Hybrid FinBERT-LSTM Deep Learning Framework for Stock Price Prediction: a Sentiment Analysis Approach Using Earnings Call Transcripts

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Abstract. Stock market prediction remains a critical area of research due to its significant economic implications and inherent complexity. With advancements in machine learning, research interest has grown substantially in understanding the impact of textual data on financial forecasting. This study presents a hybrid FinBERT-LSTM model that combines sentiment analysis of quarterly earnings conference calls with traditional price prediction methods. We evaluate our model's effectiveness against standalone LSTM approaches across six major US stocks from the financial and technology sectors. Experimental results demonstrate that the sentiment-enhanced hybrid model achieves superior predictive accuracy for four of the six studied stocks, as measured by Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Accuracy metrics. Most notably, Citibank and Meta demonstrated substantial improvements when incorporating sentiment analysis, with MSE scores approximately 38 percent lower compared to predictions without sentiment data. Our findings contribute to the growing body of research on textual analysis in financial forecasting and offer practical implications for investment decision-making.

Keywords: Stock Price Prediction, Earnings Conference Calls, Sentiment Analysis, FinBERT, Deep Learning.

1 Introduction

The prediction of stock prices remains a critical area of investigation in both industry and academia, driven by its potential to minimize investment risks and maximize returns. While traditional approaches to stock price prediction have relied primarily on structured financial data, recent advances in machine learning and deep learning have opened new avenues for incorporating unstructured data sources into predictive models. Of particular interest is the emerging field of natural language processing (NLP) and its application to financial text analysis, which has demonstrated promising correlations between textual sentiment and stock price movements.

Several studies have established significant relationships between stock prices and various forms of textual data, including social media sentiment (Jing et al. 2021), news article content (Gu et al. 2024), and corporate earnings call transcripts (Medya et al. 2022). The growing importance of content and textual tone analysis in financial decision-making has led researchers to investigate how the linguistic characteristics of corporate disclosures can reveal underlying management intentions and market signals.

This study focuses specifically on analyzing the impact of corporate earnings conference calls on stock price prediction through a novel combination of FinBERT and LSTM algorithms. Earnings conference calls, conducted quarterly by publicly listed companies, serve as crucial communication channels between corporate leadership and market participants. During these calls, key executives, typically including the CEO and CFO, discuss recent performance metrics and provide future guidance. The calls include question-and-answer sessions addressing critical topics such as mergers and acquisitions, litigation, dividend policies, and share buybacks. The regulatory requirements for fair disclosure in countries like the United States enhance the significance of these communications, as evidenced by observable market volatility before, during, and after these events.

The foundation for this research builds upon extensive prior work in stock price prediction, from traditional financial studies (Fama 1965; Patell 1976; Poterba et al. 1988; Ou et al. 1989) to modern machine learning applications (Saad et al. 1998; K.-j. Kim 2003; Pai et al. 2005; Vijh et al. 2020). Long Short-Term Memory (LSTM) neural networks have demonstrated particular effectiveness in analyzing time-series data (Fu et al. 2016; Trinh et al. 2018; Sarkar et al. 2019) and specifically in stock price prediction (Roondiwala et al. 2017; Selvin et al. 2017; Pawar et al. 2019; Sunny et al. 2020; Moghar et al. 2020; Mehtab et al. 2021).

In parallel, sentiment analysis has evolved as a robust methodology for extracting insights from textual data (Medhat et al. 2014; Poecze et al. 2018; Alaei et al. 2019; Rawat et al. 2021), with the development of FinBERT (Huang et al. 2023) specifically addressing the unique characteristics of financial text. Recent studies have successfully applied sentiment analysis to financial texts (Jing et al. 2021; Li et al. 2022; J. Kim et al. 2023; Shobayo et al. 2024; Gu et al. 2024) and earnings conference calls specifically (Chakraborty et al. 2020; Chin et al. 2023; Hasani et al. 2024), with some researchers examining the relationship between earnings call sentiment and stock price movements (Jayaraman et al. 2020; Ma et al. 2020; Medya et al. 2022).

