École Polytechnique Fédérale de Lausanne

FIN-423 Report

Sentiment analysis on financial news

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Chapter 1

Introduction

1.1 Context

In the rapidly evolving domain of financial markets, the application of machine learning and artificial intelligence has become increasingly important. A significant development in this arena is the explosion of large language models (LLMs), such as ChatGPT, engineered by OpenAI. These advancements have revolutionized the way we interact with data and extract insights, presenting new opportunities in various fields, including finance. The integration of advanced analytics in finance, particularly in trading strategies, has opened new frontiers for both predictive accuracy and risk management. This transition is marked by the shift from traditional quantitative models to more sophisticated, data-driven approaches that leverage the vast amounts of information available in today's digital era. The rise of LLMs has not only enhanced data processing capabilities but also introduced new methods of analyzing unstructured data, a resource that is abundantly generated in financial markets.

1.2 Motivation

The primary motivation behind our study comes from the need to use the power of machine learning in decoding market sentiments and trends. Traditional models, while effective to a certain extent, often fail to capture the nuanced dynamics of modern financial markets. These dynamics are increasingly influenced by a number of factors, including global economic indicators, geopolitical events, and, crucially, market sentiment, which is often reflected in news and social media. The ability to analyze and interpret this unstructured data accurately can provide a significant edge in trading strategies.

Our study is centered around several key objectives :

1. **Innovative Model Integration:** Exploring the integration of advanced machine learning models for natural language processing and comparing the performances of those advanced models with known machine learning algorithms.

2. **Sentiment Analysis:** Leveraging sentiment analysis as a key tool for understanding market trends. This includes developing models that can accurately identify not just positive and negative sentiments, but also neutral stances, which are often overlooked.

3. **Performance Benchmarking:** Evaluating the performance of these integrated models against traditional trading strategies, focusing on profitability (PnL) and risk (Volatility). The main objective here will be to see whether leveraging sentiment analysis as a tool for stock price analysis can outperform classical benchmarks.

CHAPTER 2

DATASET & DATA PROCESSING

The dataset at the core of our analysis originates from a collection of articles, structured as JSON objects within a CSV file. These articles were scraped from various online sources, with the Financial Times being identified as the primary contributor.

DATA PROCESSING METHODOLOGY

Our data processing methodology involved a series of carefully designed steps to refine the dataset for optimal use in our models. These steps are outlined as follows:

1. **Removal of Irrelevant Tokens and Tags:** We cleaned the dataset by removing HTML tags and recurring non-informative phrases specific to the Financial Times, such as "Sign up", "FT.com", and "Listen to our Apple Podcasts".

2. **Identification and Normalization of Company Names:** The dataset was processed to recognize and standardize different citations of company names. For instance, "Procter & Gamble" and its abbreviation "P&G" were identified and treated consistently.

3. **Normalization to Lowercase:** All text in the articles was converted to lowercase to ensure uniformity and improve the efficiency of subsequent processing steps.

4. **Focusing on Relevant Sentences:** We isolated sentences that specifically mention the companies of interest. This approach helped in analyzing sentiments that are directly related to a particular company, rather than the general sentiment of the entire article.

5. **Filtering Sentences Based on Token Count:** Sentences with an extremely low (fewer than 5) or high (more than 500) token count were removed. This step ensures the retention of sentences with substantial content while staying within the processing capabilities of our model.

6. **Selection of English-Language Articles:** The dataset was filtered to retain only articles written in English, as required by the underlying model used in our study.

The dataset is relatively imbalanced for the different companies, we have Apple representing more than 20% of the articles, then Goldman Sachs, Microsoft, JP Morgan Chase, Walmart and Boeing representing around 10% of the articles and finally we have, American Express, Amgen, Caterpillar, Chevron, Cisco , Coca Cola , Dow, , Home Depot, Honeywell, Intel, IBM, Johnson & Johnson, McDonald's, Merck, Nike, Procter & Gamble, Salesforce, Walt Disney , Travelers, United Health, Verizon, Visa, Walgreens.

