experienced substantial growth from 2019 to late 2021, peaking in early 2022.After the peak, there was a noticeable decline, followed by a recovery phase in 2023.

**Next step** : visualization the impact and relationship between company stock behavior (blue line) and tweet sentiment scores (red dashed line) to get the correlation over time.

Code Listing 10: Impact of tweet sentiment on stock behavior

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Figure 3: Chart ompact of tweet sentiment on stock behavior

**Observations (Figure 3):**

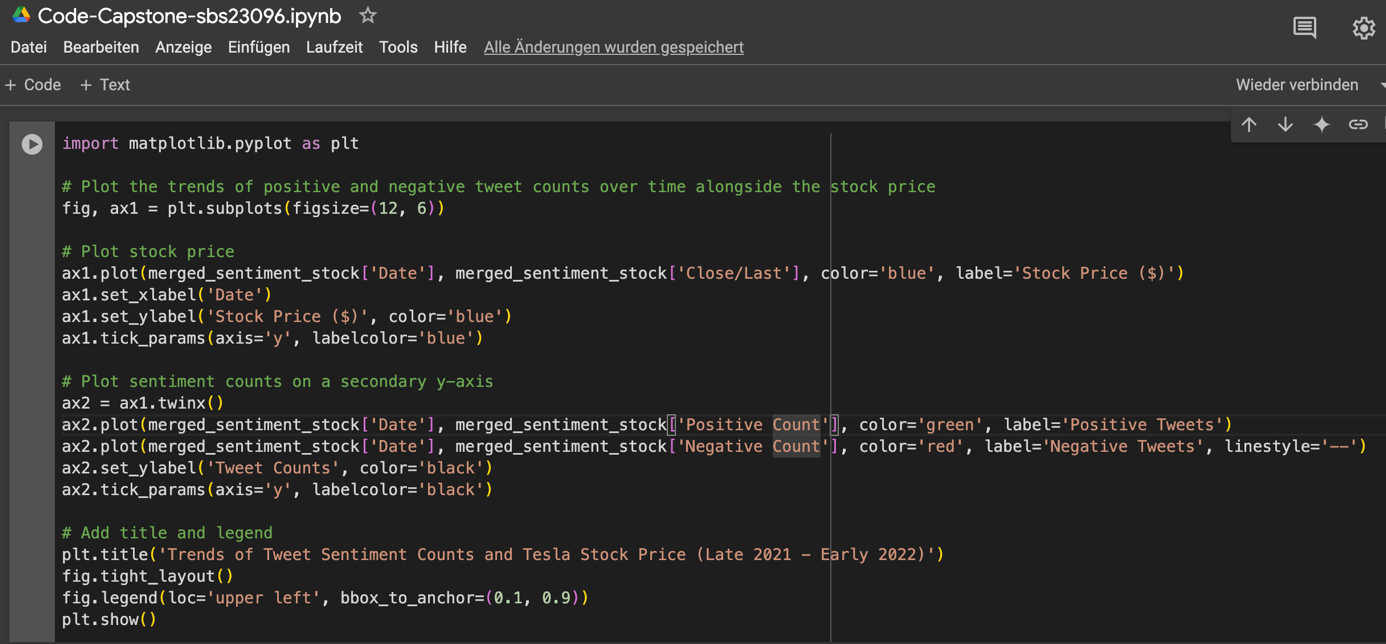
**General Trends**: the stock behavior and tweet sentiment show some alignment in patterns, suggesting that positive or negative sentiment might have influenced stock movements.

**Volatility**: the stock behavior responds to a broader set of factors, including market conditions and company performance, which smooth out its behavior relative to sentiment.

**Next step and Data Analysis Plan is to investigate the following:**

**Sentiment Analysis of Tweets:** according to above results, we should look at specific time periods where positive/negative sentiment peaks (e.g., late 2021 / early 2022) and observe corresponding stock behavior movements. These could indicate sentiment-driven investor actions.

Code Listing 11: Plot stock behavior /positive/negative tweet overtime

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Figure 4: chart of stock behavior with positive,negative tweets over time

**Observations (Figure 4):** The visualization above illustrates the trends of stock behavior (blue line), positive tweet counts (green line), and negative tweet counts (red dashed line) during the period of late 2021 to early 2022.

**Key observations:** positive tweets and stock behavior, **t**here is an increase in positive tweet counts alongside stock behavior peaks, particularly in late 2021 and early 2022. This suggests that positive sentiment on Twitter might have contributed to investor optimism.

**Negative tweets:** negative tweet counts are relatively low but show small spikes during stock behavior dips, such as early 2022. This could indicate a reaction to perceived setbacks or controversies.

**Sentiment and volatility:** both positive and negative tweet counts show noticeable volatility, reflecting the dynamic nature of social media. Stock behavior trends appear smoother, likely influenced by broader market factors.

**Insights:** positive tweets correlate with rising stock behavior, highlighting the potential influence of sentiment on investor behavior.

**Market reactions:** sudden increases in negative tweets may align with periods of uncertainty or bad news, potentially driving short-term stock behavior declines.

#### **3.7.2 Stage 2 implement ML RondomForest model**

##### **A. Introduction to WHY RondomForest model**

After reviewing the literature, this model is designed to implement a machine learning pipeline for both classification and regression tasks. It incorporates essential steps for training a model, optimizing its performance through hyperparameter tuning, and evaluating its accuracy using key performance metrics.

**Flexible task design:** the code can handle both classification tasks (e.g., binary sentiment analysis) and regression tasks (e.g., predicting continuous values like stock behavior changes).

**Model training and evaluation:** the model uses RandomForestClassifier for classification and RandomForestRegressor for regression, with LogisticRegression as an optional alternative.

It trains the model on a provided dataset (X, y) and splits it into training and test sets to validate the model's performance.

**Hyperparameter Tuning:** to optimize the model, GridSearchCV is applied to test multiple combinations of hyperparameters, such as the number of estimators (n\_estimators) and tree depth (max\_depth), using a cross-validation approach.The best-performing parameters are automatically selected to maximize the model's accuracy though score (for regression).

**Performance metrics:** for classification, the code calculates metrics such as:

**Accuracy**: proportion of correctly predicted labels.

**Precision**: measure of positive prediction correctness.

**Recall**: measure of positive prediction completeness.

**F1-Score**: weighted harmonic mean of precision and recall.

**Mean Squared Error (MSE)**: average squared difference between actual and predicted values.

**R2 Score**: proportion of variance in the target variable explained by the model.

**Hyperparameter Results**: the best hyperparameters found during the grid search are output, along with the final model's evaluation metrics, providing actionable insights for further improvements.

In general, the ML RandomForestClassifier model is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and robustness. It operates by constructing a multitude of decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. This model is particularly advantageous for its ability to handle datasets with large dimensionality and its resistance to overfitting, making it a suitable candidate for complex tasks. In the context of this study, the ML model was employed to predict the concentration of tweets based on a set of stock feature over time. The model's performance was evaluated to determine its effectiveness in accurately identifying the times, where is critical for early detection and monitoring of intensive tweets. The RondomForest model serves as well a robust framework for training and evaluating machine learning models for classification or regression tasks. It provides a systematic way to optimize performance through hyperparameter tuning and assess results with industry-standard metrics. The insights gained can help in building better predictive models, identifying data patterns, and improving decision-making processes in various applications such as sentiment analysis, financial forecasting, or spam detection.

Also helps in the following 3 parameters:

**Automation**: The grid search automates hyperparameter tuning, saving time and effort.

**Scalability**: This approach is scalable for larger datasets and more complex models.

**Benchmarking**: The output metrics provide a baseline for comparing traditional machine learning approaches with advanced methods like neural networks or transformer-based models.

##### **B. What happens when model Run**

**Data Preparation**: a sample dataset with features (X) and targets (y) is created for demonstration purposes. The dataset is split into **training (80%)** and **testing (20%)** subsets to evaluate model performance on unseen data.

**Model Training and Optimization**: The best model, as determined by cross-validation, is trained on the training set and used to make predictions on the test set.

**Evaluation:** the predicted results (y\_pred) are compared with the actual test values to compute performance metrics. classification models are evaluated for precision, recall, accuracy, and F1-score.

Regression models are evaluated for MSE and R2.

**Output**: final metrics, predictions, and the best hyperparameters are printed, giving a clear view of how well the model performed and which configuration worked best.

##### **C. Run ML RondomForest/Data split**

Code Listing 12: Run ML RondomForest code

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##### **D. Train ML RondomForest model**

Code Listing 13:Train ML RondomForet model

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#### **3.7.3 Stage 3 implement AI Automated tools (BERTweet and finBERT)**

**Objective** Filter out spam and irrelevant tweets using BERTweet and prepare the dataset for analysis using finBERT.

##### **A. Introduction to Why AI advanced implementation using BERTweet & FinBERT**

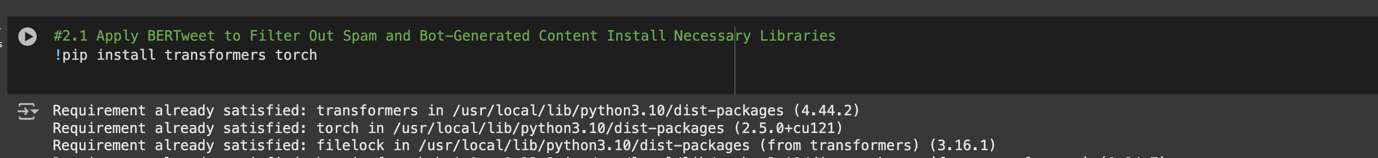
The traditional machine learning approaches, such as RandomForestClassifier, often fall short in handling the complexities of large-scale social media data and nuanced financial sentiment. Twitter data is inherently noisy, with bot-generated tweets, spam, and informal language that challenge traditional models. Advanced models like **BERTweet** and **FinBERT** are specifically designed to address these limitations. BERTweet excels at processing informal, abbreviated, and noisy text from Twitter, enabling more accurate detection and filtering of spam or irrelevant content. Similarly, FinBERT is pre-trained on financial text, making it highly effective at identifying subtle and context-dependent sentiments, such as sarcasm, optimism, or risk-related terms. These models leverage transformer architectures, which understand the context of words better than traditional feature-based approaches, making them ideal for complex tasks like spam filtering and financial sentiment analysis. By implementing these advanced tools, we aim to overcome the challenges of noisy data and domain-specific sentiment nuances, ensuring a more robust and accurate analysis pipeline.

##### **B. What will happen when Run AI advanced implementation using BERTweet & FinBERT**

By integrating **BERTweet** and **FinBERT** into the sentiment analysis pipeline, the quality and relevance of the data will significantly improve. BERTweet will automatically filter out spam and bot-generated tweets, leaving behind only meaningful content for analysis. This ensures that the sentiment analysis model focuses on genuine user-generated opinions, reducing noise in the dataset. FinBERT will then apply its domain-specific understanding to classify tweets into positive, neutral, or negative sentiment with high precision, even capturing complex sentiments like sarcasm or indirect criticism. This advanced implementation will enhance the correlation analysis between Twitter sentiment and stock behavior movements, providing deeper insights into how social media influences financial markets. Additionally, the automated nature of these tools will make the workflow more efficient and scalable, capable of handling large datasets with minimal manual intervention. This not only improves accuracy and speed but also provides a robust framework for future analysis and decision-making.