Our research extends these findings by implementing a hybrid FinBERT-LSTM model to incorporate the sentiment of earnings calls into the stock price prediction. This approach builds on recent work by (Gu et al. 2024) that demonstrated the superiority of FinBERT-LSTM models over traditional DNN and LSTM approaches in news sentiment analysis. We apply this methodology to six US public companies, combining sentiment scores derived from earnings conference calls with historical price data to predict future stock movements. Our analysis reveals compelling evidence for the differential impact of sentiment analysis across various stocks. Among the six companies studied, four demonstrated improved prediction accuracy with the sentiment-enhanced model, with Citibank and Meta showing particularly notable improvements of 38 percent reduction in MSE scores. However, traditional LSTM models performed better for JP Morgan Chase and Autodesk, suggesting that the effectiveness of sentiment incorporation may be influenced by company-specific characteristics and market dynamics.

The remainder of this thesis is structured as follows. The Related Work section comprehensively reviews existing literature on stock price prediction, sentiment analysis, and their intersection in financial markets. Figure 1 presents a workflow diagram that illustrates the evolution of research in this domain and the positioning of our contribution within the existing body of knowledge. The Methodology and Implementation section details our novel approach to extracting sentiment scores from earnings conference calls (ECC) and integrating them with historical stock prices for predictive modeling. This is followed by our experimental results, a discussion of the findings, and conclusions with implications for future research.

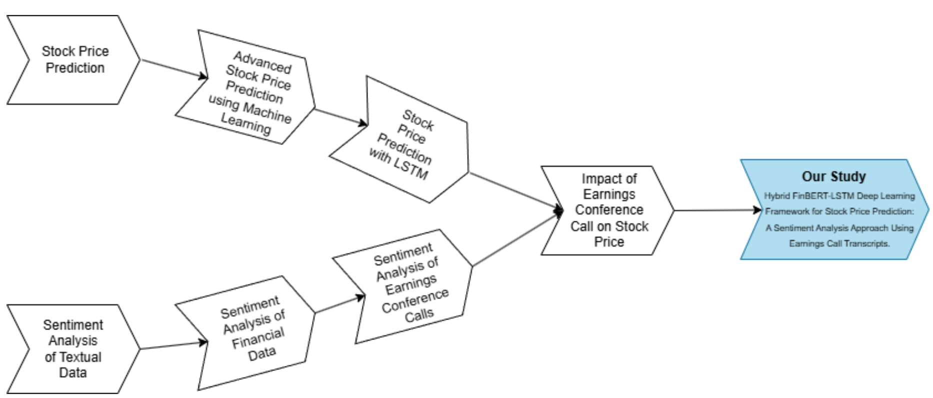

Fig. 1. Study Flow Overview.

Figure 1 explains the study flow overview in our respective domain.

2 Related Work

The intersection of stock price prediction and natural language processing represents a dynamic field of research that has evolved significantly over recent decades. This review of the literature examines three primary streams of research that inform our study: the evolution of stock price prediction methodologies from classical approaches to modern machine learning techniques; the advancement of sentiment analysis with a particular focus on financial applications; and the emerging field of earnings conference call analysis. By examining these interconnected areas, we establish the theoretical and methodological foundation for our hybrid approach combining FinBERT-based sentiment analysis with LSTM-driven price prediction.

2.1 Evolution of Stock Price Prediction Research

The study of stock price prediction has remained a focal point of financial research for decades, driven by its complexity and significant impact on the global financial system. While the Efficient Market Hypothesis (Fama 1965) suggests that stock prices are inherently unpredictable using historical information, subsequent research has demonstrated that superior information processing capabilities can provide a competitive advantage in stock market investments (Pedersen 2015). This tension has motivated continued research into various predictive factors, including social media sentiment, news article analysis, and earnings conference call interpretation.