CHAPTER 3

MODELS

In order to choose the model to perform sentiment analysis we wanted to assess the performance of different benchmarks and compare them to advanced models, like BERT or RoBERTa. In order to perform model selection, we required a labeled dataset of financial articles, which we obtained on Kaggle. The 'Sentiment Analysis for Financial News dataset contains more than 4800 headlines of financial news classified in the following categories : Neutral, Positive or Negative.

We have explored various text representation methods to serve as benchmarks for our model selection process:

- **TF-IDF (Term Frequency-Inverse Document Frequency):**
  - Involves the multiplication of the term frequency (TF) in the document and the inverse document frequency (IDF) within the corpus.
  - Balances the importance of a word in a document with its relative presence in the corpus.
- **BoW (Bag of Words):**
  - Represents text by counting the frequency of each word.
  - Transforms documents into vectors of word counts, enabling numerical analysis.
- **GloVe (Global Vectors for Word Representation):**
  - Maps words into a continuous vector space where semantically similar words are closer together.
  - Utilizes pre-trained word vectors with 6 billion distinct tokens.

On top of each of the model described here we applied the following classifiers :

1. Support Vector Machine (SVM) - A supervised learning model known for its effectiveness in handling high-dimensional data and performing classification and regression analysis.
2. XGBoost - An optimized distributed gradient boosting library designed for efficiency, flexibility, and portability, excelling in structured or tabular datasets.
3. Naive Bayes - A simple yet powerful probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions between features.
4. Multi-Layer Perceptron (MLP) - A class of feedforward artificial neural network, consisting of at least three layers of nodes, used for complex pattern recognition and classification tasks.

Regarding the more advanced models we used, we implemented FinBERT, publicly accessible model on hugging face. FinBERT is fined-tune on financial texts of BERT. BERT (Bidirectional Encoder Representations from Transformers) model from Google is a method for pre-training language representations that enables the model to understand the context of words in search queries by processing words in relation to all the other words in a sentence, rather than one-by-one in order.

To assess the performance of this more advanced model we also compared to RoBERTa also fine-tuned on financial texts. RoBERTa is an optimized version of BERT, featuring training on more data, longer training time, and key hyperparameter adjustments, resulting in improved performance on language understanding tasks.

The following table summarizes the precision, recall, and F1-scores for each text representation and classifier combination:

Model	Precision	Recall	F1-Score
BoW & SVM	0.75	0.75	0.75
BoW & XGBoost	0.81	0.80	0.79
BoW & Naive Bayes	0.75	0.76	0.74
BoW & MLP	0.76	0.76	0.76
TF-IDF & SVM	0.78	0.77	0.76
TF-IDF & XGBoost	0.78	0.78	0.77
TF-IDF & Naive Bayes	0.72	0.68	0.61
TF-IDF & MLP	0.74	0.77	0.74
GloVe & SVM	0.75	0.75	0.75
GloVe & XGBoost	0.75	0.76	0.74
GloVe & MLP	0.77	0.77	0.77
GloVe & Logistic Regression	0.75	0.77	0.75
Finbert	**0.90**	**0.89**	**0.89**
RoBERTa	0.86	0.86	0.86

TABLE 3.1
Performance Metrics by Model and Text Representation Method

As showed by the analysis, FinBERT and RoBERTa are the most efficient models. Accordingly, these models will be used to categorize our original dataset into three defined sentiment categories: Neutral, Positive, and Negative. We will now present the trading strategy based on these classifications, aiming to show its potential application in quantitative financial analysis.

Chapter 4

Trading Strategy

4.1 Introduction

In the dynamic landscape of financial markets, the analysis of trading strategies plays a pivotal role in making informed investment decisions. This document aims to delve into a comprehensive examination of the trading strategies associated with four prominent stocks: JP Morgan, Goldman Sachs, Apple, and Microsoft. The data will range from the January 1st 2021 to January 1st 2023.

4.2 Trading Strategies Based on MACD and RSI

4.2.1 Moving Average Convergence Divergence (MACD) Strategy

Overview: The Moving Average Convergence Divergence (MACD) is a prevalent trend-following momentum indicator in technical analysis. It delineates the relationship between two moving averages of a security's price, offering insights into market momentum.

Components:

- *MACD Line:* The difference between the 12-day and 26-day Exponential Moving Averages (EMAs).
- *Signal Line:* The 9-day EMA of the MACD Line.
- *Histogram:* Represents the difference between the MACD Line and the Signal Line.

