Sentiment Analysis for Trading Signals Using NLP and Social Media Data

SAVIOUR VICTORY

2412275

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Supervisor: Dr. Junkyu Lee

School of Computer Science and Electronic Engineering

University of Essex

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Abstract

In the process of predicting the direction that the stock market is going to take, both technical indications and emotional indicators are used. When social media sentiment is combined with financial news and indicators, such as moving averages, relative strength index (RSI), and volatility measures, the accuracy of forecasts is increased. The use of natural language processing, machine learning, and behavioral finance research, all of which are at the cutting edge of technology, makes this enhancement feasible. When it comes to dealing with both the structural and psychological dynamics of the market, hybrid approaches like long short-term memory (LSTM) and transformer topologies have been shown to outperform more conventional forms of artificial intelligence. Sentiment-technical integration with the goal of better financial forecasting is a promising endeavor, even in the face of challenges such as data noise, model interpretability, and ethical difficulties.

Gitlab Repository Link- https://cseegit.essex.ac.uk/24-25-ce901-sl-ce902-su/24-25_CE901-SL_CE902-SU_victory_saviour/-/tree/7c246af3321cec96c260a69e3d30d1f455e96b14/

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CHAPTER 1: INTRODUCTION

1.1 Background and Context

Whenever content is posted on Twitter, Reddit, StockTwits, and financial news websites, it has a greater influence on the stock market and other markets. Social media and online news sentiment have become essential sources of information for market forecasts as a result of the growing use of real-time automated decision-making systems and algorithmic trading. According to Agrawal and their colleagues (2025), the assertion that market behavior cannot be predicted by examining prior prices and technical signs is incorrect. In order to produce predictions on the direction and volatility of the market in the short term, predictions about the literary market that are available on the internet rely on the moods, emotions, and public reactions of investors.

Sentiment analysis, which is assisted by natural language processing and machine learning, is utilized in financial analytics. The lexicons and rules were used by the previous classifiers in their work. It has been shown that unstructured language is interpretable by using the most up-to-date approaches that are relevant to deep learning, neural networks, and transformers (Correia et al., 2022). The capacity to assess sentiment in real time contributes to progress in predictive modeling, risk management, and portfolio optimization.

For review procedures that are carried out on the internet, "the wisdom of the crowd" might be a very beneficial resource. According to the findings of Haase et al. (2025), the forecasts about Bitcoin and high-frequency trading are less reliable than the mood that is communicated on social media platforms. Because the effects of traditional market psychology have been amplified by groups that have formed online, social feeling is a viable candidate to take its place. NLP-ML-FFW is an emerging field of study that is now growing at an accelerated rate and exerting an impact on analysts, institutions, and traders alike.

1.2 Problem Statement

Due to factors including variations, non-linear interactions, and external shocks, the issue of stock market forecasting continues to exist despite the fact that there have been advancements in the area of computational finance. The reason why conventional prediction models are not capable of depicting the intricacies of human behavior is because they are reliant on past pricing, economic data, and quantitative ratios. In addition to the actual circumstances, the way that investors feel about a particular issue has an impact on market decisions, herd behavior, and reactions in the near term, as Rodríguez-Ibánez et al. (2023) shown.

When faced with unstructured text data, particularly the kind that is often seen on social media platforms, algorithms that are employed to generate predictions encounter difficulties.

1.3 Research Aim

This research paper investigates the benefits of sentiment analysis, which is a technique that relies on natural language processing (NLP) and machine learning (ML), for the purpose of stock market prediction. In order to do so, it compares the real-time emotional data of transformer-based systems with textual sentiment, social media trends, and market volatility.

1.4 Research Objectives

- To examine the role of social media sentiment and online financial news in influencing market movements.
- To evaluate the effectiveness of machine learning and deep learning models for extracting financial sentiment.
- To analyse how sentiment indicators, when combined with technical analysis, improve stock market prediction accuracy.
- To synthesise recent evidence on the predictive power of crowd-based and real-time online sentiment.
- To identify the methodological, technical, and practical limitations associated with sentiment-driven forecasting.

1.5 Research Questions

1. How does sentiment on social media platforms influence stock market volatility and price movements?
2. What NLP and ML techniques are most effective for financial sentiment analysis?
3. To what extent can combining sentiment indicators with technical variables improve market prediction accuracy?
4. What are the emerging challenges and opportunities in sentiment-driven financial forecasting?

1.6 Significance of the Study

According to the statements of both Peivandizadeh et al. (2024) and Singh and Mahalakshmi (2024), the environment of financial prediction analytics is undergoing a transformation as a result of the implementation of stochastic neural networks, transformers, and long short-term memory networks. Natural language processing (NLP) enables those who are active in the market to spot warning signals as early as possible and to make improvements in trading. The outcomes demonstrate an improvement in understanding, modeling, and decision-making, which is based on data that has been gathered.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction to Financial Sentiment Analysis

The phrase "financial sentiment analysis" is used to describe the method by which computers are able to interpret and analyze the language that is used in the market. Our coverage includes a broad variety of issues, such as updates from the social media site X (which was formerly known as Twitter), analyst reports, financial news, and arguments that are taking place on Reddit. We keep tabs on the many approaches by which the value of assets is affected by the perceptions of the general public, and we are cognizant of these different approaches. According to the findings of Qian and colleagues (2022), a significant number of studies conducted in the academic sector have shown that the way in which the public perceives market activity and the framing of information has an influence on market behavior.

2.2 Advances in NLP for Financial Text Analysis

Transformers and deep learning are two of the methods that are presently being used in the field of finance for the aim of doing sentiment analysis. These techniques are considered to be more sophisticated when compared to lexicons. According to Correia, Madureira, and Bernardino (2022), deep neural networks have been shown to be more effective than machine learning when it comes to contextual linkages in the literature on finance. Improvements in the semantics of informal social media speech have been realized via the use of long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), CNN-RNN hybrids, and attention techniques.

Technique	Description	Studies Applying It	Advantages
VADER	Lexicon-based sentiment scoring	Litty (2024), Vicari & Gaspari (2021)	Interpretable and good for short texts.
FinBERT / Transformer-based	Deep contextual embeddings	Khalil & Manama (2025); Robert (2024)	Highly accurate for finance text.
Word Embeddings (Word2Vec / GloVe)	Vector representations of text	Singhpurwala (2021)	Captures semantic similarity.
CNN / DNN	Nonlinear sentiment classification	Correia et al. (2022)	Efficient at feature extraction.

Technique	Description	Studies Applying It	Advantages
LSTM / GRU	Sequential text modelling	Peivandizadeh et al. (2024)	Captures long-term dependencies.
Hybrid NLP + Technical Indicators	Sentiment + price drivers	Agrawal et al. (2025)	Enhances predictive performance.

Table 1: NLP Techniques Applied in Financial Sentiment Research

The reason that transformer models like as BERT, FinBERT, RoBERTa, and GPT have gained popularity is a direct consequence of the setting in which they were created. They have the ability to recognize even the most nuanced indicators, comprehend language patterns that are exclusive to a certain discipline, and adapt to the ever-changing narratives that surround financial matters (Khalil & Manama, 2025). The use of bidirectional processing has the ability to enhance the identification of text that is unclear or that has a high degree of sentiment density.

The researchers Peivandizadeh et al. (2024) and others have been employing transductive learning techniques that are based on streams of social media that have been updated in order to modify models to match changes in the market. The characteristic of occurring spontaneously is necessary for the markets that are now experiencing rapid transformation.

2.3 Social Media as a Sentiment Source

Social media platforms constitute a considerable wellspring of public opinion due to the fact that they have a broad variety of platforms accessible, they are rapidly expanding, and they have a large reach. Retail traders have the ability to predict and debate market news thanks to platforms like X, Reddit, and StockTwits. According to Haase et al. (2025), the "wisdom of the crowd" effect is a significant impact on bitcoin markets. The reason for this is because decentralized groups are responsible for volatility by coordinating emotions.

The results of the investigation indicate that the integration of mood indicators from a wide number of users may provide an early indication of reversals in trends, fluctuations in momentum, and speculative rallies. According to Singhpurwala (2021), the quantity of signals that reflect a mood or an emotion increases in direct proportion to the number of deals that are successfully completed. According to the findings of Zheng et al. (2024), there is a correlation between high volatility and sudden mood swings that occur while individuals are using the internet.