Early seminal work on stock price prediction (Patell 1976; Poterba et al. 1988; Ou et al. 1989) established fundamental frameworks for understanding market behavior. Notably, (Ou et al. 1989) pioneered the exploration of relationships between financial statement sentiment and stock price movements, though they acknowledged limitations in distinguishing sentiment-based signals from risk factors.

The advent of machine learning technologies marked a significant advancement in stock prediction methodologies. The researchers, including (Saad et al. 1998),(K.-j. Kim 2003),(Pai et al. 2005), and (Vijh et al. 2020), performed comparative analyzes of various models such as ARIMA, ANN, and SVM, consistently identifying opportunities to improve predictive accuracy through additional parameters.

Recent studies have demonstrated the particular effectiveness of RNN-LSTM models in stock price prediction. Research by (Roondiwala et al. 2017), (Selvin et al. 2017),(Pawar et al. 2019), (Sunny et al. 2020), (Moghar et al. 2020), and (Mehtab et al. 2021) consistently showed superior performance of LSTM models across multiple markets globally. These studies also emphasized the potential for further improvement through parameter optimization and LSTM configuration refinement.

2.2 Advances in Sentiment Analysis

The analysis of unstructured data has emerged as a crucial research direction, with sentiment analysis becoming increasingly sophisticated across various domains. Significant contributions include applications in social media analysis (Poecze et al. 2018), tourism (Alaei et al. 2019), and cybersecurity (Rawat et al. 2021).

In the financial domain, sentiment analysis has gained particular prominence. Recent studies by (Jing et al. 2021) and (Li et al. 2022) have explored sentiment impacts in financial markets using various analytical approaches. A significant advancement came with the development of FinBERT by (Huang et al. 2023), a BERT-based model specifically trained on financial texts. Subsequent research by (J. Kim et al. 2023), (Shobayo et al. 2024), and (Gu et al. 2024) has validated FinBERT's superior performance in financial applications.

2.3 Earnings Conference Call Analysis

Specific attention has been directed toward analyzing earnings conference call transcripts, with notable contributions from (Chakraborty et al. 2020), (Chin et al. 2023), and (Hasani et al. 2024). These studies successfully identified underlying tonal patterns in transcripts and suggested correlations with market behavior. Further research by (Jayaraman et al. 2020), (Ma et al. 2020), and (Medya et al. 2022) established concrete relationships between transcript sentiment and stock market movements.

Our research builds upon these foundational works, introducing a novel approach that combines earnings conference call sentiment analysis using FinBERT with LSTM-based stock price prediction. This methodology parallels recent work in adjacent areas, such as (Gu et al. 2024) analysis of news sentiment and (Jing et al. 2021) investigation of social media sentiment, both of which demonstrated promising results using similar hybrid approaches. As illustrated in Figure 2, this research direction emerged from a systematic evaluation of previous studies, which helped narrow down our methodological choices to the most promising approaches.

3 Methodology and Implementation

This section presents our experimental methodology and implementation approach for combining earnings call sentiment analysis with stock price prediction. We detail our comprehensive experimental procedure and evaluation metrics used to validate the efficacy of our proposed technique and model.

3.1 Dataset

Our research utilizes a comprehensive dataset of earnings conference calls from US-listed companies, spanning from May 2019 to February 2023. The dataset

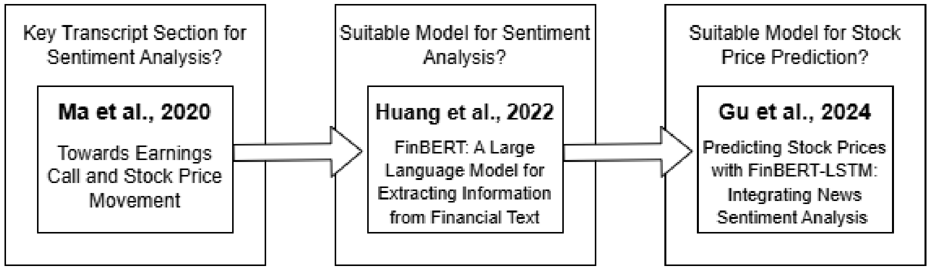

Fig. 2. Evaluation Flow Overview.