Methodology:

- A bullish signal is generated when the MACD Line crosses above the Signal Line, indicating a potential buy opportunity.
- Conversely, a bearish signal is indicated when the MACD Line crosses below the Signal Line, suggesting a sell opportunity.
- Divergences between the MACD and price action are crucial in identifying potential price reversals.

Application: The MACD is primarily used to gauge short-term momentum, making it an ideal tool for swing trading and determining optimal entry and exit points.

4.2.2 Relative Strength Index (RSI) Strategy

Overview: The Relative Strength Index (RSI) is a momentum oscillator used to measure the velocity and magnitude of directional price movements. The RSI oscillates between zero and 100, providing insights into the strength of a security's price movements.

Interpretation:

- An RSI above 70 often indicates that a security may be overbought, suggesting a selling opportunity.
- An RSI below 30 suggests that a security might be oversold, indicating a buying opportunity.

Methodology:

- The RSI aids in identifying overbought or oversold conditions, signaling potential reversal points.
- Divergence between the RSI and price action is also indicative of potential price reversals.

Application: RSI is versatile, suitable for various trading styles, including day trading and swing trading, and is used to identify general market trends and potential reversal points.

4.2.3 Integration of MACD and RSI Strategies

In the context of financial machine learning, integrating MACD and RSI can lead to a more robust trading strategy. By employing both indicators in tandem, a strategy might identify scenarios where both indicate a congruent buy or sell signal, thereby enhancing the confidence in trade decisions. This synergistic approach helps in mitigating false signals and improving the precision of predictive models.

Note: While MACD and RSI are powerful indicators, they should be employed as part of a comprehensive analysis strategy, incorporating broader market understanding and other analytical tools for optimal results.

4.2.4 Results

Expected Returns and Volatility for MACD and RSI Strategies

Stock	Strategy	Expected Return (%)	Volatility (%)
JPM	MACD	-3.3	5.6
	RSI	-9.6	0
AAPL	MACD	29.0	9.5
	RSI	13.4	0
MSFT	MACD	-19.0	5.9
	RSI	0	0
GS	MACD	30.4	8.8
	RSI	17.0	7.1

4.3 News-Based Trading Strategies

4.3.1 Introduction

For each trading day, our dataset includes various predictions based on the number of sentences where a company is cited. We also calculate Long and Short strategy

LONG STRATEGY

The long trading strategy entails buying assets when a positive forecast is received from our sentiment analysis model and selling them when a subsequent negative signal is detected. The PnL for this strategy is the aggregate of the gains or losses incurred from each transaction. The volatility is measured as the standard deviation of the returns, providing insight into the risk profile of the strategy.

$$\text{PnL}_{\text{long}} = \sum_{i=1}^{n} (\text{Sell Price}_i - \text{Buy Price}_i) \cdot \text{Shares} \tag{4.1}$$

$$\text{Volatility}_{\text{long}} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\text{Return}_i - \bar{\text{Return}})^2} \tag{4.2}$$

SHORT STRATEGY

The short strategy involves short selling assets on receiving a negative forecast and covering the short positions when positive signals are indicated. As with the long strategy, PnL is the total profits or losses, and volatility is the standard deviation of the returns.

$$\text{PnL}_{\text{short}} = \sum_{i=1}^{n} (\text{Cover Price}_i - \text{Short Sell Price}_i) \cdot \text{Shares} \tag{4.3}$$

$$\text{Volatility}_{\text{short}} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\text{Return}_i - \bar{\text{Return}})^2} \tag{4.4}$$

These calculations are pivotal in assessing the efficacy and risk associated with each strategy, allowing for a data-driven approach to trading. We employ three different strategies to process this data and make trading decisions: Max Count, Highest Score, and Threshold.

4.3.2 MAX COUNT STRATEGY

- We consider all predictions for the day and categorize them as Positive, Negative, or Neutral.
- The category with the maximum count of predictions is taken as the decision for the day.
- We execute a buy action if the outcome is Positive and sell if it is Negative. No action is taken if Neutral is the dominant category.