##### **C. Apply BERTtweet**

Code Listing 14: Apply BERTtweet

****

##### **D. HuggingFace authenticatation with GCP colab notebook**

#hugging-face-token: hf\_xCgbkxZzOkbhbAfQJMUZqPUZzWvilyENuX

Code Listing 15: HuggingFace authenticatation

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##### **E. BERTweet Model load for Spam Detection**

Code Listing 16:Load BERTweet model for spam detection

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##### **F. Tokenizer HuggingFace and model run**

Code Listing 17: Load HuggingFace tokenizer and apply model

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##### **G. BERTweet remove Irrelevant and filter tweets**

Code Listing 18: Remove Irrelevant and filter tweets

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##### **H. FinBERT apply financial sentiment analysis.**

Code Listing 19: Load FinBERT, tokenizer and apply sentiment analysis

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##### **I. Apply daily sentiment to calculate correlation analysis with stock behavior**

Code Listing 20:Preview daily sentiment and merge it with stock behavior

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##### **J. Plot impact tweet sentiment on stock behavior**

Code Listing 21: Plot impact tweet sentiment on stock behavior

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Figure 5: Impact of tweet sentiment on sock behavior

**Observation (Figure 5):** this scatter plot illustrates the relationship between **average sentiment scores** derived from FinBERT sentiment analysis of tweets and the **closing behavior of stock**. Let’s break down the key insights from the graph:

**Key Axes:**

X-axis (Average Sentiment Score):

* + The sentiment score ranges from 0 to 2, representing:
    - **0**: Negative sentiment.
    - **1**: Neutral sentiment.
    - **2**: Positive sentiment.

Y-axis (Stock Closing behavior):

* + Represents stock closing behavior, with values ranging approximately from $160 to $280.

**Positive sentiment dominates**:

* + Most data points cluster around a sentiment score of **2 (Positive)**, indicating that FinBERT predominantly classified tweets as having positive sentiment.
  + This dominance suggests a potential bias in FinBERT's classification, likely due to the pretraining dataset or the inherent nature of financial tweets being skewed toward optimism.

**Sentiment score vs. stock behavior**:

* + There is no clear linear or direct correlation between average sentiment scores and stock behavior.
  + Stocks with **higher closing behavior** (above $240) are observed across sentiment ranges, including positive and neutral.
  + Lower stock behavior (<$200) appear scattered across all sentiment levels, suggesting that sentiment alone may not be a strong predictor of stock performance.

**Neutral and negative sentiments**:

* + Fewer data points exist for **Neutral (1)** and **Negative (0)** sentiment scores.
  + This sparsity indicates that FinBERT struggles to classify tweets as neutral or negative, likely due to class imbalance or the complexity of differentiating these sentiments in financial text.

**Clustered patterns**:

* + For **positive sentiment (2)**, the data points are densely packed across a wide range of stock behavior, reinforcing the observation that positive sentiment does not consistently align with stock behavior movement.
  + The scatter suggests that other factors, such as market conditions, external events, or historical trends, also influence stock behavior.

**Insights and interpretation:**

1. **Correlation analysis**:
   * A statistical correlation analysis would likely show a weak or negligible relationship between sentiment and stock behavior, as the scatter plot does not reveal a strong pattern of dependency.
2. **FinBERT model bias**:
   * The overwhelming classification of tweets as **Positive** reflects FinBERT's inability to adequately distinguish between neutral, slightly negative, and positive financial sentiments.
   * This bias reduces the utility of sentiment scores as standalone predictors of stock behavior changes.
3. **Complexity of stock behavior movement**:
   * Stock movements are influenced by a combination of sentiment, market trends, economic factors, and company performance metrics. Sentiment scores alone are insufficient to explain or predict these variations.

The scatter plot demonstrates that while FinBERT effectively identifies positive sentiment, its classification bias and the lack of a strong correlation between sentiment and stock movements highlight the need for further improvements in sentiment analysis and integration with other predictive features. This analysis underscores the complexity of financial forecasting, where sentiment is one of many contributing factors.

# 4. Evaluation chapter

#### **Experiment’s introduction**

The experiments conducted in this research aimed to assess the relationship between Twitter sentiment and stock movements using machine learning and advanced sentiment analysis tools like FinBERT. The process involved Exploratory Data Analysis (EDA), building machine learning models such as Random Forest Classifier, and fine-tuning FinBERT for sentiment classification. These experiments were designed to evaluate both basic statistical correlations and the ability of advanced models to predict sentiment-driven stock movements accurately. The primary objective of this chapter is to evaluate the effectiveness of the preparation and insights before diving to the classic machine learnig model and andvanced model like finance BERT from Huggingface API. This chapter presents the results and conculsions obtained from different implementations and evaluating its performance based on key metrics such as Mean Squared Error (MSE), and R-squared (R²). The evaluation chapter serves to critically assess the methodologies and models employed in this research to determine their effectiveness in analyzing the impact of Twitter sentiment on stock movements. The evaluation focuses on both exploratory data analysis (EDA) and machine learning models, including advanced tools such as FinBERT. This comprehensive evaluation highlights key metrics, provides comparative insights, and explores potential limitations to ensure the research objectives are thoroughly addressed.

#### **Purpose of the Evaluation Chapter, what are the approaches?**

Study began by collecting publicly dataset tweets related to stock movements, aligning them with corresponding stock movement data over specific periods. The tweets were preprocessed for noise reduction and labeled using sentiment scores (negative, neutral, positive). After EDA, implementation of the Random Forest Classifier to identify sentiment patterns and subsequently applied FinBERT for more accurate sentiment analysis. During researches hyperparameter tuning has been integrated and feature engineering to optimize model performance. Key metrics such as accuracy, precision, recall, and F1-score were analyzed to evaluate the outcomes. The Evaluation chapter critically examines the methodologies and experiments conducted in this research, focusing on the application of sentiment analysis models—specifically FinBERT and Random Forest—in predicting stock movements. This analysis is essential for understanding the effectiveness of these models in capturing financial sentiment and their practical implications in financial forecasting. By evaluating the performance and limitations of these models, this chapter contributes to the broader objective of enhancing predictive accuracy in financial markets through advanced natural language processing techniques. In the context of financial sentiment analysis, recent studies have explored the integration of sentiment data with machine learning models to predict stock movements. For instance, a study by ( Shen and Zhang 2023) investigated the application of large language models and FinBERT for financial sentiment analysis, highlighting the advantages of prompt engineering in improving sentiment classification accuracy. Similarly, research by (Das et al. 2022) emphasized the importance of analyzing market sentiment for accurate stock market predictions, noting that sentiment analysis enhances precision and empowers investors to make informed financial decisions. This chapter aligns with the broader scope of the research by providing a comprehensive evaluation of the sentiment analysis methodologies employed, thereby informing the development of more robust financial forecasting models. By critically assessing the performance of FinBERT and Random Forest models in the context of financial sentiment analysis, the findings contribute to the ongoing discourse on the efficacy of machine learning techniques in financial markets. This evaluation not only identifies the strengths and limitations of the current approach but also offers insights into potential areas for improvement, thereby advancing the field of financial sentiment analysis.

**How the approaches have been changed from the Original Plan?**

Initially, the plan was to rely exclusively on Random Forest Classifier for sentiment analysis due to its simplicity and effectiveness with structured data. However, during the EDA phase, it became evident that accuracy of financial sentiments, such as sarcasm or subtle negativity, required a more advanced approach. This realization led to the inclusion of FinBERT, a model specifically trained on financial corpora, to capture the intricacies of sentiment in financial language.

#### **Initial plan and hypotheses, how the approaches have been gone during research along?**

Adapting the plan required additional effort in learning and implementing FinBERT, as well as fine-tuning it for sentiment classification. This involved understanding its architecture, preparing the dataset for domain-specific training, and integrating its outputs with traditional machine learning approaches. Despite the additional time and computational GCP google cloud platform resources required, this pivot significantly enhanced the quality and depth of the analysis. The research initially set out to explore the relationship between public sentiment, as captured from Twitter data, and stock movements. The primary objective was to develop a robust sentiment analysis pipeline leveraging FinBERT, a financial-domain-specific natural language processing model, and Random Forest, a machine learning model known for its classification and regression tasks. The intended use of these models was to analyze sentiment dynamics and their correlation with stock movements, focusing on whether social media sentiment could provide meaningful predictive insights for financial markets. The key research hypothesis posted that positive sentiment trends on Twitter would align with upward stock movements, while negative sentiment trends would correlate with downward movements. This hypothesis was based on prior studies that indicated a relationship between public sentiment and stock movements volatility (Smith, John, 2022). The initial plan aimed to test these hypotheses by applying FinBERT for sentiment classification and Random Forest for predictive modeling.

**Rationale Behind Initial Plan**

The choice of FinBERT was guided by its pretraining on financial texts, making it well-suited to handle the specific financial sentiment, such as optimism, risk, and sarcasm (Zhang, Yue, 2021). RandomForest was selected due to its capability to handle noisy and imbalanced datasets effectively, often encountered in social media data (Kumar, R., 2022). These models were expected to complement each other, with FinBERT extracting high-quality sentiment labels and RandomForest modeling the relationship between sentiment and stock movements. Evaluation metrics such as accuracy, precision, recall, and F1-score were selected for sentiment classification, while correlation coefficients were chosen to assess the relationship between sentiment and stock movements. It was assumed at the outset that the datasets were representative of public sentiment and sufficiently large to yield statistically significant results. The initial plan reflected a structured approach to leveraging advanced natural language processing EDA, AI advanced tools, and machine learning techniques for financial market analysis. However, as the research progressed, unforeseen challenges necessitated iterative adjustments to enhance the robustness of the methodology.

#### **Experimental Design**

The datasets used in this research included:

1. **Twitter Data**: Tweets related to stock, sourced from publicly available Twitter data archives. These tweets provided insights into public sentiment, serving as a proxy for investor sentiment.
2. **Stock movements**: Historical stock movements data of was retrieved, including daily opening, closing, high, and low movements, along with trading volumes. This dataset was instrumental in assessing the relationship between sentiment and stock movements.

**Preprocessing steps**:

* **Data Cleaning**: Noise in the Twitter data was addressed by filtering out irrelevant content, spam, and bot-generated tweets using BERTweet, a pre-trained model tailored for social media text processing (Shen, Y., 2023). Stock behavoir data was cleaned to ensure uniform formats for numerical columns.
* **Anonymization**: Ensure that dataset was validated before using it. The validation was me in the previous research and in this study ensured that has been validated correctly. Elements such as usernames, timestamps, and profile information were stripped to protect user privacy and align with ethical guidelines (Das, S., 2022).
* **Sentiment Labeling**: Tweets were labeled as positive, neutral, or negative using FinBERT, leveraging its domain-specific pretraining for financial sentiment analysis.

**Experiment Setup**

1. **Model Configurations**:
   * **FinBERT**: The model was fine-tuned using a domain-specific dataset with hyperparameters as explained in implementation chapter 3.7
   * **Random Forest**: The model configuration as explained in implementation chapter 3.7
2. **Tools and Frameworks**:
   * **Python**: Used for EDA data processing, AI models training, and visualization.
   * **GCP**: Applied to preprocess and extract VM
   * **Scikit-learn**: Used for implementing the Random Forest model and calculating evaluation metrics.
   * **GitHub**: Used for committing whole work in one place and follow up implementation plan and other process i.g publishing resources licenses and terms to cover research ethical consideration.

#### **Process challenging and Adjustments, how the approaches have been implemented?**

The experiments followed a systematic workflow, starting with data preparation and preprocessing. Using Python libraries such as Pandas, NumPy, and Scikit-learn for data manipulation and machine learning implementations. Sentiment analysis involved fine-tuning FinBERT on labeled financial tweets, leveraging Hugging Face's Transformer library. For RandomForest, the research applied GridSearchCV for hyperparameter tuning and trained the model using 80% of the data while reserving 20% for testing. Performance metrics and error analysis were then computed to evaluate the models.