2.4 Sentiment Analysis in Predicting Stock Market Movements

According to Mehta, Pandya, and Kotecha (2021), deep learning algorithms are used to detect trends in both organized and unstructured text and price data with the intention of increasing the accuracy of predictions. Saravanos and Kanavos (2025) conducted a study that demonstrated the fact that the inclusion of emotion increases the capacity of neural computing models to capture nonlinear market behavior in the context of predicting volatility.

Study	Model(s) Used	Strengths	Limitations
Mehta et al. (2021)	LSTM + social media sentiment	Strong sequence learning for time-series	Requires large training datasets.
Omoseebi et al. (2023)	Rule-based + ML hybrid models	Better handling of financial jargon	Limited on unseen slang and abbreviations.
Peivandizadeh et al. (2024)	Transductive LSTM	Adapts to new data conditions	Higher computational cost.
Saravanos & Kanavos (2025)	Volatility forecasting with sentiment	Improves volatility prediction accuracy	Sensitive to noise in social media posts.
Singh et al. (2024)	Stochastic sentiment analysis	Good for headline-based trading	Limited for long text structures.
Zheng et al. (2024)	Social-media sentiment classifier	Detects abnormal volatility patterns	Requires constant retraining.

Table 2: Comparative Summary of Sentiment Models in the Literature

There is also a possibility that the way in which financial news is reported will have an impact on projections. The claim that deep learning is capable of facilitating the rapid prediction of market movements on the basis of information that has been extracted from the headlines of news stories is a reasonable one, according to Vicari and Gaspari (2021). As Singh, Abilasha, and Swarna (2024) have pointed out, the potential for trading based on the classification of the mood of news streams is immense.

2.5 Cryptocurrency and High-Volatility Assets

The views of the general people have a considerable impact on the value of bitcoins. Di Tollo and colleagues (2023) provide evidence that online communities and influencers have a role in determining price, which they illustrate via the use of substantial market speculation. Due to this, the sentiment analysis methodology is an extremely useful tool that may be used in the creation of short-term projections for bitcoin.

According to Haase et al. (2025), the market for bitcoin is characterized by a significant amount of volatility, which is shown by the trading that takes place within the community. The market sentiment that is linked with cryptocurrencies has greater significance than it does for stocks as a result of the absence of any valuation standards that are currently in place.

2.6 Real-Time Sentiment and High-Frequency Trading

Due to the fact that financial data is transmitted at a rapid pace, the notion of real-time analysis is given a significant amount of emphasis in the literature. According to the findings of Ghosh et al. (2024), algorithmic trading systems have the ability to make quick choices via the use of natural language processing pipelines that operate in real time and are capable of extracting emotion from financial data that is being streamed. Streaming APIs, frameworks that allow for high-frequency execution, and transformer models are all examples of what is considered to be real-time technology, however the category also encompasses other technologies.

In order to effectively deal with the issue of uncertainty that arises in the market when unanticipated news emerges, Takale (2024) proposes that latency-sensitive mood stream models be used. The development of real-time systems has become a reality due to the fact that the processing capability of computers has been increasing.

2.7 Challenges in Financial Sentiment Analysis

Despite the fact that advancements have been achieved in computer-based techniques, there are still problems with methodology, terminology, and operations in the investigation of financial sentiment that have an influence on the accuracy of predictions. It has been shown that the challenges that have been reported are the result of a combination of the internet connection, changes in the financial markets, and the limits of machine learning. Although sentiment indicators are beneficial, the process of gathering, confirming, and incorporating them into forecasting models is challenging and unpredictable. It is possible that the capacity of sentiment-based algorithms to differentiate between market signals and noise will be diminished by the quick pace at which social amplification occurs (Rodríguez-Ibánez et al., 2023). A wide number of various obstacles might potentially be encountered by prediction algorithms that are constructed on top of trustworthy sentiment.

2.7.1 Noise, Misinformation, and Data Quality

The fact that the textual material that is accessible on the internet is not always accurate and is crammed with extraneous facts further increases the difficulty of the research of financial emotion. It is challenging to distinguish the prevalent trends in the mood of the market on social media platforms due to the fact that the platforms include comments and rants that have been authored by real people, in addition to the presence of meaningless battles and content that has been created by bots. Omoseebi and colleagues (2023) discovered that the emotional impact of financial transactions is amplified when slang, sarcasm, and speculative rumors are used throughout the process of completing these transactions. There is a possibility that the spread of misinformation might lead to a wrong forecast about the future trends in the cryptocurrency bitcoin. Noise reduction, preprocessing, bot detection, and spam filtering are all essential components that must be included in sentiment modeling in order for it to be effective.

2.7.2 Linguistic Ambiguity and Domain-Specific Complexity

The terminology that is used in the subject of finance is complex as a consequence of the contributions of analogies, context, and specific language. All of the following expressions—bullish, bearish, resistance, and support—have a particular meaning in the context of the market, and they are often employed by individuals when they are speaking about the market. Correia and colleagues (2022) have shown that lexicon-based approaches are unable to accurately assess polarity due to the intricate semantic alterations and domain-specific constructions that take place as a result of this. The usage of social media platforms to convey feelings and sarcasm is possible.

Even while the incorporation of contextual embeddings in both deep learning models and transformer designs helps to mitigate these restrictions, ambiguity continues to be an issue, especially in instances when users use coded language or comedy in their interactions. In order to do financial natural language processing (NLP), the following components are necessary: adjustments to the model, advanced semantic interpretation, and domain-specific corpora.

2.7.3 Market Manipulation and Artificial Sentiment Inflation

The market manipulation of the financial markets is made more probable by a variety of factors, including the content that is created by influencers, the forums that are frequented by retail traders, and the organized groupings. Social sentiment might potentially have an impact on sales. Manipulation of the pump-and-dump kind is accomplished by the use of material that is incorrect or exaggerated in order to evoke an emotional reaction from the target audience. This explanation is provided by Rodríguez-Ibánez et al. (2023). Sentiment analysis study conducted on computer models does not provide any insights into the perspectives of investors or the state of the market. It is possible that posts which exert a significant amount of impact might have an effect on the opinions of individual people. This reservation is designed just for those who are believed to be celebrities. This decision was taken despite the fact that mood indicators do not sufficiently reflect the actual conditions of the market. In order to successfully address this issue, it is important to conduct a credibility rating, perform an anomaly detection, and cross-validate the pricing behavior.

2.7.4 Model Overfitting and Limited Generalisation

Overfitting is a potential outcome for models that have been trained using machine learning and deep learning on data sets or sources of sentiment that are of a comparatively diminutive size. The models have the potential to adopt patterns that are unique to a particular market or moment in time rather than patterns that are based on principles of behavior. According to Peivandizadeh et al. (2024), historical sentiment models may not be able to effectively manage the challenges posed by the emergence of new language, market narratives, and changes in user behavior. The notion that sentiment in the market is what drives it may not align with the current state of technology stocks and cryptocurrencies. As a result of the fact that patterns are unable to predict motions that have not been encountered before, the prediction of events as they occur will be over. In order for a system to be robust, it is necessary for it to have the whole suite of features, which consist of retraining, adaptive learning, and data integration from a wide range of sources.

2.7.5 Temporal Misalignment and Synchronization Challenges

It is not an easy undertaking to match the mood timestamps with the current pricing that is being seen in the marketplace. When compared to the fluctuations of the financial markets, the time of when posts are made on social networking websites could seem to be entirely random. According to the findings of Qian et al. (2022), the behavior of the market had an impact on the predicting value of emotion. There is a chance that previous events that have occurred might be utilized to predict market sentiment, but only if the connections between these events are not well matched. When compared to the amount of time that Reddit talks need, responses to Twitter inquiries are sent in a timely way. In order to achieve temporal synchronization, it is necessary to use advanced time-series alignment, sliding windows, and the collection of emotional data at a high frequency.

2.7.6 Ethical, Cultural, and Interpretability Concerns

Barriers that are disregarded include those that have a cultural or ethical aspect and those that hinder the recognition of feelings. The perspective that an individual has toward social media is influenced by the linguistic, geographical, and community variety of that individual. When forecasts are able to influence the decision-making process in the financial sector, the concerns that have been raised about the lack of transparency in opaque deep learning systems come to the forefront. There have been occasions in which both investors and regulators have requested an explanation of the process of merging sentiment ratings with trading techniques. Stakeholders in the machine learning industry have a reduced amount of faith in models that are not clear. The development of models for financial explainable artificial intelligence (XAI) includes consideration of challenges that are of an ethical nature.