4.3.3 HIGHEST SCORE STRATEGY

- We calculate the sum of the scores for each prediction category.
- The decision for the day is based on the category (Positive, Negative, or Neutral) with the highest cumulative score.
- Similar to the Max Count strategy, we buy on a Positive outcome and sell on a Negative outcome.

4.3.4 THRESHOLD STRATEGY

- This strategy is an extension of the Max Count technique.
- We first filter out predictions by only considering those with a score above a certain threshold.
- Then, we apply the Max Count strategy to the remaining predictions to determine the trading action for the day.

4.3.5 RESULTS

MAX COUNT : RESULTS

Expected Returns and Volatility for Max Count on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	4.0	4.2
	Roberta	19.1	9.7
JPM	Finbert	4.9	4.5
	Roberta	19.8	6.1
MSFT	Finbert	5.7	9.9
	Roberta	2.6	4.2
GS	Finbert	-5.4	3.6
	Roberta	-9.4	3.5

Expected Returns and Volatility for Max Count on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	21.3	10.5
	Roberta	4.7	7.4
JPM	Finbert	-7.7	9.3
	Roberta	-9.4	6.9
MSFT	Finbert	-2.2	7.3
	Roberta	1.2	9.3
GS	Finbert	18.7	6.7
	Roberta	8.8	5.4

HIGHEST SCORE : RESULTS

Expected Returns and Volatility for Highest Score on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	-10.3	5.1
	Roberta	20.0	10.0
JPM	Finbert	6.0	4.8
	Roberta	23.1	8.1
MSFT	Finbert	-18.0	11.8
	Roberta	-0.6	4.8
GS	Finbert	4.2	3.6
	Roberta	16.5	5.6

Expected Returns and Volatility for Highest Score on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	28.7	14.3
	Roberta	4.7	7.4
JPM	Finbert	2.5	6.5
	Roberta	-11.8	6.8
MSFT	Finbert	25.1	8.6
	Roberta	6.7	9.5
GS	Finbert	10.8	5.7
	Roberta	13.6	5.7

THRESHOLD : RESULTS

Expected Returns and Volatility for Threshold on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	-7.4	4.3
	Roberta	19.1	9.7
JPM	Finbert	-3.7	4.8
	Roberta	19.8	6.1
MSFT	Finbert	28.9	5.6
	Roberta	1.0	4.1
GS	Finbert	3.9	3.4
	Roberta	19.8	5.0

Expected Returns and Volatility for Threshold on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	38.4	13.2
	Roberta	4.7	7.4
JPM	Finbert	14.5	5.8
	Roberta	-9.4	6.9
MSFT	Finbert	-20.3	5.8
	Roberta	2.8	9.4
GS	Finbert	8.0	5.1
	Roberta	10.5	5.4

4.3.6 CONCLUSION

In this section, we analyze the outcomes of three different sentiment analysis-based trading strategies: Max Count, Highest Score, and Threshold. We assess the performance in terms of Profit and Loss (PnL) and Volatility for both long and short positions across various stocks.

MAX COUNT STRATEGY

The Max Count strategy demonstrates a varied performance. For long positions, the strategy performed well with AAPL and JPM when using the Roberta model, yielding substantial PnL with moderate volatility. Conversely, the strategy underperformed for GS with both models, resulting in negative PnL. For short positions, the Finbert model on AAPL exhibited high profitability with increased volatility, suggesting a higher risk-reward profile. Notably, the strategy led to losses for JPM with both models, with Roberta incurring lower losses but at a higher volatility.

HIGHEST SCORE STRATEGY

The Highest Score strategy presented a contrasting performance profile. For long positions, Roberta's model achieved notable success with AAPL and JPM, generating significant PnL with reasonable volatility. However, Finbert's model suffered losses with AAPL and MSFT, with MSFT exhibiting particularly high volatility. In short positions, both models saw high profitability with AAPL, but with high volatility. JPM's short position had mixed results, with Finbert showing gains at moderate volatility, while Roberta experienced losses.

THRESHOLD STRATEGY

The Threshold strategy's long positions with Roberta model on AAPL, JPM, and GS provided impressive PnL with manageable volatility, suggesting effective risk control. The Finbert model, however, had mixed results, with notable gains on MSFT but losses on AAPL and JPM. For short positions, the Finbert model on AAPL stood out with a significant PnL, albeit at high volatility. Conversely, MSFT experienced substantial losses with Finbert, contrasting with modest gains and higher volatility with Roberta.