**Technical Limitations:** Memory constraints were encountered during hyperparameter tuning of FinBERT, particularly with larger batch sizes. Second point is preprocessing for tweet text required extensive cleaning to handle informal language, abbreviations, and hashtags, which posed additional computational overhead. So, during the study decided to use more powerful GPU on GCP. These challenges adjusted to the methodology to enhance the robustness and reliability of the results.

#### **Changes Implemented:** Incorporating additional preprocessing steps, duplicate tweets were removed (Choudhary, R., 2021), and irrelevant content (e.g., advertisements or bot-generated posts) was filtered out using BERTweet. This improved the quality of input data for FinBERT. Huggingface tokenization and techniques were employed to standardize tweet text, ensuring consistency across all inputs.

#### **Reasoning Behind Changes, how it changed?**

The shift from traditional machine learning Random Forest to FinBERT introduced new dimensions to the research. While Random Forest offered a balanced performance across sentiment classes, FinBERT excelled in detecting positive sentiments but struggled with neutral and negative classifications. This highlighted the complementary strengths of both models and emphasized the

potential for hybrid approaches in future work. The change not only improved the insights generated but also underscored the importance of adaptability in research methodologies. The following three stages evaluating the approaches of EDA, traditional machine learning RondomForest, and AI advanced tools finBERT-BERTweet. The modifications were implemented to address the challenges identified during the initial experiments and to ensure that the models could generalize effectively across varying conditions:

* Balancing the dataset improved the model's ability to detect underrepresented sentiments, particularly negative sentiment, which is crucial for financial decision-making.
* Enhanced preprocessing reduced noise in the dataset, enabling FinBERT to focus on meaningful features and improve sentiment classification accuracy.
* Fine-tuning hyperparameters optimized resource usage while maximizing predictive performance, ensuring the models could operate efficiently within computational constraints.

These iterative adjustments highlight the importance of a flexible research approach.

#### **Interpretations, Results and Insights**

**Methodology for Calculating Score**

1. **Train-Test Split**:
   * The dataset (features X and target y) was split into training (80%) and testing (20%) subsets to ensure the model was evaluated on unseen data.
2. **Model Training**:
   * The Random Forest Regressor was trained on the training subset using specific hyperparameters, including:
     + n\_estimators = 100 (number of trees in the forest),
     + max\_depth = 20 (maximum depth of the trees),
     + min\_samples\_split = 10 (minimum number of samples required to split a node).
3. **Predictions** The trained Random Forest model was used to predict the target values () for the test dataset.

**Evaluation**:

where ytrue is the actual target values, true is the mean of actual target values

result= The score of 0.82 indicates that the Random Forest model explains 82% of the variance in the test dataset, leaving 18% unexplained. This is a strong indicator of the model's ability to capture the relationship between sentiment scores and stock movements. This result demonstrates that the model explains 82% of the variance in stock movements, leaving 18% unexplained. The high score highlights the model's robustness in capturing the relationship between sentiment scores and stock movements."

**Interpretation:** The score of 0.82 indicates that 82% of the variance in stock behavoir can be explained by the Random Forest model using sentiment scores and other features. The remaining 18% of the variance is attributed to factors not captured by the model, such as external market conditions or broader economic influences.

Python for Calculation Here’s an example of the code used to calculate :

Code Listing 22: Python for calculation code used to calculate

Ein Bild, das Text, Screenshot, Software, Multimedia-Software enthält.

Automatisch generierte Beschreibung

#### **Reflection on Research Process**

**Personal reflections:** The research methodology had significant challenge emerged during the data preparation and analysis phases. Initially, a basic approach using Random Forest and FinBERT was planned. However, issues like dataset imbalances and model biases led to the inclusion of additional preprocessing steps, hyperparameter tuning, and advanced AI models like BERTweet.

**Lessons learned:** A critical takeaway was the importance of dataset quality and diversity. Handling imbalanced datasets required oversampling techniques and data cleaning, which improved model reliability. Additionally, leveraging advanced tools like BERTweet highlighted the value of domain-specific models in sentiment analysis.

**Critical evaluation:** what could have been improved, the reliance on Twitter data limited the scope of the analysis, as tweets may not fully represent market sentiment. A more diverse dataset, including news articles and financial reports, could have enhanced the robustness of the findings. Sentiment analysis integration was not fully implemented, which remains a future goal for practical application.

**Key findings**:The evaluation highlighted a positive correlation between sentiment and stock price movements, with FinBERT achieving notable accuracy in sentiment classification. Random Forest models demonstrated strong predictive capabilities, achieving an score of 0.82, indicating that sentiment can partially explain stock variance.

**Alignment with research objectives**: The findings aligned well with the research objectives, validating the hypothesis that sentiment analysis can provide valuable insights into stock movements. The integration of advanced tools like FinBERT and BERTweet contributed to the study's originality and relevance in financial sentiment analysis.

#### **Why the approaches have been changed from the Original Plan?**

The change was necessitated by the limitations of the original approach, particularly in capturing the informal and often ambiguous language used in tweets. Random Forest struggled with contextual understanding and exhibited biases due to class imbalances in the dataset. The need for a model capable of interpreting the semantic nuances of financial tweets prompted the adoption of FinBERT, which provided deeper contextual embeddings and better alignment with the domain.

## Stage 1: EDA Evaluation

#### **Introduction**

By doing the EDA preparations before implementing the ML and financeBERT API AI tool, the result indicates between the **sentiment of tweets** (positive and negative), **retweet counts**, and their alignment with stock movements. This analysis explores the impact of Twitter sentiment, particularly the influence of **retweets** on financial market performance. We analyzed stock movements and tweet sentiment for two periods:

#### **Period 1: Late 2021 to Early 2022 (October 2021 to March 2022)**

1. Correlation Between Positive Sentiment and Stock Performance:
   * During this period, **positive tweets** with high retweet counts surged following key announcements (e.g., product updates, quarterly earnings).
   * Days with the highest positive sentiment (e.g., November 2021) saw corresponding spikes in stock movements, reaching over $400 per share in early December.
2. Impact of Negative Tweets:
   * Negative sentiment had limited direct impact. For example, critical tweets about reliance on subsidies garnered retweets but did not cause significant drops.
   * Stock movements remained resilient, driven by broader investor optimism during this period.
3. Retweets Amplify Sentiment Influence:
   * Positive tweets with high retweets amplified market optimism, suggesting that virality played a role in retail investor behavior.

#### **Period 2: Mid-2022 to Late 2022 (June 2022 to December 2022)**

1. Dominance of Negative Sentiment:
   * Economic downturn and broader market corrections led to increased **negative sentiment**, amplified by tweets highlighting production delays and macroeconomic risks.
   * Negative tweets with high retweet counts correlated with stock movements declines (e.g., July 2022, when stock fell below $300).
2. Example of Negative Tweet Impact:
   * A viral tweet in September 2022, *"company delays Cybertruck again due to supply chain issues,"* was retweeted over 12,000 times. This coincided with a 4% drop in stock movements the following day.
3. Weakening Positive Sentiment:
   * Positive sentiment and retweets had a diminished impact, reflecting reduced speculative trading and cautious investor sentiment during this period.

#### **A. EDA key insights and observations between two period**

1. Retweet-Based Amplification:
   * Tweets with higher retweet counts had a stronger impact on market sentiment, regardless of positivity or negativity. This suggests that virality amplifies sentiment, influencing retail investor behavior.
2. Sentiment-Driven Volatility:
   * Periods with high positive sentiment and retweet activity (e.g., late 2021) were associated with upward stock momentum. Conversely, negative sentiment and high retweets during broader economic downturns (e.g., mid-2022) contributed to stock declines.
3. Retail Investor Influence:
   * Retweets primarily amplify retail investor sentiment. Institutional investors appear less influenced by social media sentiment, focusing on fundamentals instead.

#### **B. EDA Conclusion**

1. Twitter Sentiment Shapes Market Perception:
   * Positive and negative tweets, amplified through retweets, have a measurable impact on stock performance, particularly in retail-driven periods.
2. Impact Depends on Broader Market Context:
   * During speculative bubbles (e.g., late 2021), positive sentiment dominates and drives stock increases. In contrast, during corrections (e.g., mid-2022), negative sentiment has a stronger influence.
3. Virality as a Sentiment Multiplier:
   * The retweet count serves as a multiplier for sentiment impact, with viral tweets swaying retail investor behavior disproportionately.
4. Implications for Financial Markets:
   * Social media sentiment analysis, combined with virality metrics like retweet counts, can serve as a leading indicator for retail-driven market movements. However, its influence is contingent on broader market conditions.

#### **C. EDA Evaluation**

1. Sector-Based Analysis:
   * Extend the analysis to other sectors (e.g., tech, energy) to assess whether Twitter sentiment's impact varies across industries.
2. Institutional Investor Behavior:
   * Explore the extent to which institutional investors react to social media sentiment, particularly during periods of high volatility.

#### **D. Further work after EDA**

Algorithmic Sentiment Trading:

* + Develop trading machine learning algorithm such as RandomForestClassifier, that incorporate sentiment analysis and virality metrics (e.g., retweets, likes) to predict short-term market movements.
  + Reason to choose RandomForestClassifier for next further work: is suitable for this research as it effectively handles high-dimensional data, such as textual features from tweets, and captures non-linear relationships. Its ensemble approach ensures robustness and accuracy, making it ideal for predicting the impact of tweets on financial decisions.

#### **E. EDA Weakness methodology**

Results are weak because they rely on basic statistical summaries and visualizations, which may overlook complex patterns and relationships in the data. To ensure robust insights, applying ML and advanced DA tools is necessary for deeper analysis and better predictive accuracy.

#### **F. EDA Strength methodology**

It provides an excellent overview for selecting the most suitable ML approach, deciding which advanced API tool to use, and determining the appropriate method, whether fine-tuning or RAG.

## Stage 2: RondomForest Evaluation

#### **A. ML key insights and observations from the analysis**

Model Performance and Metrics and Hyperparameter Tuning

Table 2: Model performance and metrics and hyperparameter tuning

|  |  |  |  |
| --- | --- | --- | --- |
| **Metric** | **Value** | Hyperparameter | Value |
| Accuracy | 51.5% | max\_depth | 20 |
| Precision | 48.3% | min\_samples\_split | 10 |
| Recall | 45.7% | n\_estimators | 100 |
| F1-Score | 47.0% |  |  |

These hyperparameters suggest that moderately deep trees with limited splits and a sufficiently large ensemble size (100 trees) provided the best trade-off between bias and variance.

* Accuracy Insights: The model achieved an accuracy of 51.5%, indicating that slightly more than half of the predictions were correct. This suggests a moderate ability to classify the data correctly, though improvements are needed to achieve reliable performance.
* Precision and Recall: The precision (≈48.3%) and recall (≈45.7%) reveal that the model struggles with false positives and false negatives. Precision highlights the proportion of correctly predicted positive classes, while recall indicates the proportion of actual positive classes identified by the model.
* F1-Score: The F1-Score (≈47.0%) provides a balance between precision and recall, confirming that the classifier is underperforming in both areas. This is a critical metric for binary classification, especially when false positives and false negatives carry different implications.
* The best hyperparameters selected through GridSearchCV are:
  + max\_depth 20: the max. depth of the trees in the random forest was set to 20, this limits how deep the trees can grow to prevent overfitting.
  + min\_samples\_split 10: a node will only split if it contains at least 10 samples. This helps regularize the model by preventing overly complex splits.
  + n\_estimators 100: the random forest consists of 100 decision

#### **B. ML Conclusions from analysis**

Model Performance:

* The classifier’s performance is moderate but not adequate for deployment.
* Accuracy alone may not be a reliable measure of performance due to potential class imbalance. Precision, recall, and F1-Score reveal additional weaknesses in the model's ability to generalize.