Figure 2 illustrates how systematic evaluation of prior studies guided our choice of promising methodologies.

Table 1. Summary Statistics of Dataset

Statistic	date	exchange	q	ticker	transcript
Count	18755	18755	18755	18755	18755
Unique	6059	2879	25	2876	17592

comprises 17,592 earnings call transcripts from 2,876 companies, originally sourced from Motley Fool's website and made accessible through Kaggle. Each record in the dataset contains essential parameters including the conference call date and time, quarterly period, stock exchange identifier, ticker symbol, and the complete call transcript.

To complement the transcript data, we collected corresponding stock closing prices through Yahoo Finance's public API. The temporal alignment between market dates and conference calls was established using the USFederalHolidayCalendar library, ensuring accurate correspondence between transcript sentiment and market reactions.

Table 2. Sample Dataset Entries

index	date	exchange	q	ticker	transcript
0	Aug 27, 2020, 9:00 p.m. ET	NASDAQ: BILI	2020-Q2	BILI	Prepared Remarks: Operator Good day, and wel...
1	Jul 30, 2020, 4:30 p.m. ET	NYSE: GFF	2020-Q3	GFF	Prepared Remarks: Operator Thank you for sta...

3.2 Data Processing and Preparation

Our data preparation methodology emphasizes precise temporal alignment between earnings calls and market responses. We standardized conference call timestamps by removing redundant elements and converting them to a uniform format. For calls occurring after market hours (post 4 PM EST), we associated them with same-day closing prices, while earlier calls were paired with the previous trading day's closing price.
The transcript processing followed a rigorous approach inspired by (Ma et al. 2020), preserving both the prepared remarks and question-answer sessions. We cleaned the raw transcripts by removing non-conversational elements while maintaining the complete dialogue between call opening and closing. This process included filtering non-sequential transcripts for our studied stocks to ensure data continuity. The processed data was then consolidated into stock-specific datasets containing chronologically aligned transcript and price information.

Table 3. Transcript and Stock Data

Index	Transcript	Date	Closing Price
1	Good afternoon. My name is France, and I will ...	2021-04-28	307.100006
2	Good afternoon. My name is France, and I will ...	2021-10-25	328.690002
3	Good afternoon. My name is France, and I will ...	2022-02-02	323.000000

3.3 FinBERT Sentiment Scoring

Our sentiment analysis implementation leverages the FinBERT language model developed by (Huang et al. 2023), specifically utilizing the "yiyanghkust/finbert-tone" pre-trained model. This advanced transformer-based architecture, which builds upon Google's BERT model, has been specifically trained on financial datasets to capture the nuanced context of financial communications. The model processes financial text through its encoder architecture, which has been optimized to comprehend complex financial terminology and context.
The sentiment extraction process begins with tokenization of the transcript text according to the model's pre-trained parameters, operating within its 512-token limit. The model processes these tokenized inputs to generate logits for different sentiment classes, which are then transformed into probabilities through a softmax transformation. The final sentiment score is computed by subtracting the negative sentiment probability from the positive probability, providing a nuanced measure of transcript sentiment for our prediction model.

3.4 LSTM Model Architecture for Stock Price Prediction

The stock price forecasting component of our methodology employs a Long Short-Term Memory (LSTM) neural network, initially developed by (Hochreiter 1997). We implemented an architecture comprising a single LSTM layer with 50 neurons followed by a dense output layer. The model utilizes the ADAM optimizer with a fixed learning rate of 0.0001, processing sequences of length 5 with a batch size of 16. Training is conducted over 100 epochs using mean square error as the loss function.
To ensure robust evaluation, we employed a 70:30 training-testing split and normalized the input data using MinMaxScaler. Random seeds were fixed throughout the implementation to ensure reproducibility of results. This architecture was chosen based on its demonstrated effectiveness in handling time-series data while mitigating the vanishing gradient problem common in traditional recurrent neural networks.