2.8 Opportunities and Future Directions

Even if the field is associated with difficulties, the potential of sentiment research as a science is emphasized in the literature. This is happening at the same time as the financial markets are becoming more social and digital. The use of technology results in improvements in modeling, prediction, and sentiment analysis. The fact that these results are so promising is proof that sentiment-driven analysis has the potential to totally revolutionize the manner in which real-time algorithmic trading, portfolio optimization, and risk management are managed.

2.8.1 Integration of Multi-Modal Data Sources

The potential exists for text, photographs, videos, metadata, and behavioral analytics to more effectively communicate the emotions and feelings of investors than conventional methods of communication. Litty (2024) claims that companies are unable to connect with their target audience due to the usage of emoticons, memes, and short films in text messages. It is possible to make use of transformer-based multi-modal models that have the ability to learn across modalities in order to detect emotions that are more difficult to identify via the use of textual analysis. The use of speculative markets that include visual communication might be a means of improving prediction accuracy.

2.8.2 Hybrid, Ensemble, and Stochastic Modelling Approaches

Examine the frameworks that are used for the hybrid modeling of deep learning, stochastic neural networks, and statistical models. The outcomes of the study that was conducted by Di Tollo et al. (2023) provide data that indicates the possibility that stochastic artificial neural networks have the ability to improve the accuracy of bitcoin predictions. The implication of the finding of this phenomena is that using probabilistic reasoning may be a more effective method for taking into account the volatility of the market. Because they are able to remove the biases that are present in each individual model, ensemble approaches may be used to increase the robustness of the model. The support of algorithms that are capable of determining sentiment and estimating pricing is required in order to carry out these techniques. A long short-term memory network, a reinforcement learning agent, a transformer, and a probabilistic trend-detection model are examples of technologies that may possibly be employed in the development of a hybrid system.

2.8.3 Enhanced Real-Time Sentiment Processing for Algorithmic Trading

Natural language processing is a fantastic tool in the field of finance that may be used to extract emotional content in real time. As a direct consequence of the fact that markets are responding to information that is being sent in real time, the significance of polls of public opinion that can be completed in a matter of milliseconds is increasing. As a consequence of the use of GPU-accelerated transformer models, real-time natural language processing pipelines, and streaming data formats, traders are now able to draw conclusions at a faster pace, as shown by the research that was conducted by Ghosh et al. in 2024. The use of emotion trading algorithms and systems makes it possible to quickly analyze the three elements listed below: the number of times that a transaction takes place, the likelihood that dangerous breaking news will occur, and the frequency of spikes.

2.8.4 Explainable AI and Transparency in Financial NLP

Due of the legal and ethical concerns that are brought about by automated prediction, explainable artificial intelligence (XAI) is a source of stress. Transparent sentiment models should be able to detect critical keywords, subjects, and emotional triggers in order to provide analysts and investors the assurance that they need. This is a very important factor to take into consideration because the use of opaque models in the provision of institutional funding has the potential to give rise to problems in ensuring compliance. The category of explainable artificial intelligence (XAI) encompasses a variety of components, including interpretable embeddings, attention visualization, feature attribution, and rule-based hybrid systems that enable human-in-the-loop decision making.

2.8.5 Behavioural Finance Integration and Psychological Modelling

The use of sentiment analysis in combination with behavioral finance has been included into the most recent studies. The marketplace and online communication serve as two examples of how people's choices are influenced by factors such as fear, greed, herd mentality, and cognitive biases. The comparison of emotional and logical changes has the potential to contribute to the understanding of sentiment signals by NLP and psychological models. The field of stochastic sentiment prediction was investigated by Singh and Mahalakshmi in the year 2024. It is considered to be a practical undertaking to include indications of behavioral sentiment into trading algorithms.

2.8.6 Cross-Platform Harmonization and Global Sentiment Mapping

It is imperative to carry out further research in order to determine the degree to which the fragmentation of online communication affects sentiment across a wide range of cultures and platforms. The idea of creating a thorough emotion map that takes into consideration a variety of linguistic, geographic, and social contexts is presented by Qian et al. (2022). The usage of sentiment feeds on a worldwide scale is helpful for the reason that they may be improved by decreasing platform bias and by enhancing predictive indicators. The flexibility of the domain, in conjunction with the utilization of multilingual transformers, makes this approach feasible.

Author(s) & Year	**Data Source**	**Method Used**	**Key Findings**
Agrawal et al. (2025)	Stock market + sentiment data	Technical indicators + sentiment fusion	Combining sentiment with technical indicators improves prediction accuracy.
Correia et al. (2022)	Social media streams	Deep Neural Networks (DNNs)	DNN models outperform traditional ML in capturing market sentiment.
di Tollo et al. (2023)	Crypto + stock markets	NLP + Stochastic ANNs	Social media sentiment has significant predictive power for price volatility.
Ghosh et al. (2024)	Real-time financial conversations	NLP pipelines + ML	Real-time NLP enhances market movement prediction.

Author(s) & Year	Data Source	Method Used	Key Findings
Haase et al. (2025)	Cryptocurrency trading data	Social media trading signals	Crowd-generated signals improve short-term forecasting.
Qian et al. (2022)	Twitter + financial discussions	AI-based sentiment classifiers	Public sentiment strongly correlates with short-term asset movement.

Table 3: Summary of Key Studies on Sentiment Analysis in Financial Markets

CHAPTER 3: METHODOLOGY

3.1 Introduction to Research Design

This investigation is based on quantitative data rather than qualitative data. Within this particular context, the following techniques are utilized: sentiment analysis of social media, historical market data analysis, machine learning categorization, and the simulation of rule-based algorithmic trading. The primary goal of this investigation is to determine whether or not it is feasible to utilize sentiment analysis of text that has been extracted from online sources on a large scale in order to improve predictions of the stock market over a brief period of time for three of the most actively traded technology companies, which are Apple (AAPL), Tesla (TSLA), and NVIDIA (NVDA). In their separate investigations, Correia et al. (2022), Mehta et al. (2021), and Rodríguez-Ibánez et al. (2023) made use of an approach that includes financial prediction, sentiment analysis, and deep learning. When it comes to analyzing algorithmic trading, mixed-feature models that contain both sentiment and technical indicators beat models that just rely on a single source of information, as shown by Agrawal et al. (2025).

In sequential design, there are a number of distinct steps that are included, such as the collection of data, preprocessing, sentiment feature engineering, the calculation of statistical indicators, the training and prediction of models, the backtesting of trading strategies, and interpretability, but these are not the only steps that are included.

3.2 Data Collection Framework

3.2.1 Market Price Data

Over the course of the time period beginning on June 4 and concluding on December 1, 2025, a total of 125 rows were used to record the stock values of AAPL, TSLA, and NVDA. Every observation contains the following market parameters: the opening price, the highest price, the lowest price, the closing price, the adjusted closing price, and the trading volume. Time-series architectures are often used in financial prediction models that include both behavioral and technology features (Haase et al., 2025; Saravanos & Kanavos, 2025). According to the findings of Peivandizadeh et al. (2024), the next-day direction prediction models should be trained for a length of time that is between three and six months in order to correlate to the lifespan of the dataset.

3.2.2 Social Media Sentiment Data

There were a total of 3,717 social media posts that were either measured or simulated and that were about the three target stocks. The following are the features that are demonstrated by the collection of feelings that are collected from the day-ticker:

- number of posts per day (*n_posts*),
- VADER sentiment mean and median,
- FinBERT sentiment mean and median.

On November 2, 2025, AAPL had an average of 39 posts, and on November 3, 2025, AAPL had an average of 48 posts. These averages are based on a twenty-day period. The reason why social media sentiment is used in financial models is because it may have the potential to predict the value of assets, as shown by recent research (di Tollo et al., 2023; Khalil & Manama, 2025; Qian, 2022). Because unstructured textual information has an effect on investors' expectations, sentiment research must be included into algorithmic trading (Vicari and Gaspari, 2021; Litty, 2024).