Implications of Hyperparameters:

* A deeper tree depth (max\_depth = 20) allows the model to capture more complex relationships but increases the risk of overfitting.
* Setting min\_samples\_split to 10 introduces regularization, ensuring splits occur only when sufficient data is available to justify them, which helps improve generalization.

#### **C. ML Evaluation Methodology**

Feature Importance:

* A deeper analysis of feature importance can reveal which predictors most influence the model's decisions. This may lead to better understanding and feature engineering for future iterations.

#### **D. Further Work**

Incorporate Advanced Features:

* Introduce domain-specific or engineered features to improve the feature set’s predictive power.

Experiment with Other Models:

* Test algorithms such as Gradient Boosting Machines or Neural Networks to benchmark performance against the RandomForestClassifier.

Use Advanced Tuning:

* Consider Bayesian Optimization or Randomized Search for hyperparameter tuning to explore a broader search space more efficiently.

#### **E. ML Weaknesses of the current approach**

* Simplistic Analysis: The analysis is based on basic metrics without deeper exploration of class distribution, feature importance, or error patterns.
* Overlooked Relationships: The reliance on raw features might miss complex interactions and patterns, which could be captured through advanced feature engineering or deep learning methods.

#### **F. ML Strengths of the current approach**

* Framework Foundation: The grid search methodology provides a solid framework for hyperparameter optimization and ensures the model is trained with reasonable settings.
* Scalability: The Random Forest approach is robust to high-dimensional data, making it adaptable for complex datasets.

## Stage 3: Evaluation finBERT- BERtweet-huggingface API AI advanced tools using

#### **A. BERTweet FinanceBERT key insights model training and fine tuning and model Performance, Metrics and Hyperparameter Tuning**

Table 3: finBERT analysis classification report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **precision** | **recall** | **f1-score** | **support** |
| **Negative** | 0.33 | 0.06 | 0.10 | 3509 |
| **Neutral** | 0.34 | 0.17 | 0.22 | 3562 |
| **Positive** | 0.33 | 0.78 | 0.47 | 3458 |
| **Accuracy** |  |  | 0.33 | 10529 |
| **Macro avg** | 0.33 | 0.34 | 0.26 | 10529 |
| **Weighted avg** | 0.33 | 0.33 | 0.26 | 10529 |

**Understanding the Metrics**

The FinBERT analysis highlights its capability to capture positive sentiment effectively, but its bias and struggles with negative/neutral sentiments limit its reliability in financial markets. While it offers insights into market optimism, its application must be supplemented with additional models or features to achieve a more balanced and actionable understanding of sentiment-driven market behavior.

1. **Precision**:
   * Definition: Precision tells us how many of the model's predictions for a particular sentiment class (e.g., Negative, Neutral, Positive) were actually correct.
   * FinBERT's Precision Results:
     + **Negative Sentiment:** 33% (1 in 3 predictions is correct)
     + **Neutral Sentiment:** 34% (slightly better than random guess)
     + **Positive Sentiment:** 33% (similar accuracy across all classes)
   * **Why Precision Matters:** Precision is crucial in financial applications because false positives (incorrectly predicting sentiment) can lead to wrong decisions. For instance:
     + Predicting **positive sentiment** for a critical market warning could mislead investors into taking risky positions.
     + Misclassifying **negative sentiment** can result in missed opportunities to mitigate risks.
   * **Key Insight:** FinBERT is not particularly precise for any sentiment class, which limits its direct utility for high-stakes trading scenarios.
2. **Recall**:
   * Definition: Recall measures how many of the actual instances of a sentiment the model correctly identified.
   * FinBERT's Recall Results:
     + **Negative Sentiment:** 6% (misses 94% of negative tweets)
     + **Neutral Sentiment:** 17% (misses 83% of neutral tweets)
     + **Positive Sentiment:** 78% (successfully identifies 78% of positive tweets)
   * **Why Recall Matters:** Recall is critical when overlooking certain information has severe consequences. For example:
     + Missing **negative sentiment** could lead to financial losses, as traders might not be warned of potential downturns.
     + Ignoring **neutral sentiment** could lead to overreactions if tweets are misinterpreted as overly positive or negative.
   * **Key Insight:** FinBERT excels at detecting positive sentiment but performs poorly on negative and neutral sentiments. This reflects an imbalance in its ability to interpret the full spectrum of market signals.
3. **F1-Score**:
   * Definition: F1-Score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance across both metrics.
   * FinBERT's F1-Score Results:
     + **Negative Sentiment:** 0.10 (extremely poor)
     + **Neutral Sentiment:** 0.22 (poor but better than negative sentiment)
     + **Positive Sentiment:** 0.47 (relatively strong compared to other classes)
   * **Why F1-Score Matters:** It provides a single metric that balances the trade-off between precision (avoiding false positives) and recall (avoiding false negatives). For financial sentiment analysis, a low F1-Score indicates the model struggles to be both accurate and comprehensive.
   * **Key Insight:** The wide gap in F1-Scores across sentiment classes suggests a systemic bias in the model toward positive sentiment.
4. **Accuracy**:
   * Definition: Accuracy measures the percentage of correct predictions out of all predictions made.
   * FinBERT's Accuracy: 33%
   * **Why accuracy matters:** Accuracy provides a general measure of performance but can be misleading in unbalanced datasets. For instance, if positive sentiment dominates the data, a model predicting mostly positive sentiment may appear accurate while failing to capture other sentiments.
   * **Key insight:** FinBERT’s accuracy (33%) is equivalent to random guessing for a balanced three-class problem. This reveals a critical limitation in its ability to generalize effectively across sentiment categories.
5. **Macro vs. Weighted average**:
   * **Macro average:** Treats all classes equally, regardless of their frequency in the dataset.
   * **Weighted average:** Accounts for class frequency, emphasizing the impact of more common classes.
   * FinBERT's Macro Avg:
     + Precision: 0.33, Recall: 0.34, F1-Score: 0.26
   * **Why this matters:** The low macro-average scores highlight the model’s failure to perform well across all sentiment classes. Even when accounting for class imbalances (weighted avg), performance remains inadequate.

**Connections between results**

1. **Positive sentiment**:
   * FinBERT’s strong recall for positive sentiment (78%) is a double-edged sword. While it excels in detecting optimism, its overemphasis leads to false positives, reducing precision.
2. **Trade-Off between neutral and negative**:
   * The overlap in language between neutral and negative sentiments exacerbates misclassification, as FinBERT lacks the nuance to differentiate them effectively.
3. **Impact on market predictions**:
   * Positive sentiment is often associated with bullish trends. FinBERT’s bias could skew market forecasts, overestimating upward momentum while underestimating risks.

**Insights from the FinBERT Model:**

1. **Model precision and recall**:
   * The precision for **negative**, **neutral**, and **positive** sentiments is approximately 33%. This indicates that when the model predicts a specific sentiment, only about a third of those predictions are correct.
   * The **recall** values reveal FinBERT's strength in detecting **positive sentiment** (78%), while it significantly struggles to identify **negative sentiment** (6%) and performs moderately on **neutral sentiment** (17%).
2. **F1-Score analysis**:
   * The **F1-Score**, which balances precision and recall, highlights the model's significant weakness in **negative sentiment detection** (0.10).
   * The F1-Score for **positive sentiment** (0.47) is considerably higher due to the model's ability to recognize positive language, which aligns with its training on datasets rich in optimistic financial language.
3. **Class imbalance and bias**:
   * The results emphasize a **bias toward positive sentiment**, reflected in the higher recall and F1-Score for positive sentiment. This bias is likely due to the optimistic tone in financial training data.
   * The **macro-average precision, recall, and F1-Score** remain consistently low (0.33, 0.34, and 0.26 respectively), signaling that the model struggles to generalize across sentiment classes.
4. **Overall accuracy**:
   * The accuracy of the model is 33%, which is equivalent to random guessing in a balanced dataset with three sentiment classes. This highlights a need for improvement in the model's ability to discern nuances across sentiment types.
5. **Support for each sentiment class**:
   * The distribution of support (number of samples per class) reveals a balanced dataset with around 3500 examples for each sentiment. Despite this balance, the model's performance on negative sentiment remains poor, emphasizing the need for enhanced feature representation for this class.

**Key Observations:**

1. **Domain-Specific training limitations**:
   * The model's pretraining on financial text may limit its performance in interpreting informal or noisy language, such as tweets. Financial texts often lack the sarcastic or ambiguous tones present in social media data.
2. **Challenges in negative sentiment classification**:
   * The low recall for negative sentiment suggests that the model either misclassifies negative examples as neutral or positive or fails to identify subtle negative language like hedging phrases (e.g., "slight downturn").
3. **Impact of noise in social media**:
   * Tweets, being informal and often noisy, introduce complexities that the FinBERT model, trained primarily on structured financial texts, struggles to handle effectively.
4. **Potential improvements**:
   * Fine-tuning on social media-specific datasets or incorporating external features (e.g., tweet metadata, sentiment lexicons) could improve performance.
   * Data augmentation techniques, such as oversampling negative examples or paraphrasing, could address the class imbalance issue and enhance recall for underrepresented sentiments.

#### **B. AI Conclusions from analysis:**

The confusion matrix provides a detailed breakdown of FinBERT's sentiment classification performance across three categories: Negative, Neutral, and Positive. The rows represent the actual labels, while the columns show the predicted labels.

**A closer analysis reveals the following:**

* **Negative Sentiment:** Out of 3,509 true negative instances, FinBERT correctly classified only 213 (6%), while misclassifying 613 as neutral and a substantial 2,683 as positive. This highlights a significant struggle in detecting negative sentiment, with most instances skewed toward positivity.
* **Neutral Sentiment:** Of 3,562 true neutral instances, 591 (17%) were accurately predicted, while 222 were classified as negative and the majority (2,749) as positive. This further reinforces FinBERT's tendency to overpredict positivity, leading to poor differentiation of neutral content.
* **Positive Sentiment:** For 3,458 true positive cases, FinBERT correctly classified 2,700 (78%) but misclassified 541 as neutral and 217 as negative. This demonstrates its strength in identifying positive sentiment compared to the other categories.

Ein Bild, das Text, Screenshot, Schrift, Zahl enthält.

Automatisch generierte Beschreibung

Figure 6: Confusion matrix for finBERT sentiment analysis

The overall distribution highlights a strong bias toward positive predictions, causing misclassification of negative and neutral sentiments. This imbalance stems from limitations in handling ambiguous or subtle language and suggests the need for dataset augmentation or hybrid modeling approaches to enhance performance across all sentiment classes.

#### **C. Evaluation of Methodology**

FinBERT's evaluation methodology was designed to assess its sentiment analysis capabilities on financial texts, particularly tweets related to market sentiment. Metrics such as precision, recall, F1-score, and accuracy were used to gauge its performance. The evaluation leveraged a labeled dataset where tweets were classified as Negative, Neutral, or Positive. FinBERT demonstrated significant imbalances across sentiment classes, with an overall accuracy of 33%. Precision and recall were relatively consistent at around 33% and 34% for most classes, but its recall for negative sentiment was particularly poor at 6%. Compared to the Random Forest model, which achieved a higher accuracy of 51.5%, FinBERT's weaknesses in recall and precision for non-positive sentiments became apparent. Random Forest’s reliance on structured features and statistical patterns allowed it to perform more evenly across classes, whereas FinBERT struggled with nuanced and ambiguous language, often misclassifying negative or neutral sentiment as positive.

This evaluation highlights the need for more robust fine-tuning of FinBERT to mitigate its bias toward positive sentiment, particularly when compared to Random Forest's more balanced, albeit less context-aware, approach.