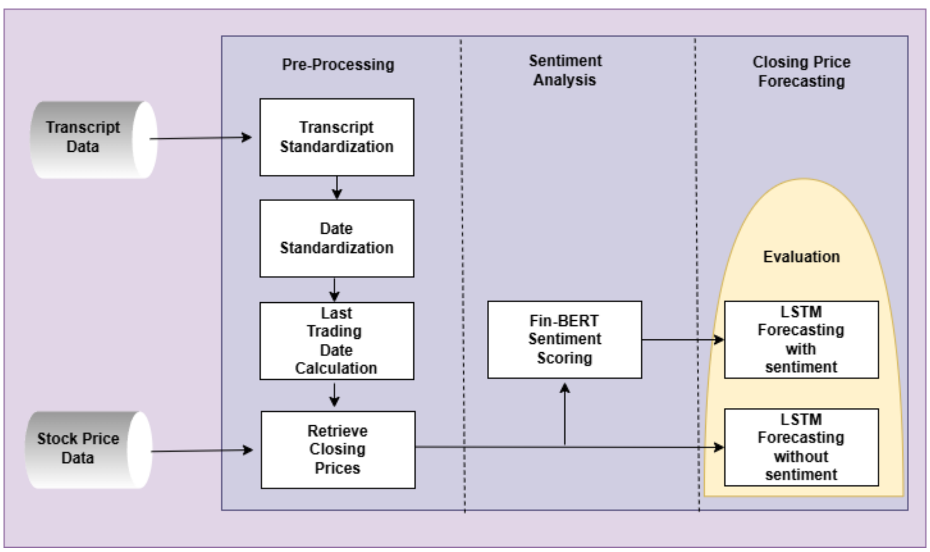

Fig. 3. Methodological Approach.
Figure 3 explains the workflow and sequence of actions performed.

3.5 Experimental Design

Our experimental validation focuses on six randomly selected high-market-capitalization stocks: Microsoft, Visa, Citibank, Meta, Autodesk, and JP Morgan Chase. For each stock, we conducted comparative analyses of prediction accuracy between models trained on historical price data alone and those incorporating both price data and earnings call sentiment scores. Model performance is evaluated using Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Accuracy, providing comprehensive insight into prediction accuracy and model robustness.

4 Evaluation and Results

This chapter presents a comprehensive analysis of our Fin-BERT-LSTM hybrid model's predictive performance compared to traditional LSTM approaches. We conducted experiments on six US-listed stocks: Microsoft, Visa, Citibank, Meta, Autodesk, and JP Morgan Chase. All experiments were performed using Python on a system equipped with an AMD Ryzen 5 5500U processor and 16GB RAM, with fixed random seeds to ensure reproducibility.

4.1 Performance Metrics

The effectiveness of our proposed model was evaluated using three complementary performance metrics: Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Accuracy. These metrics provide comprehensive insight into the model's predictive capabilities across different dimensions of performance.

MSE: Mean Squared Error(MSE) measures the average squared difference between predicted and actual values, defined as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MAPE: The mean absolute percentage error (MAPE) quantifies the average proportional discrepancy between forecasted and actual values, offering a scale-independent measure of prediction accuracy.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

where y_i represents the actual value and $\hat{y}_i$ represents the predicted value. Lower MSE and MAPE values indicate superior model performance.