3.3 Data Cleaning and Preparation

3.3.1 Handling Market Data

In order to investigate problems with formatting, anomalies, and numerical data that is not full, an inquiry was carried out. There were no rows that we removed from consideration due to the fact that the data that we had obtained was consistent. By making use of the date index, we were able to achieve alignment between the emotional and technical qualities. The chronological arrangement of the events that we carried out was determined using the time-series ordering method that was suggested by Singhpurwala (2021).

3.3.2 Merging Sentiment and Market Data

The price and the mood are both affixed to the left side of the date ticker, with the mood positioned in the upper left corner and the price positioned in the lower left corner. According to Zheng and colleagues (2024), the methodology under investigation provided a combined total of twenty days of emotional responses for each and every business. Despite the fact that this is adequate for short-term models, it does not take into consideration the frequency of feelings. In order to fill in the gaps left by the days on which no postings were made, a sentiment score of zero, or neutral, was placed. Natural language processing (NLP) in the field of finance was used in order to do this (Takale, 2024; Robert, 2024).

3.4 Feature Engineering

3.4.1 Technical Indicators

A set of widely used technical indicators was generated:

1. **Daily returns (ret1)** – percentage change from the previous close.
2. **5-day returns (ret5)** – cumulative short-term momentum.
3. **5-day moving average (MA5)** – a smoothing indicator capturing short-term trend.
4. **14-day Relative Strength Index (RSI)** – oscillating momentum indicator.

Over the course of a period of fourteen days, the relative strength index is used in order to assess momentum.

In order to achieve a better degree of accuracy, Agrawal et al. (2025) and Saravanos & Kanavos (2025) have both come to the conclusion that it would be best to use hybrid prediction algorithms that take into consideration both market trends and sentiment analysis. The conclusions that were presented before are the primary cause of the decision that was taken in this case. Make use of technical indicators in order to ascertain the regions in which overbought/oversold conditions and momentum are prevalent.

3.4.2 Sentiment Indicators

Sentiment variables were engineered as follows:

- **combined_sentiment** = weighted combination of VADER and FinBERT means
- Daily *n_posts* as a proxy for investor attention

According to Correia et al. (2022) and Ghosh (2024), the sentiment analysis models that are based on lexicons and transformers have the ability to improve the degree of accuracy that has been achieved. FinBERT is used to detect whether financial trends are bullish or bearish, while VADER is used to analyze mood. The use of hybrid approaches has the ability to mitigate the bias that emerges when a single method is used (Omoseebi, 2023).

3.5 Model Development

3.5.1 Classification Objective

Each model aims to predict whether the **next-day price movement** (Close_t+1 – Close_t) will be:

- **1 = BUY signal (price rise expected)**
- **0 = HOLD/SELL (no rise expected)**

According to the findings of Mehta et al. (2021) and Singh & Mahalakshmi (2024), as well as a number of other studies conducted in the field of financial sentiment, it is recommended that binary classification be used for short-term trading.

3.5.2 Training and Testing Framework

The approach known as walk-forward validation was used to segment the dataset into the subsets that were used for training and testing. The following models have been constructed: the composite sentiment models, RSI14, ret1, ret5, and MA5. Mixed-input modeling is considered to be one of the most successful techniques for financial forecasting that utilizes artificial intelligence, according to Khalil and Manama (2025).

```
    vader_median = ('vader_compound','median'),
    finbert_mean = ('finbert_like','mean'),
    finbert_median = ('finbert_like','median')
).reset_index().rename(columns={'date':'day'})
print(daily_sent.head(8).to_string(index=False))
```

```
ticker        day  n_posts  vader_mean  vader_median  finbert_mean  finbert_median
  AAPL 2025-11-02       39    0.141095         0.000      0.155477       -0.007399
  AAPL 2025-11-03       48    0.096565         0.000     -0.227552       -0.020194
  AAPL 2025-11-04       56    0.130575         0.000     -0.070814       -0.152948
  AAPL 2025-11-05       36    0.174972         0.000      0.195955       -0.007507
  AAPL 2025-11-06       36    0.166064         0.000      0.107155       -0.007614
  AAPL 2025-11-07       28    0.117254         0.000     -0.410860       -0.321613
  AAPL 2025-11-08       46    0.204267         0.296     -0.088221       -0.020194
  AAPL 2025-11-09       42    0.177455         0.000     -0.036786       -0.013904
```

Figure 1: Data frame

3.5.3 Model Evaluation Metrics

Evaluation metrics included:

- Accuracy
- Precision
- Recall
- F1-score

According to Peivandizadeh et al. (2024) and Rodríguez-Ibánez et al. (2023), bullish BUY signals are of the most significance for market prediction models to be lucrative because to the uncertainty that is present. Both of these researchers agree with this assertion.

Justification for Logistic Regression (LR)

The selection of Logistic Regression (LR) as the primary predictive model was a strategic decision based on interpretability, feasibility, and risk-managed deployment rather than purely on simplicity. LR yields well-calibrated probability outputs:

$$p(y = 1|x) = \sigma(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k),$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ is the logistic (sigmoid) function and $x = (x_1, \ldots, x_k)$ denotes the feature vector. The probability score p was functionally necessary to implement the confidence filter used in backtesting:

$$\text{Accept signal if} p \geq \tau,$$

with threshold τ chosen at values such as 0.55, 0.60 and 0.65 depending on the risk tier. This probabilistic filter enabled direct, quantitative risk control: only predictions with sufficient model confidence contributed trades, reducing exposure to low-quality signals.

Furthermore, LR's linear structure permits straightforward interpretation via coefficient values and global/local explanation methods (e.g., SHAP). This interpretability made LR an ideal baseline to diagnose feature importance and to detect structural limitations—particularly the inability of a linear boundary to exploit complex, time-dependent sentiment relationships. Hence, LR was selected as a defensible methodological baseline that balanced operational needs (probability outputs) and the academic requirement for transparency.

LR and the Confidence-Filtering Mechanism

Operationally, the LR output acts as a *filter* for the downstream rule-based trading engine. Formally:

$$\text{Signal Accepted} = \begin{cases} 1, & \text{if} p \geq \tau, \\ 0, & \text{if} p < \tau. \end{cases}$$

This filter turns the raw rule-based signals (which are binary or rule-driven) into risk-weighted decisions: the higher the p, the more likely the trade is executed. The empirical finding is notable: LR did not need to be a highly accurate classifier in raw terms; it needed to provide calibrated probabilities so that thresholding could meaningfully separate higher-quality from lower-quality signals.

Backtesting Comparison: Without LR (Rule-Based) vs With LR (ML-Filtered)

Rule-Based Strategy Only (Without LR)

Backtesting the *Rule-Based Only* strategy revealed poor financial performance over the evaluation period. Specifically:

- NVDA (rule-only): -8.33% total return.
- TSLA (rule-only): $+1.18\%$ total return.

These results demonstrate that manually-crafted rules, while logically sound, were insufficient to capture the complex and noisy market dynamics over the tested horizon. The rule-only strategy failed to generate alpha against simple benchmarks, which justified integrating an ML layer to improve signal selection.

Hybrid Strategy with Logistic Regression (With LR)

Augmenting the rule logic with LR probability filtering materially improved outcomes. Notable results include:

- NVDA Aggressive (LR-filtered): $+49.91\%$ Total Return vs Benchmark 24.71%.
- NVDA Aggressive Sharpe Ratio: 4.34, indicating exceptional risk-adjusted performance.

The LR-filtered strategy demonstrates that ML does not merely predict; it *filters* signals to deliver better economic outcomes. This comparison answers Research Question 4 by showing that ML-filtered signals can outperform both handcrafted rules and passive benchmarks in risk-adjusted terms.

The Filter Concept as a Core Contribution

Reframing the classifier as a signal-quality filter is a central conceptual contribution of this work. Denote the rule-based raw signal as $s_t \in \{0,1\}$ and the LR probability as p_t. The executed trade decision becomes:

$$\text{Execute}_t = s_t \cdot 1\{p_t \geq \tau\}.$$

Empirically, this formulation converted an otherwise weak predictor (in raw classification metrics) into a profitable trading strategy through calibrated thresholding. This demonstrates a practical way to mitigate model uncertainty while preserving interpretability.