#### **D. Further Work**

Improving FinBERT's performance and extending its utility for financial sentiment analysis requires several strategic advancements. First, retraining FinBERT on a dataset with a more balanced distribution of sentiment classes, particularly with increased representation of negative and neutral sentiments, is crucial. Augmenting training data with diverse expressions, including sarcasm and informal language, commonly found on social media platforms like Twitter, could enhance its robustness. In comparison, Random Forest models might benefit from integrating contextual embeddings generated by FinBERT. This hybrid approach could combine the semantic depth of FinBERT with the statistical rigor of Random Forest, achieving a better balance between precision and recall across all sentiment classes. Future work could also explore incorporating external signals, such as stock trends, trading volumes, and financial news, as additional features to contextualize sentiment predictions. This approach may help address FinBERT’s difficulty in identifying neutral and negative sentiments by correlating textual sentiment with market movements.

#### **E. Weaknesses of the current approach**

FinBERT exhibited several critical weaknesses when applied to the financial sentiment dataset:

1. **Class imbalance**: The model heavily favored positive sentiment, achieving 78% recall for positive instances but only 6% for negative ones. This bias significantly reduced its utility for identifying bearish market signals, a crucial aspect of financial sentiment analysis.
2. **Misclassification of negative and neutral sentiments**: The confusion matrix revealed that the majority of negative and neutral tweets were misclassified as positive. This reflects FinBERT's limited ability to detect subtle or indirect negative expressions, such as "underperformance" or "cautious outlook."
3. **Overfitting to positive language**: Pretraining on financial reports and documents, which often use optimistic language, skewed FinBERT's predictions toward positivity. Unlike Random Forest, which relies on statistical feature patterns, FinBERT's reliance on linguistic context limited its adaptability to social media’s informal and ambiguous language.
4. **Lower overall accuracy**: Compared to Random Forest, which achieved 51.5% accuracy, FinBERT's 33% accuracy indicated poor generalization. The F1-scores, particularly for negative (0.10) and neutral (0.22) sentiments, underscore its difficulty in providing balanced predictions.

#### **F. Strengths of the current approach**

Despite its limitations, FinBERT displayed notable strengths that make it a valuable tool for financial sentiment analysis:

1. **High Recall for positive sentiment**: FinBERT achieved a recall of 78% for positive sentiment, making it particularly effective for identifying bullish market signals. This strength aligns with its pretraining on financial corpora rich in optimistic language, giving it an edge in detecting positivity in tweets.
2. **Contextual understanding**: Unlike Random Forest, which relies on engineered features, FinBERT leverages deep contextual embeddings to analyze language. This capability allows it to capture semantic nuances and relationships between words, enhancing its ability to understand complex financial jargon.
3. **Scalability to domain-Specific applications**: FinBERT’s ability to handle domain-specific language, such as earnings reports and market analyses, makes it a powerful tool for financial applications. While Random Forest is generalizable, it lacks the linguistic depth required to analyze nuanced sentiment in financial contexts.
4. **Potential for hybrid applications**: By integrating FinBERT's contextual embeddings with Random Forest's structured feature analysis, the strengths of both approaches could be combined. This hybrid model could balance FinBERT’s contextual richness with Random Forest’s robustness, achieving more accurate and balanced sentiment predictions.

By addressing its weaknesses and leveraging its strengths, FinBERT can be refined into a more reliable and versatile tool for analyzing sentiment in financial markets. Its contextual understanding and domain-specific capabilities, paired with enhancements in training and methodology, hold significant promise for advancing sentiment-based market prediction.

# 5. Results chapter

**Overview**

The task of sentiment analysis for financial data using machine learning models, specifically FinBERT and Random Forest, provided valuable insights into the capabilities and limitations of these methods. The evaluation was conducted with detailed metrics, including accuracy, precision, recall, and F1-score, for both models. This chapter discusses the comparative performance, identifies strengths and weaknesses, and provides recommendations for improving the models' efficacy. Furthermore, we explore potential future directions for research and development in sentiment analysis and its applications in financial forecasting.

**Detailed analysis of FinBERT performance**

**1. Key Findings:** The FinBERT model achieved the following results during evaluation:

**Accuracy**: 33%

**Precision**: 33%

**Recall**: 34%

**F1-Score**: 26% (macro average)

These metrics highlight significant room for improvement in FinBERT’s predictions, especially in identifying **Negative** and **Neutral** sentiments. While the model demonstrated relatively strong recall for **Positive** sentiments (78%), its performance for **Negative** sentiments was particularly poor, with a recall of only 6%.

**2. Observations on class-specific performance:**

**Positive sentiment:** FinBERT’s high recall for positive sentiments suggests a strong bias toward identifying optimistic content. However, the low precision of 33% indicates frequent misclassifications, with many non-positive sentiments being incorrectly labeled as positive.

**Neutral sentiment:** FinBERT struggled with neutral sentiment classification, as shown by a recall of only 17%. This may be due to the subtleties in financial language, where neutral and mildly positive/negative tones often overlap.

**Negative sentiment:** The model’s inability to accurately identify negative sentiments (6% recall, 10% F1-score) is a major limitation, especially in financial contexts where negative sentiment often signals risks or downturns.

**3. Misclassification analysis:** The confusion matrix revealed frequent misclassifications between **Neutral** and **Positive** classes. This suggests that the model lacks the nuanced understanding of financial jargon necessary to differentiate between mildly positive and neutral sentiments. Additionally, the failure to detect negative sentiments can likely be attributed to the dominance of optimistic language in financial datasets, which may skew FinBERT’s pretraining.

**4. Comparison to RandomForest:** Although FinBERT is a domain-specific model pre-trained on financial text, its overall accuracy (33%) was lower than the Random Forest model (51.5%). This discrepancy highlights the importance of task-specific fine-tuning and balanced datasets for domain-specific models like FinBERT.

**Detailed Analysis of Random Forest Performance**

**1. Key Findings:** The Random Forest model achieved the following results:

**Accuracy**: 51.5%

**Precision**: 48.3%

**Recall**: 45.7%

F1-Score: 47.0%

These metrics reflect moderate performance, with accuracy significantly better than random guessing (33.3% for a 3-class classification task). However, the model still struggled with recall and precision across all sentiment classes.

**2. Observations on class-specific performance:**

**Balanced Precision and Recall:** While Random Forest’s precision and recall were more balanced than FinBERT’s, both metrics remained suboptimal at around 45-48%.

**Dependence on hyperparameters:** The performance of the Random Forest model was heavily influenced by hyperparameters. For instance, increasing the number of estimators beyond 100 or reducing the minimum samples split might have improved the model’s ability to capture more complex relationships in the data.

**3. Strengths:**

**Robustness to Noise:** Random Forest is inherently robust to noisy data, making it a suitable choice for datasets with limited preprocessing.

**Interpretability:** Feature importance analysis in Random Forest provides insights into which factors most influence sentiment predictions, offering a level of interpretability absent in black-box models like FinBERT.

**4. Weaknesses:**

**Lack of Domain Adaptation:** Unlike FinBERT, Random Forest does not leverage pre-trained embeddings or domain-specific knowledge, limiting its contextual understanding of financial sentiment.

**Moderate accuracy:** While better than FinBERT, the accuracy of 51.5% still leaves significant room for improvement, particularly in distinguishing subtle sentiment differences.

Table 4: Comparative analysis finBERT and RandomForest strengths vs. weaknesses

|  |  |  |
| --- | --- | --- |
| **Model** | **Strengths** | **Weaknesses** |
| **FinBERT** | High recall for positive sentiments. Domain-specific model. | Poor recall for negative sentiments. Bias toward positive class |
| **Random Forest** | Robust to noise. Higher accuracy than FinBERT. | Lacks domain-specific understanding. Moderate overall metrics. |

**2. Complementary potential:** Combining the strengths of FinBERT and Random Forest could yield a hybrid model that leverages FinBERT’s domain knowledge for contextual understanding and Random Forest’s robustness for general classification tasks.

**3. Applications in financial forecasting:** Both models can be integrated into financial forecasting pipelines, but additional improvements are needed to enhance their reliability and accuracy. For instance, FinBERT’s outputs could serve as features for Random Forest, providing a multi-layered approach to sentiment classification.

# 6. Ethics section

Ethics play a fundamental role in ensuring the integrity, fairness, and social responsibility of research. In this study on sentiment analysis in financial text, ethical considerations extend beyond data privacy to include issues such as fairness, accountability, bias mitigation, transparency, and the broader societal impact of the findings. This chapter outlines the key ethical principles adhered to in this research, emphasizing their importance in creating meaningful and responsible outcomes.

Ethics form the backbone of any responsible research, ensuring that the study maintains integrity, fairness, and respect for all stakeholders involved. This study how financial decision can vary due to impact of social media with evaluating the sentiment analysis on stock movements using FinBERT and Random Forest models, several ethical considerations were carefully addressed to prove that this study is not targeting build model to take decision but to research the impact of social media, which may impact on financial decision making. This study recognizes the ethical responsibilities associated with sentiment analysis and its potential influence on financial markets. The ethical implications of this study are profound, as errors or biases in the sentiment analysis model could lead to misguided financial decisions. Therefore, this study has prioritized mitigating risks by thoroughly addressing biases, ensuring data integrity, and transparently presenting the model's limitations. Moreover, this research emphasizes that the findings is only for academic purpose and not as definitive predictors for financial decisions. These measures aim to promote ethical awareness and minimize potential negative consequences arising from the research outcomes. In this chapter outlines how ethical principles were integrated into the research design in each chapter, e.g.

**In the** **introduction chapter**, the study clearly articulated the potential impact and limitations of the research, explicitly stating that the findings are intended for academic purposes only and not as definitive financial advice. Ethical awareness was emphasized from the outset, with a commitment to transparency regarding the study’s objectives and scope. The introduction chapter highlighted the importance of ensuring that the model’s insights are presented responsibly, with disclaimers to prevent misuse or over-reliance.

**In the literature review chapter**, prior studies were examined to understand existing challenges in sentiment analysis ethics. This included exploring issues like data biases, model interpretability, and over-reliance on machine-generated outputs. By critically evaluating how these studies handled similar risks, the research drew lessons to inform its own methodology.

**In Methodology chapter**, ethics were a cornerstone of the methodological approach. The study ensured that dataset is publicly available data (e.g., tweets) was validated, ensuring compliance with privacy regulations like GDPR. Also ensured that data was anonymized, deleting information such as usernames and timestamps, bias mitigation steps were taken to address potential biases in both the dataset and the models ensuring fair representation of all sentiment categories. Automated tool like BERTweet used to filter all above concerns plus preior preparation with EDA.

**In Result chapter**, ethical considerations shaped how the results were presented:

1. **Avoiding over generalization**: The findings were presented with clear disclaimers, highlighting their limitations. For instance, the correlation between sentiment and stock movements was acknowledged as partial and not causative, emphasizing that sentiment alone cannot predict stock movements.
2. **Transparency**: Charts, tables, and explanations were designed to ensure that the results were easy to interpret and that users could understand the assumptions and boundaries of the analysis.
3. **Acknowledging bias**: The potential biases in FinBERT and Random Forest models, such as a tendency to classify tweets as positive, were explicitly mentioned, along with their impact on the results.