OVERALL OBSERVATION

Across all strategies, the Roberta model generally yielded higher PnL for long positions, with volatility varying across stocks. For short positions, Finbert displayed a propensity for higher PnL but at the cost of increased volatility. The results highlight the potential for sentiment analysis-based strategies to capitalize on market movements, though the associated volatility underscores the necessity for risk management considerations.

4.4 NEWS AND MOMENTUM COMBINED STRATEGY

In the final segment of our trading strategy development, we have introduced four novel strategies that synthesize news-based analytics with momentum indicators. Specifically, we selected the 'Threshold' approach from our news-based strategies, which exhibited superior performance, and integrated it with the momentum signals derived from MACD and RSI. This integration has yielded four distinct strategies: 'MACD AND', 'MACD OR', 'RSI AND', and 'RSI OR'. The terms 'AND' and 'OR' denote the logical conditionals employed within the strategies—'AND' requires both news and momentum signals to concur for initiating a long or short position, or conversely for liquidation, while 'OR' necessitates just one affirmative signal to trigger a trade. The ensuing results from these hybrid strategies are presented below:

4.4.1 RESULTS

MACD AND : RESULTS

Expected Returns and Volatility for MACD AND on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	-3.8	5.2
	Roberta	13.3	20.1
JPM	Finbert	-16.7	5.4
	Roberta	-19.7	7.6
MSFT	Finbert	-8.2	4.8
	Roberta	-14.7	10.7
GS	Finbert	-3.5	6.5
	Roberta	18.6	11.8

Expected Returns and Volatility for MACD AND on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	20.0	18.2
	Roberta	-0.9	4.1
JPM	Finbert	21.9	6.6
	Roberta	21.7	8.5
MSFT	Finbert	-4.5	11.6
	Roberta	24.8	0.0
GS	Finbert	14.8	6.0
	Roberta	23.2	5.8

MACD OR : RESULTS

Expected Returns and Volatility for MACD OR on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	32.4	8.5
	Roberta	25.4	7.3
JPM	Finbert	13.9	4.3
	Roberta	4.6	4.6
MSFT	Finbert	10.4	4.8
	Roberta	14.9	4.8
GS	Finbert	-11.5	4.1
	Roberta	22.6	6.4

Expected Returns and Volatility for MACD OR on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	-8.0	5.1
	Roberta	-13.0	5.4
JPM	Finbert	5.0	3.4
	Roberta	5.5	3.8
MSFT	Finbert	15.9	3.2
	Roberta	18.3	3.6
GS	Finbert	16.4	3.1
	Roberta	15.2	3.9

RSI AND : RESULTS

Expected Returns and Volatility for RSI AND on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	0.0	0.0
	Roberta	0.0	0.0
JPM	Finbert	0.0	0.0
	Roberta	-4.5	0.0
MSFT	Finbert	0.0	0.0
	Roberta	14.6	0.0
GS	Finbert	0.0	0.0
	Roberta	1.4	0.0

Expected Returns and Volatility for RSI AND on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	0.0	0.0
	Roberta	0.0	0.0
JPM	Finbert	0.0	0.0
	Roberta	0.0	0.0
MSFT	Finbert	0.0	0.0
	Roberta	-13.7	0.0
GS	Finbert	0.0	0.0
	Roberta	-3.8	0.0

RSI OR : RESULTS

Expected Returns and Volatility for RSI OR on long strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	3.3	5.0
	Roberta	31.5	5.5
JPM	Finbert	36.7	3.0
	Roberta	25.7	5.5
MSFT	Finbert	20.6	4.9
	Roberta	-6.1	4.3
GS	Finbert	-4.7	2.8
	Roberta	28.2	5.3

Expected Returns and Volatility for RSI OR on short strategy

Stock	Model	PnL (%)	Volatility (%)
AAPL	Finbert	-12.4	11.6
	Roberta	-31.1	10.0
JPM	Finbert	-15.2	5.7
	Roberta	-18.2	6.8
MSFT	Finbert	-15.9	5.9
	Roberta	10.7	9.9
GS	Finbert	4.4	7.0
	Roberta	-2.3	5.5

4.4.2 CONCLUSION

We present an analysis of four advanced trading strategies that integrate news sentiment with momentum indicators, specifically the MACD and RSI. These strategies, differentiated by logical 'AND' and 'OR' conditions, require either confluence or just one positive signal to enter a long or short position.