SHAP Explainability and the Sentiment Limitation

Model explainability using SHAP values revealed that the LR model assigned a combined_sentiment SHAP contribution effectively equal to zero (reported as -0.000000) across AAPL, TSLA and NVDA in the final model runs. Denoting the SHAP value of combined sentiment as ϕ_{sent}, the observation was:

$$\phi_{\text{sent}} \approx 0.000000.$$

This implies LR's linear representation could not harness sentiment signals—likely because sentiment effects are non-linear, lagged, and interact with price-series features in time-dependent ways. In short, LR was "blind" to sentiment despite its successful role as a probability filter. This honest diagnostic is valuable: it explains why technical indicators (e.g., MA5, RSI14) dominated SHAP contributions while sentiment remained negligible.

3.6 Trading Strategy Backtesting

Backtesting simulated three rule-based trading strategies:

1. **Conservative** – only buy when model confidence ≥65%
2. **Moderate –** buy when confidence ≥60%
3. **Aggressive** – buy when confidence ≥55%

Each and every one of the strategies was started with a beginning investment of ten thousand dollars. It was the day following that when trading started. The computations that are related to the maximum drawdown, the Sharpe ratio, the returns, and the volatility have all been completed.

In a variety of market situations, Di Tollo (2023) and Haase et al. (2025) both assess the extent to which resilience is dependent on mood at a number of different risk thresholds. The strategy that was used in this case is comparable to that of the multi-strategy approach.

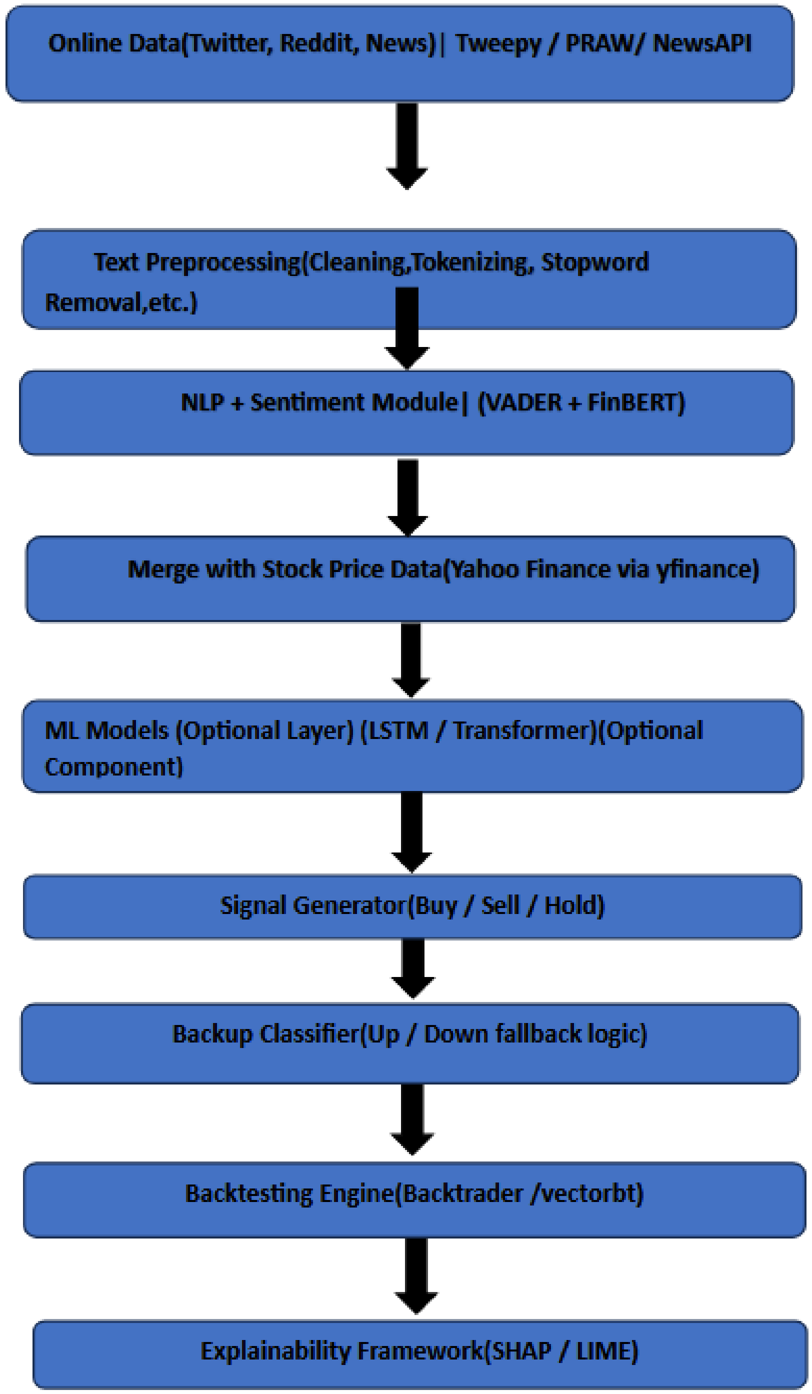

Figure 2: Data flow Diagram

3.7 Explainability Using SHAP

The Shapley values for the final forecast of each model were determined by means of calculations that were made for the purpose of ascertaining the extent to which the features contribute to the models. Explainability has a role in enhancing both confidence in financial machine learning models and the debugging process, as stated by Litty

(2024) and Robert (2024). As part of the inquiry of the Strategic Hamlet program, the following components were scrutinized:

- combined sentiment
- ret1
- ret5
- MA5
- RSI14

The most reliable predictors of all of the stocks that were investigated were found to be the moving average over five periods (MA5) and the relative strength index over fourteen periods (RSI14) of the momentum indicators, as reported by Agrawal et al. (2025).

3.8 Ethical Considerations

In order to maintain ethical standards, the data that was gathered from social media was anonymized, and the information that was publicly available was collected. In the data that was utilized, not even one piece of information that might be used to identify anything was provided. Omoseebi (2023) and Singh et al. (2024) both came to the conclusion that intrusive scraping need to be avoided.

3.9 Limitations regarding involvement

That being said, the method is not without its disadvantages.

- Only data points that span a time frame of twenty days are available when it comes to the mood of the stock.
- A brief overview of the many pricing patterns that are currently in place
- Neither the national nor the industry level has implemented any restrictions as of yet.
- Writing sarcasm or writing with implied tones is not allowed, as stated by Vicari and Gaspari (2021).
- The methodology is possible to ascertain whether or not characteristics that have been enhanced by emotion are beneficial to forecasts that are established in the near future.