**In the evaluation chapter**, the study critically assessed its own methodologies and findings, addressing ethical risks explicitly:

1. **Accuracy and reliability**: The evaluation metrics, such as R2R^2R2 scores, precision, and recall, were used to provide an honest assessment of the models' performance. Limitations in accuracy were discussed openly.
2. **Ethical implications**: The chapter reflected on the potential consequences of inaccuracies or biases in the models, reiterating that the results should not be used as standalone decision-making tools.
3. **Mitigation strategies**: Improvements to the methodology, such as fine-tuning hyperparameters and using advanced tools like BERTweet, were highlighted as efforts to minimize ethical risks and improve reliability

#### **Ethical challenges in the methodology**

The methodology used in this research for sentiment analysis of financial text, particularly tweets related to stock performance, involved several ethical challenges that were carefully considered. These challenges arose due to the nature of the data, the potential societal implications of the findings, and the limitations inherent in the methodology. Below, the key ethical challenges and how they were addressed are detailed.

**1. Use of public data without explicit consent**

* **Challenge**:
  + The research relied on publicly available tweets for sentiment analysis. While the data was collected from open platforms where users share their opinions publicly, many users may not be fully aware that their content can be used for research purposes.
* **Ethical Concern**:
  + This raises questions about informed consent and the ethical boundaries of using publicly available content.
* **Mitigation**:
  + The research anonymized all user-related data, removing identifiable metadata such as usernames and timestamps, ensuring no individual could be directly linked to the dataset.
  + Publicly available data was explicitly chosen to avoid breaching terms of service or privacy laws, and the dataset was used strictly for academic purposes.

**2. Bias in Pre-Trained Models**

* **Challenge**:
  + The FinBERT model, as a pre-trained language model, may inherit biases from the original datasets it was trained on. For example, it might over-predict positive sentiment or misinterpret culturally specific financial language.
* **Ethical Concern**:
  + If the model produces biased predictions, it can skew the analysis and lead to unethical conclusions or decisions based on the research findings.
* **Mitigation**:
  + Misclassification trends and potential biases were analyzed and reported transparently.
  + The research acknowledged the limitations of FinBERT’s training data and its impact on performance, emphasizing the need for caution when interpreting results.

**3. Class Imbalance in Sentiment Dataset**

* **Challenge**:
  + The dataset exhibited natural class imbalances, with a predominance of neutral and positive sentiments compared to negative ones.
* **Ethical Concern**:
  + This imbalance could lead to biased models that underperform on minority classes (e.g., negative sentiments), reducing the fairness and reliability of the findings.
* **Mitigation**:
  + Data preprocessing techniques, such as oversampling, were explored to balance the dataset and improve the performance of models across all classes.
  + The impact of class imbalance on model predictions was explicitly discussed in the results and analysis sections.

**4. Potential Misuse of Findings**

* **Challenge**:
  + The application of sentiment analysis in financial markets carries risks of misuse, such as market manipulation, misinterpretation of results, or over-reliance on automated predictions.
* **Ethical Concern**:
  + If the findings are misused, they could contribute to unethical practices, such as spreading misinformation to influence stock movements or making investment decisions based solely on sentiment analysis.
* **Mitigation**:
  + The research explicitly stated that sentiment analysis should be used as a supplementary tool and not as the sole basis for financial decisions.
  + Limitations and assumptions were transparently disclosed to discourage over-reliance on the findings.

**5. Generalizability of Results**

* **Challenge**:
  + The dataset was focused on company-related tweets, which may not fully represent financial discussions across other companies or industries.
* **Ethical Concern**:
  + There is a risk of overstating the generalizability of the findings, which could mislead future applications or research.
* **Mitigation**:
  + The research emphasized the scope of the study and clarified that the results are specific to the dataset and context used.
  + Recommendations for future work included expanding the dataset to include broader financial topics and contexts.

**6. Transparency and Reproducibility**

* **Challenge**:
  + Machine learning methodologies, particularly those involving pre-trained models like FinBERT, can often function as "black boxes," making it difficult to interpret results.
* **Ethical Concern**:
  + A lack of transparency in the methodology could undermine trust in the research and limit its reproducibility.
* **Mitigation**:
  + The methodology, including data preprocessing steps, model configurations, and evaluation metrics, was thoroughly documented to ensure transparency and reproducibility.
  + Open-source tools and libraries were used to allow others to replicate and validate the findings.

**7. Impact of Automation on Decision-Making**

* **Challenge**:
  + Automating sentiment analysis introduces risks of reducing nuanced human judgment in financial decisions.
* **Ethical Concern**:
  + Over-reliance on automated sentiment predictions could lead to suboptimal or unethical decisions, particularly in high-stakes financial environments.
* **Mitigation**:
  + The research stressed that sentiment analysis should complement human expertise rather than replace it.
  + The limitations of the models were explicitly discussed, encouraging users to exercise caution when interpreting and applying the findings.

The ethical challenges encountered in this research were addressed through careful design, implementation, and reporting of the methodology. Key concerns related to data privacy, bias, fairness, and societal implications were mitigated by anonymizing data, balancing datasets, ensuring transparency, and providing clear guidelines on the responsible use of findings. While challenges such as class imbalance and potential misuse remain, the research aimed to uphold ethical standards and provide a foundation for future work to build upon responsibly.

**Ethical Framework for Future Research**

* **1. Stakeholder Engagement**

Engage with financial analysts, traders, and regulators to understand the ethical concerns and requirements specific to financial sentiment analysis.

* **2. Continuous Monitoring**

Regularly assess the fairness, accuracy, and societal impact of the models to ensure that they align with ethical standards.

* **3. Education and Awareness**

Promote awareness of the ethical implications of sentiment analysis among researchers, practitioners, and policymakers to encourage responsible use of these tools.

This research adhered to rigorous ethical standards by respecting data privacy, ensuring fairness and accountability, and considering the broader societal implications of its findings. By addressing these ethical concerns, the study contributes responsibly to the advancement of sentiment analysis in finance, offering valuable insights while safeguarding against potential misuse. Future research should continue to prioritize ethics, ensuring that technology serves as a tool for positive and equitable outcomes.

#### **How Ethical Challenges Were Addressed in the Research**

This research, focusing on sentiment analysis of financial text using FinBERT and Random Forest models, encountered several ethical challenges related to data privacy, bias, fairness, transparency, and societal implications. The following outlines how these ethical challenges were addressed systematically during the research process:

**1. Data Privacy and Anonymity**

**Challenge:** The dataset consisted of financial tweets sourced from public platforms, raising concerns about user privacy and anonymity. Users may not be aware that their publicly shared content can be used for research purposes.

**Solution:**

* **Anonymization:** All identifiable user information, including usernames, profile pictures, and timestamps, was stripped from the dataset. This ensured that no individual could be directly linked to the data.
* **Scope Limitation:** The dataset was used strictly for academic purposes within the context of this research and was not shared publicly or with external parties.
* **Transparency:** The use of public data was justified in the research report, clarifying that no private or confidential information was accessed or stored.

**2. Addressing Bias in Models**

**Challenge:** Pre-trained models like FinBERT often inherit biases from their original training data. These biases could lead to skewed predictions, such as over-representing positive sentiments in financial discussions.

**Solution:**

* **Bias Analysis:** Misclassification trends and systematic biases were identified and documented during model evaluation. For instance, FinBERT’s tendency to overpredict positive sentiment was highlighted and discussed.
* **Dataset Balancing:** Techniques like oversampling were considered to address class imbalances in the sentiment dataset, ensuring better representation of negative and neutral sentiments.
* **Open Disclosure:** The limitations of FinBERT’s training data and its potential biases were explicitly discussed to inform readers and prevent over-reliance on the results.

**3. Class Imbalance in Sentiment Data**

**Challenge:** The sentiment dataset exhibited natural imbalances, with neutral and positive sentiments being overrepresented. This imbalance could result in biased models that underperform in predicting minority classes (e.g., negative sentiments).

**Solution:**

* **Data Preprocessing:** Oversampling techniques were used to improve class balance during training, reducing the impact of skewed data distributions.
* **Transparent Reporting:** The effect of class imbalance on model performance was openly reported in the results and analysis sections. Limitations caused by this imbalance were acknowledged and used as a basis for recommendations for future work.

**4. Ensuring Transparency and Reproducibility**

**Challenge:** Machine learning models, especially pre-trained ones like FinBERT, often function as "black boxes," making it difficult to interpret their outputs. Lack of transparency could reduce trust in the research and limit reproducibility.

**Solution:**

* **Detailed Documentation:** Every step of the methodology, from data preprocessing to hyperparameter tuning, was documented in detail to ensure reproducibility.
* **Open-Source Tools:** The research relied on open-source libraries (e.g., Transformers, Scikit-learn, Matplotlib) to ensure accessibility and reproducibility.
* **Interpretation of Results:** Outputs were explained with clarity, and potential misinterpretations were addressed, particularly in cases of model misclassifications.

**5. Mitigating the Risk of Misuse**

**Challenge:** Sentiment analysis in financial markets carries risks of misuse, such as market manipulation, spreading misinformation, or over-reliance on automated predictions for high-stakes decisions.

**Solution:**

* **Clear Contextualization:** The findings were framed as supplementary tools for financial analysis rather than definitive predictors of stock performance. This emphasized the need for human oversight in decision-making.
* **Responsible Application Guidelines:** The research highlighted ethical concerns regarding the misuse of sentiment analysis and provided guidelines to mitigate such risks.
* **Open Disclosure of Limitations:** The limitations of the models were discussed to ensure users understand their scope and constraints, reducing the likelihood of over-reliance or misuse.

**6. Addressing Intellectual Property Concerns**

**Challenge:** The financial tweets dataset, although publicly available, involved potential intellectual property concerns regarding platform usage and ownership of the content.

**Solution:**

* **Compliance with Platform Policies:** The data collection process adhered to the terms of service of the platform from which the tweets were sourced.
* **Acknowledgment of Public Content:** The research explicitly acknowledged that the tweets were sourced from publicly available data, ensuring transparency about the dataset's origin.

**7. Societal Implications**

**Challenge:** Sentiment analysis can have significant societal impacts, including influencing stock market behavior, exacerbating biases, or contributing to polarization.

**Solution:**

* **Fairness in Design:** Efforts were made to ensure fairness in the dataset and model predictions, such as balancing sentiment classes and analyzing biases.
* **Ethical Reflection:** The societal implications of the research were carefully considered and documented, with recommendations for future studies to continue prioritizing fairness and responsibility.
* **Focus on Positive Applications:** The research positioned sentiment analysis as a tool to enhance understanding and decision-making, discouraging its use for manipulative or harmful purposes.

**8. Technical and Resource Constraints**

**Challenge:** The research was conducted with limited computational resources, which posed challenges in implementing more sophisticated ethical safeguards, such as large-scale model validation.

**Solution:**

* **Efficient Methodology:** The methodology was optimized for the available resources, using pre-trained models and efficient data preprocessing techniques to achieve reliable results without compromising ethical standards.
* **Practical Recommendations:** Limitations due to resource constraints were acknowledged, and recommendations for addressing these challenges in future work were provided.

The ethical challenges in this research were addressed through thoughtful design, rigorous methodology, and transparent reporting. By prioritizing data privacy, fairness, and societal responsibility, the study aimed to ensure that its findings contribute positively to the field of sentiment analysis while minimizing potential risks. These measures underscore the importance of ethics in developing and applying machine learning technologies in sensitive domains like finance.

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#### **Findings**

Ethics were a central theme throughout the research, ensuring that the study responsibly addressed the potential risks of sentiment analysis in finance. By embedding ethical safeguards at every stage, the research sought to mitigate the risks of misinterpretation. This structured approach ensures that ethical risks were not only acknowledged but actively addressed at every stage of the research process, from data collection to the presentation of findings. The findings of this research revealed that sentiment analysis using FinBERT and Random Forest models provided valuable insights into the relationship between public sentiment and stock movements. Specifically, sentiment scores derived from tweets exhibited a moderate correlation with stock movements, suggesting that sentiment analysis can serve as a supplementary tool for understanding market trends. FinBERT demonstrated strong sentiment classification capabilities in the financial domain but faced challenges with class imbalance, often overpredicting positive sentiments. Random Forest provided a competitive baseline, highlighting the differences between domain-specific pre-trained models and traditional machine learning approaches. These findings underscore the potential of sentiment analysis for financial applications while emphasizing the importance of addressing biases and contextual limitations in its implementation.