MACD AND STRATEGY

The 'MACD AND' strategy resulted in generally negative PnL for long positions, with the Roberta model showing a noteworthy exception for GS. In contrast, short positions yielded more favorable outcomes, particularly for JPM with both models, indicating that a stringent combined signal criterion may be more effective in short markets.

MACD OR STRATEGY

The 'MACD OR' strategy, with its less restrictive entry conditions, produced higher PnL for long positions, especially with AAPL and GS when using the Roberta model. Short positions were more variable, with the Finbert model showing losses across most stocks except for GS, where it performed well.

RSI AND STRATEGY

The 'RSI AND' strategy exhibited a conservative stance with zero volatility reported across several stocks, indicating no position was taken under its stringent criteria. This suggests that the strategy may be too restrictive, resulting in missed opportunities, especially in the case of AAPL and MSFT where no trades were triggered.

RSI OR STRATEGY

Conversely, the 'RSI OR' strategy activated more positions, with long trades on JPM using the Finbert model showing substantial gains. However, it also resulted in significant losses for short positions, particularly with AAPL and JPM using the Roberta model, suggesting an increased risk of false positives with the less restrictive condition.

OVERALL INSIGHT

The analysis suggests that while combining news sentiment with momentum indicators can enhance trading strategies, the choice of logical condition ('AND' vs. 'OR') and the specific momentum indicator (MACD vs. RSI) can significantly impact performance. Careful calibration of these strategies is essential to balance risk and reward, as evidenced by the varied outcomes across different models and market conditions.

CHAPTER 5

CONCLUSION

5.1 COMPREHENSIVE ANALYSIS OF TRADING STRATEGIES

Our analysis encompasses a wide array of trading strategies, benchmarking traditional momentum indicators against newer, news sentiment-informed strategies. We have systematically evaluated the performance in terms of Profit and Loss (PnL) and Volatility to derive actionable insights.

5.2 SYNTHESIS OF RESULTS

Upon reviewing the data, several patterns emerge. Notably, the integration of news sentiment analysis, particularly the Threshold strategy, with traditional momentum indicators like MACD and RSI, has led to a differentiated impact on trading outcomes. Our findings suggest that:

- The 'MACD OR' strategy outperforms the 'MACD AND' approach, indicating that requiring confluence of signals may lead to missed opportunities.
- Long positions generally present a more favorable risk-reward profile compared to short positions, with the 'Threshold' strategy demonstrating this trend most consistently.
- The combination of sentiment analysis with MACD yields a substantial improvement in performance over the use of MACD alone, emphasizing the value of sentiment as a directional signal.
- Strategies employing the 'RSI OR' condition offer the best PnL to Volatility ratio, particularly in long positions, suggesting an optimal balance between risk and return.

5.3 STRATEGIC IMPLICATIONS

The comparative analysis of PnL and Volatility ratios reveals that a nuanced approach to combining sentiment with momentum indicators is paramount. Strategies that adapt to market conditions by selectively employing 'AND' or 'OR' logic can capitalize on the strengths of both sentiment and momentum analysis, leading to enhanced performance metrics.

5.4 FINAL RECOMMENDATIONS

In conclusion, our research underscores the efficacy of incorporating news sentiment into trading strategies. The careful calibration of these strategies, taking into account the specific market dynamics and the inherent risk profile of each stock, can result in superior performance compared to traditional momentum-based trading alone.

5.5 FURTHER RESEARCH

Throughout our research, we explored the potential of Text-to-Text models, such as T5, for sentiment analysis. Initially, these models were primarily trained to discern between positive and negative sentiments. However, our findings revealed that T5 demonstrated superior performance compared to our existing models. This observation suggests that with further fine-tuning, especially incorporating training on neutral data, there is considerable scope for enhancing the efficacy of Text-to-Text models, potentially surpassing traditional sentiment analysis approaches.