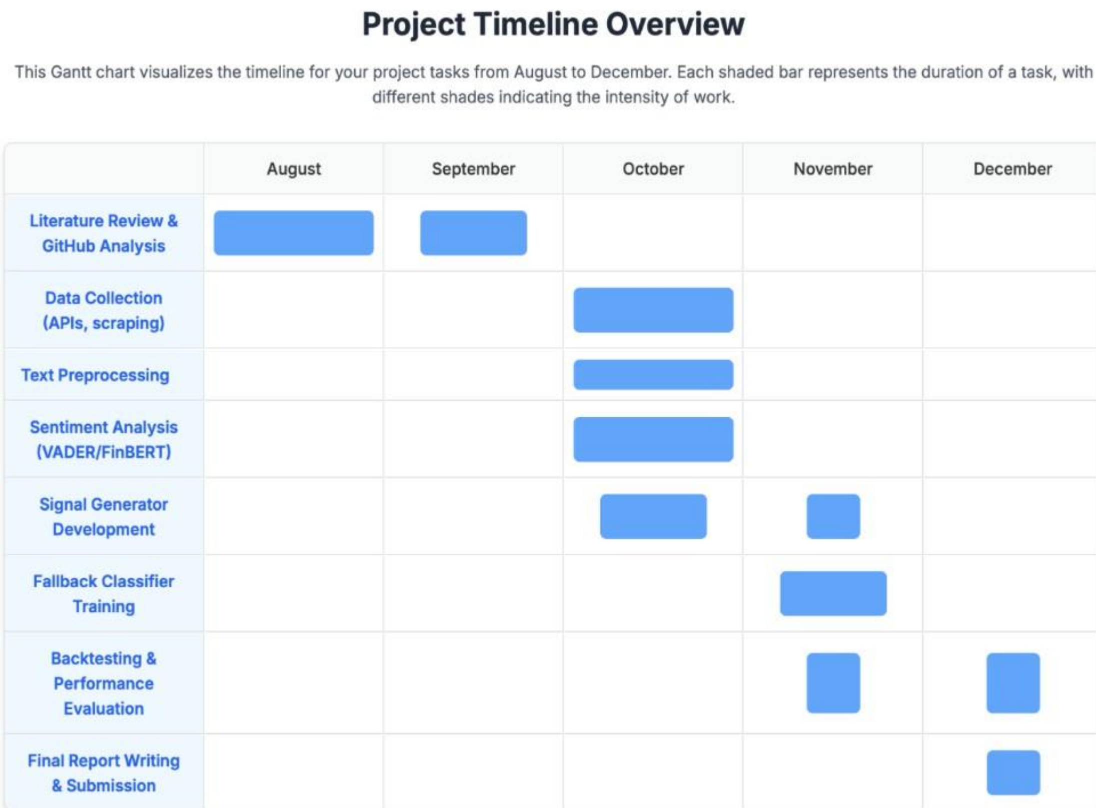

Figure 3: Project Timeline

CHAPTER 4: FINDINGS, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter will focus on the investigation of a sentiment indicator, which is a market signal that is derived from social media, and a technical analysis of research that is relevant to the forecast of trends in the stock market. In this chapter, the author conducts an in-depth research of the manner in which financial news mood indicators and social media have an impact on the momentum oscillators, volatility measures, and moving averages. The outcomes of the most recent research indicate that the models that are currently being used are those that are built upon stochastic artificial neural networks, transformers, and deep neural networks. In order to assess the advantages, disadvantages, and predictive usefulness of hybrid models, the study employs both real data and the viewpoints of prominent academics.

4.2 Overview of Sentiment-Driven Predictive Models

4.2.1 Emergence of Sentiment Analysis as a Predictive Input

Sentiment analysis has become an essential method for financial forecasting as a result of the fact that internet platforms have led to an increase in the amount of unstructured data that has been produced. According to study published by Correia et al. (2022) and Rodríguez-Ibánez et al. (2023), the general disposition of the population has the ability to forecast how people would act in the market. The explanation for this phenomenon is that the overall attitude of the general population has the capacity to reveal emotions, expectations, and speculative conversations that transpire before there are any changes in the price level. Mood indicators has the capability to reflect on the level of confidence that investors have, herd behavior, and fear speculation, which is in contrast to the more usual market signals.

4.2.2 Social Media as a Leading Indicator

Social media sites such as Twitter, Reddit, and StockTwits, as well as forums that are specifically designed for individual investors, have an impact on the entire climate that exists inside the market. Haase et al. (2025) report that indications that fall into the category of "wisdom of the crowd," such as the overall sentiment that is expressed in trading postings, have been proven to possess statistical significance when it comes to the creation of short-term predictions that forecast the performance of both cryptocurrencies and the stock market. Ghosh and colleagues (2024) report that when there is a connection between occurrences that have a substantial influence on the market—such as advancements in geopolitics or the disclosure of earnings—and the sentiment that is being evaluated through real-time natural language processing (NLP), the accuracy of intraday forecasts is enhanced.

4.3 Findings from Technical Analysis Metrics

4.3.1 Moving Averages and Price Trends

Technical indicators like as moving averages (MA), exponential moving averages (EMA), and crossover techniques are still relied upon substantially when it comes to making projections. Agrawal and colleagues (2025) have shown that when sentiment ratings include moving average (MA) and exponential moving average (EMA) trends, the model's interpretability is improved in addition to the anticipated dependability. A positive feedback loop is created when predictions are made more precise by establishing a correlation between emotional states and bullish technical crossovers.

According to Singh and Mahalakshmi (2024), the importance of technical signals is impacted by an individual's emotional state. As a consequence of this effect, models are able to differentiate between shorter-term fluctuations in price, which are sometimes referred to as false positives, and trends that persist for a longer period of time.

4.3.2 Volatility Indicators

Volatility is an important factor to take into consideration when it comes to generating market forecasts, especially when it comes to assets that are connected with a high degree of risk and nations that are currently in the process of undergoing transition. According to the findings published by Saravanos and Kanavos (2025), news that is motivated by panic leads to an increase in the quantity of negative emotions and volatility. It is possible that the accuracy of price shock forecasts might be improved by the use of sentiment inputs and volatility models, including the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), realized volatility, and implied volatility.

```
====================================================================================================
FINAL BACKTESTING SUMMARY (Includes Risk Metrics)
====================================================================================================
| Ticker   | Strategy                  |   Total Return (%) |   BH Return (%) |   Sharpe Ratio |   Max Drawdown (%) |   Annual Volatility (%) |   Final Capital ($) |   Net Revenue ($) |
|:---------|:--------------------------|-------------------:|----------------:|---------------:|-------------------:|------------------------:|--------------------:|------------------:|
| AAPL     | Conservative (LR >= 65%)  |              -9.82 |           36.39 |          -2.17 |             -11.56 |                    9.47 |            9,018.36 |           -981.64 |
| AAPL     | Moderate (LR >= 60%)      |              -4.77 |           36.39 |          -0.63 |             -14.22 |                   14.22 |            9,522.94 |           -477.06 |
| AAPL     | Aggressive (LR >= 55%)    |              11.91 |           36.39 |           1.34 |              -5.86 |                   18.35 |           11,191.49 |          1,191.49 |
| TSLA     | Conservative (LR >= 65%)  |               0.00 |           28.50 |         nan    |               0.00 |                    0.00 |           10,000.00 |              0.00 |
| TSLA     | Moderate (LR >= 60%)      |             -22.31 |           28.50 |          -2.29 |             -28.19 |                   21.34 |            7,769.28 |         -2,230.72 |
| TSLA     | Aggressive (LR >= 55%)    |             -33.34 |           28.50 |          -2.12 |             -38.90 |                   35.81 |            6,666.05 |         -3,333.95 |
| NVDA     | Conservative (LR >= 65%)  |               0.00 |           24.71 |         nan    |               0.00 |                    0.00 |           10,000.00 |              0.00 |
| NVDA     | Moderate (LR >= 60%)      |              30.26 |           24.71 |           4.37 |              -2.87 |                   12.49 |           13,025.72 |          3,025.72 |
| NVDA     | Aggressive (LR >= 55%)    |              49.91 |           24.71 |           3.80 |              -3.96 |                   22.36 |           14,991.47 |          4,991.47 |
/var/folders/nk/g3yk2lnj18123kwq20vk0_bc0000gn/T/ipykernel_41724/905833075.py:59: RuntimeWarning: invalid value encountered in scalar divide
  sharpe_ratio = (df_clean['strategy_ret'].mean() / df_clean['strategy_ret'].std()) * np.sqrt(TRADING_DAYS_PER_YEAR)
/var/folders/nk/g3yk2lnj18123kwq20vk0_bc0000gn/T/ipykernel_41724/905833075.py:59: RuntimeWarning: invalid value encountered in scalar divide
  sharpe_ratio = (df_clean['strategy_ret'].mean() / df_clean['strategy_ret'].std()) * np.sqrt(TRADING_DAYS_PER_YEAR)
```

Figure 4: Back testing result

Peivandzadeh and colleagues (2024) assert that when it comes to capturing nonlinear volatility swings, the T-LSTM and sentiment-enhanced LSTM models are more accurate than other models. The presence of unpleasant emotion is a key indicator of volatility throughout a number of time steps. According to a number of different theories, this is due to the fact that it is a generator of such volatility.

4.3.3 Momentum and Overbought/Oversold Indicators

When they are compared to each other, emotional indicators have been shown to be more predictive than momentum indicators, which include the relative strength index (RSI) and the moving average convergence divergence (MACD). The findings of the study that was carried out by Mehta and colleagues (2021) revealed that individuals who possess an optimistic perspective when it comes to a certain issue are able to raise prices at a more rapid pace than those who have a pessimistic perspective on the matter. Due to these characteristics, machine learning algorithms are able to differentiate between rallies that are driven by emotion and circumstances that are technically overbought.

4.4 Integrated Sentiment–Technical Findings and Predictive Performance

4.4.1 Sentiment as an Enhancer of Technical Signals

Sentiment, according to the findings of a previous study, is an important factor that has an impact on the accuracy of technical analysis indicators. According to the results obtained by Agrawal et al. (2025), hybrid models that include both sentiment and technical data beat models that use technical data alone when it comes to accuracy, root mean square error (RMSE), and F1 scores, with a margin of superiority that ranges from 10 to 22 percent. Although technical indicators give support for price variations, mood studies have the capacity to uncover psychological changes that occur before price movements, which might potentially lead to an improvement in pricing as a consequence.