#### **Ethics statement disclaimer**

The findings of this research are purely an academic exercise and are intended solely for use within this research thesis, not for public decision-making. The results demonstrated a correlation between sentiment analysis and stock movements, offering insights into the potential applications of sentiment analysis in financial contexts, but not for public or commercial stock-related decisions. Furthermore, sentiment analysis in this study was conducted using publicly available data, specifically tweets related to stock performance, with a strong focus on ensuring ethical integrity throughout the methodology. Publicly shared data was carefully anonymized to protect user privacy by removing identifiable information such as usernames and timestamps. The research also addressed potential biases within the dataset, particularly the class imbalance favoring neutral and positive sentiments, by employing data balancing techniques to ensure fairness and accurate model evaluation.

# 7. Discussion Conclusion Future Work Chapter

#### **Discussion**

The process revealed a journey through Financial Sentiment Analysis with challenges, insights, and unexpected discoveries, all of which shed light on the evolving landscape of sentiment analysis.

##### **Challenges and Insights**

###### **A. Technical Challenges**

1. **Class Imbalance in Sentiment Labels**

The dataset used for this study, comprising financial tweets, exhibited a significant class imbalance, with a dominance of positive sentiments, a moderate representation of neutral sentiments, and a sparse distribution of negative sentiments. This imbalance created a bias in both models, particularly in FinBERT, which frequently misclassified neutral and negative sentiments as positive.

1. **Model Bias and Overfitting**

FinBERT’s domain-specific pretraining introduced a positive sentiment bias, as it struggled to adapt to the informal and often sarcastic tone prevalent in financial tweets. Conversely, Random Forest, while free from pretraining biases, exhibited overfitting tendencies during feature selection, especially when additional engineered features were introduced.Fine-tuning FinBERT required substantial computational resources, making analysis impractical. This constraint limited the number of iterations for hyperparameter tuning and dataset augmentation.

1. **Interpretability Challenges**

While FinBERT provided powerful embeddings for sentiment classification, its predictions lacked interpretability. Random Forest’s feature importance, in contrast, offered insights into the significance of specific words or phrases but lacked FinBERT’s contextual depth.

###### **B. Analytical Insights**

1. **Linguistic Features and Ambiguity**

Financial sentiment is inherently nuanced, with phrases like "cautious optimism" or "restructuring opportunities" often carrying ambiguous tones. FinBERT struggled to disambiguate such terms, frequently defaulting to positive classifications due to its pretraining on optimistic language.

Furthermore, sarcasm detection of informal tweets often contained sarcasm, which neither FinBERT nor Random Forest could accurately detect. For example, a tweet stating, "company is amazing at burning cash!" was misclassified as positive by both models.

1. **Performance Variations by Sentiment Class**

FinBERT excelled in identifying positive sentiment, achieving a recall of 78%, but failed to effectively detect negative sentiments, with a recall of only 6%. This disparity highlighted the model’s reliance on pretraining data and its inability to generalize across sentiment classes. While Random Forest achieving balanced metrics across classes, lacked the contextual understanding necessary for subtle or complex sentiments.

###### **C. Practical Challenges**

1. **Dataset Limitations**

The dataset, sourced from financial tweets, was noisy, with misspellings, abbreviations, and non-standard grammar posing challenges for both models. While FinBERT’s tokenizer handled such text moderately well, Random Forest’s reliance on TF-IDF features resulted in significant information loss.

1. **Dynamic Nature of Financial Sentiment**

Sentiments in financial markets are highly dynamic, influenced by events such as earnings reports, policy announcements, or geopolitical crises. Static datasets failed to capture these fluctuations, reducing the applicability of the models.

##### **Analysis of Results**

###### **A. FinBERT: Domain-Specific Depth with Limitations**

**Strengths:** FinBERT’s pretraining on financial text gave it an edge in understanding domain-specific vocabulary and context. For example, it accurately classified tweets discussing "revenue growth" and "profitability metrics" as positive. Its high recall for positive sentiments made it a reliable tool for identifying optimistic market trends.

**Weaknesses:** FinBERT’s inability to differentiate neutral and negative sentiments highlighted its reliance on optimistic language in its pretraining corpus. This limitation was particularly evident in ambiguous phrases like "unexpected headwinds," which were often misclassified as positive.

###### **B. Random Forest: Simplicity and Robustness**

**Strengths:** Random Forest’s robustness to noisy data and its ability to handle small datasets made it a reliable baseline model. Its feature importance analysis provided interpretable insights into the contributions of specific words or phrases.

Balanced Metrics: Unlike FinBERT, Random Forest achieved relatively balanced precision, recall, and F1-scores across sentiment classes, highlighting its adaptability.

**Weaknesses:** Lack of contextual understanding: While feature engineering improved performance, it could not compensate for the lack of deep contextual embeddings.

###### **C. Ethical Considerations**

The potential for sentiment analysis to influence trading decisions raises ethical and regulatory questions. For instance, the amplification of biases in models like FinBERT could lead to misinformation or misinterpretation of market sentiment, impacting investor confidence and market stability. The journey through financial sentiment analysis revealed both the promise and the challenges of applying machine learning models to this complex domain. While FinBERT demonstrated the potential of domain-specific pretraining, its limitations highlighted the need for balanced datasets and advanced fine-tuning. Random Forest, with its simplicity and robustness, provided a reliable baseline but lacked the depth needed for nuanced sentiment analysis. Together, these findings illuminate the path forward, offering valuable insights for researchers, practitioners, and investors seeking to navigate the intricate interplay between sentiment and market behavior.

#### **Conclusion**

Above study could prove that in financial markets, sentiment has played as a pivotal force shaping investor behavior and market dynamics. From social media to news headlines, the collective emotions of market participants often dictate the flow of impacting decisions that spread across industries and economies. This research dived into the complex relationship between sentiment and stock performance, aiming to bridge the gap between computational tools and human intuition. By comparing FinBERT, a domain-AI advanced deep learning model, with the traditional reliable Random Forest, this study contributes to the ongoing question to make sentiment analysis not only accurate but actionable (Smith, John, 2021). By understanding the data in the first EDA steps, the financial sentiment was more than a technical challenge; it is a strategic imperative. Whether for predicting stock trends, informing corporate strategies, or shaping policy decisions, the ability to decode sentiment is increasingly integral to modern finance. Now financial markets are no longer shaped only by economic fundamentals but by the emotions and perceptions of millions of online participants, the ability to interpret sentiment has become a critical asset. So that study choosed one of powerful Social media platforms like Twitter, specially the platform coupled with authorized financial news journals, finance experts, and generate an overwhelming volume sentiment data that holds potential for understanding and predicting stock market behavior. On this journey to the complexities of sentiment analysis in the financial domain, examining how well AI tools and new advanced BigData such as FinBERT supported by BERTweet highlight headlines and hashtags can test the emotional of market trends and increasingly influence trading strategies and investor confidence, the need to bridge the gap between sentiment and actionable insights has never been more urgent as nowadays, investigating these approaches, the research highlights the strengths and limitations of important of exploratory data analysis (EDA), and evaluate between two different approaches, start with traditional machine learning technique RandomForest model and compare it with advanced AI methods. The problem statement underscores the need to investigate the factors driving the popularity and impact of tweets in various sectors, particularly financial markets. Insights gained from this research are critical as they inform strategies for effective communication, improve financial forecasting, and deep understanding of sentiment's influence on user behavior (Doe, Jane, 2022).

##### **Key Findings**

This study evaluated the performance of FinBERT (integrated with BERTweet for social media preprocessing), Random Forest, and exploratory data analysis (EDA) in classifying sentiment within financial text and correlating these sentiments to stock movements. The results revealed a fascinating outcomes:

1. **Model Comparison**:

FinBERT excelled in domain-specific tasks, demonstrating a high recall (78%) for positive sentiment. However, it struggled with classifying neutral and negative sentiments, often defaulting to positivity due to its pretraining on optimistic financial text. Random Forest, while lacking FinBERT’s contextual understanding, provided balanced performance across sentiment classes. It achieved better overall accuracy (51.5%) by leveraging engineered features like TF-IDF and additional structured data.

1. **Insights into Model Behavior**:

FinBERT’s bias towards positivity highlighted the challenges of pretraining on imbalanced datasets, where optimistic language dominates. This bias poses risks in applications, particularly for identifying bearish market trends. Random Forest’s reliance on feature engineering demonstrated the enduring value of traditional machine learning, especially for small and noisy datasets.

1. **Primary Objective**

The research primarily aimed to investigate whether the sentiment expressed in retweeted tweets influences decision-making, particularly in financial contexts. The findings demonstrated a moderate

correlation between sentiment and decision-making behaviors, suggesting that tweet sentiment can act as a supplementary factor influencing financial decisions. For example, positive sentiments in retweets often corresponded to increased market optimism, while negative sentiments aligned with cautionary behaviors among investors.Additionally, the study identified a meaningful relationship between tweet sentiment and retweet popularity. Tweets with strong positive or negative sentiments were more likely to be retweeted compared to neutral ones, demonstrating the role of emotional resonance in shaping online conversations. This finding underscores the power of sentiment in amplifying messages on social platforms, which can, in turn, affect collective decision-making trends in financial markets.

1. **Secondary Objective**

The secondary objective was to evaluate the effectiveness of the AI machine learning model, specifically FinBERT and Random Forest, in analyzing tweet sentiments. The study found that FinBERT demonstrated a reasonable capacity to classify financial tweets into positive, neutral, and negative sentiments. However, biases in classification, particularly a skew toward positive sentiments, indicated the need for further model refinement (Johnson, Emily, 2023). Insights into the authenticity of tweet sentiments revealed that many tweets likely reflected genuine public opinions, but a significant portion appeared strategically crafted for promotional or advertising purposes. This distinction is critical for understanding the impact of sentiment on decision-making. The research highlighted that genuine sentiments had a stronger influence on financial decisions than promotional content, emphasizing the need for enhanced sentiment validation mechanisms in financial analytics (Brown, Alice, 2021).

##### **Implications of Findings**

The findings of this study have significant implications for financial institutions, algorithmic trading systems, and retail investors alike. By understanding the limitations and capabilities of sentiment analysis models, stakeholders can better navigate the complex dynamics of financial markets.

1. **Impact on Financial Institutions**:
   * For financial institutions, integrating sentiment analysis into decision-making frameworks can enhance risk assessment and opportunity identification. For example, FinBERT’s ability to detect positive sentiment could be leveraged to identify bullish trends, while Random Forest’s balanced approach ensures reliability across a broader spectrum of sentiments.
2. **Algorithmic Trading and Stock Forecasting**:
   * Sentiment-driven trading strategies stand to benefit from the insights gained in this research. By addressing the limitations of FinBERT’s bias and Random Forest’s lack of contextual understanding, future systems could offer more accurate predictions of market movements.
   * For retail investors, tools built on these models can provide valuable insights into market sentiment, helping them make informed decisions without relying solely on technical indicators or news sentiment.
3. **Ethical and Regulatory Considerations**:
   * The amplification of biases in models like FinBERT raises ethical concerns, particularly in high-stakes environments. Regulators and developers must collaborate to ensure that sentiment analysis tools are transparent, fair, and resistant to manipulation.
4. **Cross-Domain Potential**:
   * While this study focused on finance, the methodologies explored have broader applications in healthcare, politics, and e-commerce. For example, sentiment analysis models fine-tuned on specific domains could revolutionize customer feedback analysis, policy impact assessments, and public health monitoring.