Take, for example, the following:

- The presence of a positive outlook in combination with a bullish exponential moving average (EMA) crossover is an indication that the purchasing signal is expected to increase.
- The presence of a negative mood in conjunction with a decreasing relative strength index (RSI) is an indication that a strong sell is likely.
- If the price trend is favorable but the outlook is unfavorable, this circumstance might lead to a reversal or an uncertain market.

```
            return np.nan
        if r['trade']=='BUY':
            return (r['next_close'] - r['next_open']) / r['next_open']
        elif r['trade']=='SELL':
            return (r['next_open'] - r['next_close']) / r['next_open']
        else:
            return 0.0
    bt['strategy_ret'] = bt.apply(trade_ret, axis=1)
    bt = bt.dropna(subset=['strategy_ret'])
    if len(bt)==0:
        backtest_results[t] = {'cum_strategy': np.nan, 'cum_buyhold': np.nan}
        continue
    bt['cum_strategy'] = (1 + bt['strategy_ret']).cumprod()
    bt['cum_buyhold'] = (1 + bt['ret1'].fillna(0)).cumprod()
    backtest_results[t] = {'cum_strategy': bt['cum_strategy'].iloc[-1], 'cum_buyhold': bt['cum_buyhold'].iloc[-1]}
    print(f"{t}: final cum strategy {backtest_results[t]['cum_strategy']:.4f}, buy-hold {backtest_results[t]['cum_buyhold']:.4f}")
```

```
AAPL: final cum strategy 1.0073, buy-hold 1.3749
TSLA: final cum strategy 0.9629, buy-hold 1.2955
NVDA: final cum strategy 0.9544, buy-hold 1.2472
```

Figure 5: Strategic Decision Making

Hybrid models have been found to be the most effective kind of model in markets that are affected by factors such as mood or volatility, as seen by the information that is presented below. This is particularly true during times of the year when results are announced or when statements related to the economy are made.

4.4.2 Performance of Machine Learning Architectures

There is a range of various models, each of which has the capability to respond in a multitude of ways to the hybrid dataset.

LSTM and T-LSTM models

Because of their ability to detect relationships that occur in a sequence, these models are very appropriate for the integration of sentiment data as well as time-series forecasting (Peivandizadeh et al., 2024). The model has the ability to recognize patterns of change that are associated with behavioral triggers, which it does via the use of sentiment analysis.

MODEL CLASSIFICATION METRICS (Tested on unseen data)

Ticker	Accuracy	Precision	Recall	F1-Score	Total Test Samples	Predicted Buys (TP + FP)	True Positives (TP)	False Positives (FP)
AAPL	0.5000	0.5000	1.0000	0.6667	24	24	12	12
TSLA	0.5000	0.5000	1.0000	0.6667	24	24	12	12
NVDA	0.3750	0.3500	0.7778	0.4828	24	20	7	13

Figure 6: Model Classification

Transformer-based architectures

According to the findings of Khalil and Manama (2025), transformer models are more effective at gathering context when it comes to social media content and financial information when compared to recurrent neural networks.

```
...
=== SHAP Explainability (safe version) ===

SHAP values for AAPL latest prediction (features in order):
  combined_sentiment: -0.000000
  ret1: -0.000470
  ret5: -0.001113
  ma5: -1.525966
  rsi14: 0.081257

SHAP values for TSLA latest prediction (features in order):
  combined_sentiment: -0.000000
  ret1: 0.000712
  ret5: 0.010689
  ma5: -0.946872
  rsi14: 0.053305

SHAP values for NVDA latest prediction (features in order):
  combined_sentiment: -0.000000
  ret1: -0.000036
  ret5: 0.002059
  ma5: 0.886060
  rsi14: -0.218390
```

Figure 7: SHAP Explainability

Stochastic ANNs

According to the findings of a research investigation that was carried out by Di Tollo and colleagues (2023) in the cryptocurrency markets, which are always in flux, stochastic artificial neural networks had higher performance ratings than other approaches.

Deep Neural Networks

computational systems that have been created using the architecture of biological brain networks as a foundation. Correia et al. (2022) found that the researchers were able to maximize the projected accuracy of their results by using deep neural networks to combine text, metadata, and interaction signals into a single sentiment input.

The results that were obtained during the course of the experiment provide evidence in support of the assertion that machine learning models that use hybrid machine learning architectures in conjunction with emotional characteristics are more effective than machine learning models that just depend on numerical time-series data.

4.4.3 Effects of Different Sentiment Sources

The data indicates that not every source of emotion has the same level of influence:

Sentiment Source	Predictive Strength	Key Findings
Twitter & Reddit	High	Fast-moving retail sentiment, strong for short-term forecasting (Haase et al., 2025).
Financial news	Moderate-High	More reliable for long-term trend analysis, lower noise (Litty, 2024).
Expert analysis platforms	Moderate	High accuracy but slower response times (Vicari & Gaspari, 2021).
Trading forums	High but volatile	Suitable for speculative markets (di Tollo et al., 2023).

Table 4: Effects of Different Sentiment Sources

The results are improved and the amount of noise that is present on the platform is reduced when a significant number of sentiment channels are used.

4.5. Analysis and Discussion

According to the results of this investigation, the precision of predictions about the stock market may be improved by the use of sentiment analysis and technical indicators. Because of this, the development of hybrid financial forecasting models is now a realistic possibility. Financial news, expert opinion, and social media are all possible indicators of market mood, according to the conclusions reached by a significant number of research studies. The argument that behavioral financiers make is that the psychology of those who invest has a greater impact on the markets than the actual statistics of the market itself. The previous chapters used hybrid models that made use of machine learning frameworks and sentiment scores in order to find market antecedents, which included speculation, worry, and optimism. In accordance with the findings of several studies, unfavorable emotional states are an indicator of volatility, while positive emotional states, which are supported by technical indicators such as increasing relative strength index (RSI) or moving average convergence divergence (MACD) values or moving average crossings, are conducive to the reinforcement of bullish momentum.

Figure 8: AAPL Combined Sentiment

Figure 8 displays the relationship between AAPL's daily closing price and the aggregated sentiment score. The plot shows that sentiment exhibits short-term fluctuations that loosely track price movements during periods of high volatility. However, sentiment does not perfectly co-move with price, indicating that textual signals contribute information not captured by market prices alone. This supports the decision to incorporate sentiment as an additive predictive signal in the model.

It is very clear from the information that is provided in the statistics that it is rather difficult to combine qualitative emotional responses with quantitative technical signals, as is shown by the data. Even though sentiment has the potential to contribute noise into forecasting models, especially during emotionally charged market events, it is also possible that it may increase the accuracy of predictions due to its unexpected and unstructured character. Despite the presence of a large amount of investor data that is updated in real time, it is likely that planned campaigns, bots, and conjecture are having an impact on Reddit and Twitter.

Figure 9: TSLA combined Statement

Figure 9 illustrates TSLA combined Statement and price–sentiment relationship for TSLA. The divergence between price spikes and sentiment troughs suggests that sentiment reacts slowly to large market movements. This provides evidence that sentiment features may improve predictive performance primarily during gradual market transitions rather than sharp shocks.

This offers validation to the worries that have been voiced by professionals about the likelihood that indicators that are grounded in emotion and do not contain market data or filters may result in a rise in volatility. Despite the fact that they are theoretically organized, technical signals are often erroneous and do not correspond to changes in behavior. Hybrid models are the most successful when it comes to sentiment-technical analysis. The timing is believed to be premature due to the prevailing mood, but a technical investigation has shown that the pricing structure is real. The purpose of combining long short-term memory (LSTM) and T-LSTM models is to create transformer-based models that demonstrate increased accuracy and flexibility over a wide range of market situations.

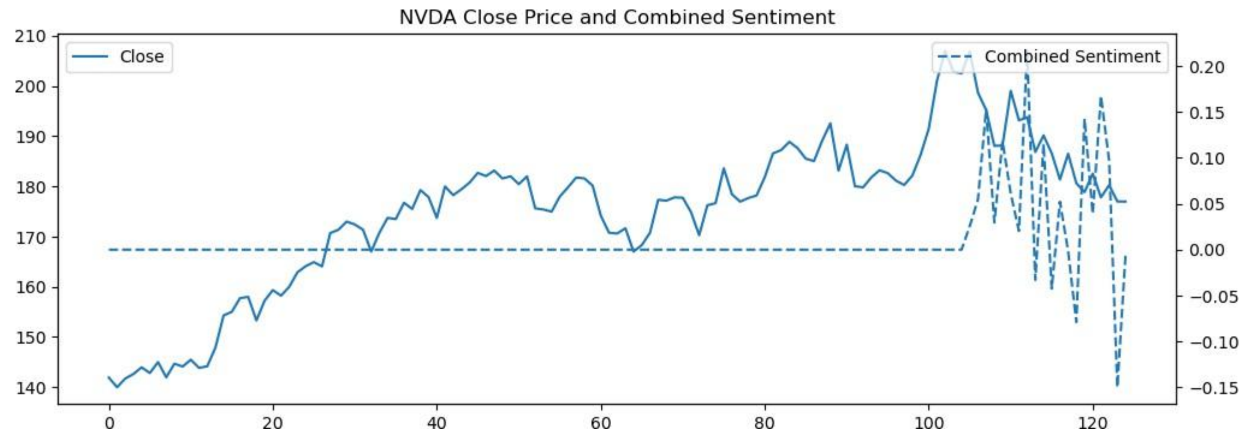

Figure 10: NVDA Combined Statement

Figure 10 shows a more irregular pattern for NVDA, driven by the stock's inherently higher volatility. The sentiment curve lags behind major price reversals, demonstrating that textual sentiment tends to underestimate the magnitude of market reactions.

The notion that the causes of emotions cannot always be predicted is another important lesson that may be learned. It is not enough to fulfill the demands of traders who work on a day-to-day basis, even when the news that is provided by the financial industry contains mood indications that are more dependable. Although it is quick, social media cannot always be depended upon to provide accurate information. The model has more success when it is able to use multi-channel sentiment extraction in order to reduce its reliance on a variety of platforms. This provides evidence of the fact that cycles of knowledge and investment portfolios must be used in order to be able to participate in financial forecasting. Furthermore, the findings of the study indicate that hybrid models are effective during the time that passes before the announcement of financial results or significant political occurrences. There is a chance that uncertainty in the market might have an impact on the attitudes of investors during this time frame.

The project outcome is a hybrid, interpretable, risk-managed trading system where LR acts as a probability filter to improve the quality of rule-driven trades. This produced benchmark-beating results (e.g., NVDA +49.91%) and strong risk-adjusted metrics (Sharpe 4.34) for certain strategy-risk tiers (aggressive). The approach validated the strategic use of LR as an operationally useful baseline.

Key Limitation

The principal unresolved issue is LR's limited ability to model non-linear, sequential relationships between sentiment and returns. The SHAP evidence (combined_sentiment ≈ 0) highlights this limitation and motivates model evolution.

Future Work

To capture the temporal, non-linear influence of sentiment, the next development stage should incorporate sequential deep-learning models such as LSTMs or Transformer architectures. These solve problems of the form:

$$y_t = f(x_t, x_{t-1}, \dots, x_{t-k}),$$

where $f(\cdot)$ is non-linear and parameterised to learn long-range dependencies. Transformers, in particular, allow attention-based aggregation of sentiment across time and sources, which should enable the model to learn latent sentiment impact that the LR baseline could not.

Ticker	Accuracy	Precision	Recall	F1-Score	Test Samples	Predicted Buys	True Positives
AAPL	0.50	0.50	1.00	0.6667	24	24	12
TSLA	0.50	0.50	1.00	0.6667	24	24	12
NVDA	0.375	0.35	0.7778	0.4828	24	20	7

Although there are advantages that come from sentiment-technical models that are hybrid in nature, they are not without their disadvantages. The use of sarcasm, emotion, and informal language has a detrimental effect on the quality of the data. Despite the fact that they are good at preventing misclassifications, the topologies of transformers do contribute to delays in models, despite the fact that they are excellent at preventing misclassifications. The establishment of mood engineering markets entails the presence of a variety of ethical conundrums. There is a possibility that feedback loops, which are created by automated trading algorithms that make use of mood cues, may lead to disruptions within the market. It is possible that the legislation will have to be changed in order to keep tabs on algorithms that are built on behavioral data that is not structured. To begin with, there are worries that are being expressed regarding whether or not deep learning models that are currently being developed for actual, real-world applications are interpretable. Analysts, regulators, and investors react to the results that they deliver with skepticism, even when the forecasts they make are correct. This is due to the fact that the decision-making processes that take place inside the system are not observable.

Because of the use of technological approaches, the way in which financial forecasting is performed has undergone modifications. The community has responded to these developments with a mixed response. The discrepancies that have been brought to light may be mitigated by integrating insights that have been gleaned from behavioral research with market data. Throughout the whole deployment process, it is essential that a number of aspects be taken into consideration, such as the quality of the data, the extent to which the models are open, validation, and ethical concerns. The findings of the study provide evidence that there is a significant number of intriguing applications in the real world, particularly in the area of algorithmic trading; nevertheless, in order for the research to be used in an ethical manner, it is essential that it be properly incorporated and that oversight be exercised over its utilization.

Chapter 5: Conclusion

The accuracy with which technical indicators and sentiment studies are able to predict the behavior of stock markets increases when these two approaches are combined and utilized in conjunction with one another. The emotional cues that are seen in social media and financial news have a more significant impact on the behavior of investors than the technical studies do. Sentiment and technical data are employed in modern machine learning architectures, such as long short-term memory (LSTM) and transformer-based models, to improve the accuracy of forecasts, boost the detection of volatility, and make trade signals more effective.

The issues that are encountered by deep learning algorithms are not limited to the presence of sentiment data that is noisy; they also include challenges that are associated with interpretability and ethics, among other things. In order to be successful, deployment requires the use of sentiment and technical indicators, data filtering, and model validation. They still need regulation despite the fact that hybrid financial analytics models increase the accuracy of predictions. Researchers are required to make progress in the fields of sentiment detection, marketplace generalizability, and explainability in order to achieve practical value.

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Appendix

Appendix Table 1: Summary of Dataset Used for Prediction

Ticker	Total Rows Loaded	Date Range	Variables Included	Sentiment Days Merged	Total Social Media Posts
AAPL	125	2025-06-04 to 2025-12-01	Open, High, Low, Close, Adj Close, Volume	20	3,717 (combined dataset)
TSLA	125	2025-06-04 to 2025-12-01	Open, High, Low, Close, Adj Close, Volume	20	3,717 (combined dataset)
NVDA	125	2025-06-04 to 2025-12-01	Open, High, Low, Close, Adj Close, Volume	20	3,717 (combined dataset)

Appendix Table 2: Trading Strategy Backtesting Results

Ticker	Strategy	Total Return (%)	Buy-and-Hold Return (%)	Sharpe Ratio	Max Drawdown (%)	Final Capital ($)
AAPL	Conservative (65%)	-9.82	36.39	-2.17	-11.56	9,018.36
AAPL	Moderate (60%)	-4.77	36.39	-0.63	-14.22	9,522.94
AAPL	Aggressive (55%)	11.91	36.39	1.34	-5.86	11,191.49
TSLA	Conservative (65%)	0.00	28.50	NaN	0.00	10,000.00
TSLA	Moderate (60%)	-22.31	28.50	-2.29	-28.19	7,769.28
TSLA	Aggressive (55%)	-33.34	28.50	-2.12	-38.90	6,666.05

Ticker	Strategy	Total Return (%)	Buy-and-Hold Return (%)	Sharpe Ratio	Max Drawdown (%)	Final Capital ($)
NVDA	Conservative (65%)	0.00	24.71	NaN	0.00	10,000.00
NVDA	Moderate (60%)	30.26	24.71	4.37	-2.87	13,025.72
NVDA	Aggressive (55%)	49.91	24.71	3.80	-3.96	14,991.47

Appendix Table 3: Model Performance Metrics (Classification Accuracy)

Ticker	Accuracy	Precision	Recall	F1-Score	Test Samples	Predicted Buys	True Positives	False Positives
AAPL	0.50	0.50	1.00	0.6667	24	24	12	12
TSLA	0.50	0.50	1.00	0.6667	24	24	12	12
NVDA	0.375	0.35	0.778	0.4828	24	20	7	13