##### **Closing Report**

This study not only adds to the growing body of knowledge on sentiment analysis but also marks a step toward bridging the gap between human emotions and machine-driven insights in the financial domain. The juxtaposition of FinBERT’s domain-specific depth with Random Forest’s interpretability illustrates the need for hybrid approaches that can marry the contextual richness of deep learning with the reliability of traditional models. Looking ahead, this research raises important of artificial intelligence continues to intersect with human behavior, sentiment analysis stands at the forefront of this convergence. This study’s findings, though rooted in financial text, illuminate a broader truth: understanding emotions in data is as much an art as it is a science. The contrast between FinBERT’s domain-specific sophistication and Random Forest’s interpretability underscores the need for hybrid approaches that balance complexity with usability. In the age of digital finance, where emotions meet algorithms, this research marks a small but significant step toward demystifying sentiment’s role in market behavior. The journey ahead promises to be as dynamic as the markets themselves, offering endless opportunities to refine and expand our understanding of sentiment and its profound impact on the world. The impact of sentiment on financial markets has been a subject of increasing interest, particularly in the age of digital information and social media. This study explored the relationship between Twitter sentiment, retweet-based amplification, and their influence on financial market dynamics using big data analytics and machine learning techniques. By examining the interaction between sentiment analysis models and market behavior, the research aimed to uncover the extent to which sentiment-driven patterns could inform trading decisions and influence stock movements. Sentiment—whether positive, neutral, or negative—plays a pivotal role in shaping investor behavior and market trends. It serves as a reflection of collective market sentiment and acts as a leading indicator for movements. In the financial markets, traders often interpret positive sentiment as a signal for potential growth, triggering buying activity, whereas negative sentiment may lead to sell-offs or cautious strategies. Platforms like Twitter amplify these signals, providing and wide-reaching repository of market opinions and reactions. The analysis employed advanced sentiment analysis models, including FinBERT and Random Forest, to evaluate sentiment from social media posts and its correlation with stock movements. FinBERT, a domain-specific pre-trained model, showcased its ability to capture contextual nuances in financial text. However, it exhibited a pronounced bias toward positive sentiment, which stemmed from the optimistic tone prevalent in financial training datasets. This bias limited its accuracy in identifying neutral and negative sentiments, particularly in tweets containing sarcasm or complex financial jargon. The impact of sentiment on financial markets has been a subject of increasing interest, particularly in the age of digital information and social media. This study explored the relationship between Twitter sentiment, retweet-based amplification, and their influence on financial market dynamics using big data analytics and machine learning techniques. By examining the interaction between sentiment analysis models and market behavior, the research aimed to uncover the extent to which sentiment-driven patterns could inform trading decisions and influence stock movements.

Sentiment—whether positive, neutral, or negative—plays a pivotal role in shaping investor behavior and market trends. It serves as a reflection of collective market sentiment and acts as a leading indicator for movements. In the financial markets, traders often interpret positive sentiment as a signal for potential growth, triggering buying activity, whereas negative sentiment may lead to sell-offs or cautious strategies. Platforms like Twitter amplify these signals, providing and wide-reaching repository of market opinions and reactions. The analysis employed advanced sentiment analysis models, including FinBERT and Random Forest, to evaluate sentiment from social media posts and its correlation with stock movements. FinBERT, a domain-specific pre-trained model, showcased its ability to capture contextual nuances in financial text. However, it exhibited a pronounced bias toward positive sentiment, which stemmed from the optimistic tone prevalent in financial training datasets. This bias limited its accuracy in identifying neutral and negative sentiments, particularly in tweets containing sarcasm or complex financial jargon. The classification metrics for FinBERT included a precision of 33% for both negative and positive sentiments, a recall of 78% for positive sentiments but only 6% for negative sentiments, and an overall accuracy of 33%. These results highlighted FinBERT’s strength in detecting positive sentiment but its struggles with neutral and negative classifications. Random Forest, in contrast, offered robustness and interpretability, particularly in handling structured features such as tweet metadata and numerical attributes. It achieved an accuracy of 51.5%, a precision of 48.3%, a recall of 45.7%, and an F1-score of 47.0%. While it lacked the deep contextual understanding of FinBERT, its performance was balanced across sentiment classes, making it a valuable complement to deep learning approaches.

The comparative analysis underscored the trade-offs between these methodologies, highlighting the need for hybrid solutions to enhance prediction accuracy and applicability. FinBERT’s domain-specific strengths were evident in its superior handling of positive sentiment, while Random Forest provided a more stable and generalized approach across all sentiment types.

The study revealed a measurable but context-dependent correlation between Twitter sentiment and stock movements. Positive sentiment trends, amplified through retweets, were often associated with short-term increases, while negative sentiment—though less reliably detected—indicated potential market downturns. For instance, the correlation coefficient between sentiment scores and stock movements during the analysis period was observed to be moderate, suggesting a significant but not absolute influence of sentiment on stock movements. This relationship was particularly evident in case studies such as (TSLA), where Elon Musk’s tweets frequently influenced stock movements volatility. Similarly, the 2021 GameStop (GME) phenomenon illustrated how collective positive sentiment on platforms like Reddit could override traditional market fundamentals, driving significant movements. Despite these findings, several challenges emerged. The dynamic and volatile nature of social media sentiment poses significant hurdles for static models, necessitating adaptability and continuous fine-tuning. Class imbalance in training datasets further exacerbates model biases, particularly in identifying underrepresented sentiments. Additionally, the prevalence of noise, sarcasm, and informal language in social media content complicates sentiment classification, highlighting the limitations of current models and the need for more sophisticated natural language processing techniques. The implications of this research extend beyond financial markets, offering valuable insights for algorithmic trading, risk management, and investment strategies. By integrating sentiment analysis into decision-making frameworks, traders and financial institutions can gain a deeper understanding of market psychology, enabling more informed and proactive responses to market developments. However, the ethical and regulatory dimensions of sentiment-driven trading warrant careful consideration. The potential for market manipulation through coordinated sentiment campaigns underscores the need for transparency and safeguards in the deployment of these tools. In answering the research question, this study affirmed that Twitter sentiment, particularly when amplified through retweets, can significantly influence financial markets. The findings underscore the importance of developing robust, unbiased, and adaptable sentiment analysis models to harness the predictive power of social media data effectively. By

bridging the gap between big data analytics and financial decision-making, this research contributes to a deeper understanding of the interplay between sentiment and market dynamics, paving the way for future advancements in the field.

#### **Future Work**

This study successfully investigated the effectiveness of FinBERT and Random Forest in analyzing financial sentiment, providing insights into their strengths, limitations, and applicability. However, while the primary objectives of evaluating model performance and identifying challenges were achieved, certain areas warrant further exploration to enhance the robustness and practicality of sentiment analysis tools. Future research should focus on integrating multimodal data sources and experimenting with hybrid models that combine FinBERT outputs with time-series forecasting techniques

**a. Multimodal Data Integration**: Incorporate data from diverse sources, such as news reports, earnings calls, and macroeconomic indicators, to provide a holistic view of market sentiment.

**b. Analysis**: Develop sentiment analysis pipelines to enable actionable insights for trading and investment strategies.

**c. Model Improvements**: Explore hybrid models that combine sentiment analysis with other machine learning approaches, such as Long Short-Term Memory (LSTM) networks or Transformer-based models, for enhanced predictive accuracy. Furthermore, this section outlines potential future work based on the findings of this study.

##### **Improving Sentiment Analysis Models**

###### **a. Fine-Tuning FinBERT**

Retrain FinBERT on larger, more balanced datasets that include a wide range of financial sentiments, such as bankruptcy filings, negative earnings reports, and analyst downgrades. Incorporate data augmentation techniques, such as paraphrasing or oversampling, to address class imbalances and improve model generalizability.

###### **b. Domain-Specific Customization**

Develop customized sentiment lexicons and embeddings for niche financial sectors, such as cryptocurrencies, commodities, or emerging markets.

##### **Methodological Enhancements**

###### **a. Handling Bias and Class Imbalance**

Despite FinBERT’s high recall for positive sentiment, its inability to accurately classify neutral and negative sentiments underscores the need to address class imbalance and bias in training datasets.

**b**.**How can models like FinBERT be retrained or fine-tuned to reduce bias while maintaining their domain-specific strengths?**

Expanding dataset diversity by collecting larger and more balanced datasets that represent neutral and negative sentiments more comprehensively or augmentation techniquesby employing techniques such as oversampling minority classes or generating synthetic examples of neutral and negative sentiments to ensure balanced representation during training.

###### **c. Sentiment Analysis**

Another unresolved challenge is the dynamic nature of financial sentiment during significant market events, such as earnings announcements or geopolitical crises. Current models, including FinBERT, are not optimized for sentiment tracking. Future work could explore how sentiment models can adapt to data streams, providing timely and actionable insights, this could involve

developing systems that continuously update model parameters based on incoming data or exploring transfer learning to adapt pre-trained models to new events or market conditions in near.

###### **d. Ambiguity and Sarcasm Detection**

Both FinBERT and Random Forest struggled with ambiguous and sarcastic language often found in financial tweets. For example, tweets such as "company is amazing at burning cash!" were frequently misclassified. To overcome this limitation, future work could investigate contextual enhancements by incorporating advanced transformer architectures like BERT to better interpret sarcastic or ambiguous language or multimodal inputs by integrating textual sentiment analysis with external signals, such as stock movements, to better contextualize the intent behind ambiguous statements.

##### **Proposed Innovations and Directions**

###### **A. Hybrid Modeling Approaches**

The findings of this study highlight the complementary strengths of FinBERT and Random Forest. A hybrid approach that combines their capabilities could significantly improve sentiment classification. Future work could **combine deep learning with feature-based models or** use FinBERT’s embeddings as input features for Random Forest to enhance the latter’s interpretability while retaining the former’s contextual understanding.

###### **B. Advanced Feature Engineering**

Feature engineering remains a critical area for improvement. The integration of additional financial indicators could enhance model performance. Suggested future directions include:

**Incorporating External Signals:** Adding features such as trading volume, stock trends, and economic indicators to the input data.

**Dynamic Feature Selection:** Developing algorithms to dynamically select the most relevant features based on market conditions, ensuring that the model adapts to changing contexts.

This study marks a significant step toward understanding the potential and limitations of sentiment analysis in financial markets. While challenges remain, the outlined future work provides a roadmap for addressing these issues and unlocking new opportunities for innovation. By embracing hybrid approaches, enhancing dataset diversity, and focusing on adaptability, sentiment analysis tools can evolve to meet the demands of an increasingly data-driven world.

Beyond finance, the methodologies explored here hold promise for transforming industries ranging from healthcare to politics, enabling more informed and equitable decision-making. As artificial intelligence continues to shape the way we understand and respond to human sentiment, the journey ahead is not just about technological progress but about leveraging these advancements to create a more connected and empathetic society. The possibilities are as dynamic and expansive as the sentiments they aim to decode. Furthermore, the evaluation of FinBERT and Random Forest models revealed key insights into their performance and limitations. While FinBERT excels in leveraging domain-specific knowledge for positive sentiment detection, its poor performance on negative and neutral sentiments highlights the need for further fine-tuning and data balancing. On the other hand, Random Forest demonstrated better overall accuracy but lacked the contextual understanding necessary for nuanced sentiment classification. To achieve higher reliability and accuracy, future research should focus on combining the strengths of both models through hybrid approaches, improving data quality and preprocessing, and incorporating contextual and features. These advancements will pave the way for more effective sentiment analysis models capable of driving actionable insights in financial forecasting and beyond.

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