The Accuracy is then derived as:

$$\text{Accuracy} = 1 - \text{MAPE}$$

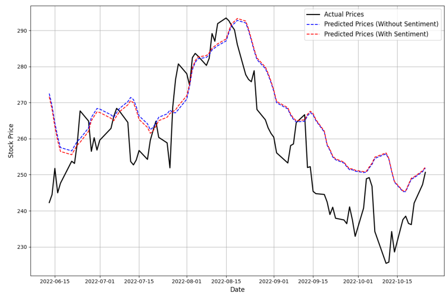

Fig. 4. Comparison of Microsoft Stock Price Prediction.

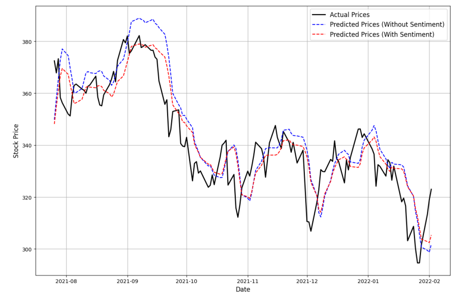

Fig. 5. Comparison of Meta Stock Price Prediction.

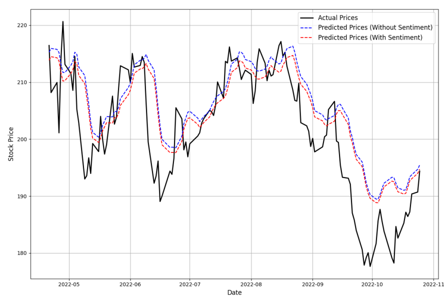

Fig. 6. Comparison of Visa Stock Price Prediction.

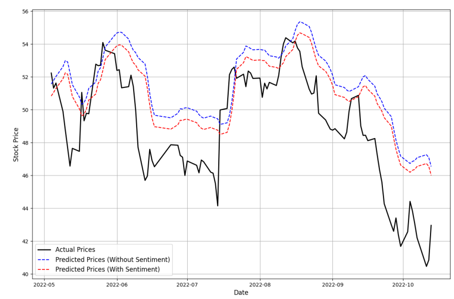

Fig. 7. Comparison of Citi Bank Stock Price Prediction.

4.2 Experimental Results and Analysis

Our comparative analysis revealed significant variations in model performance across different stocks. Most notably, Citibank and Meta demonstrated substantial improvements when incorporating sentiment analysis, with MSE scores approximately 38 percent lower compared to predictions without sentiment data. Similarly, Visa and Microsoft exhibited enhanced accuracy when sentiment scores were included in the prediction model. However, the results also revealed interesting exceptions to this pattern. Both JP Morgan Chase and Autodesk achieved superior accuracy metrics when using the traditional LSTM model without sentiment analysis. This divergence in performance suggests that the effectiveness of sentiment-enhanced prediction may vary based on company-specific factors or market dynamics. Visual analysis of the prediction curves corroborates these numerical findings, showing closer alignment between predicted and actual values for sentiment-enhanced predictions in most cases. The varying effectiveness of sentiment incorporation across different stocks highlights the importance of considering company-specific characteristics when applying sentiment-based prediction models.

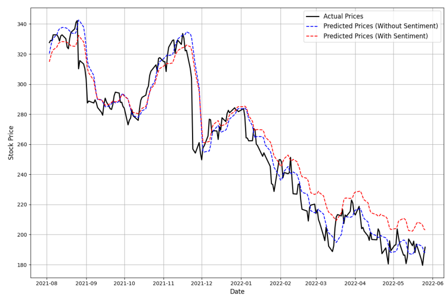

Fig. 8. Comparison of Autodesk Stock Price Prediction.

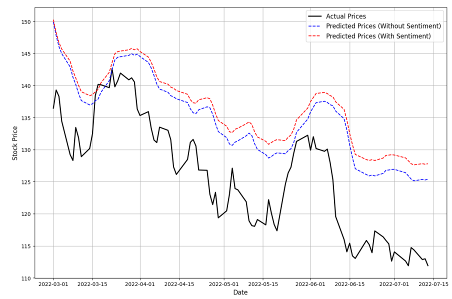

Fig. 9. Comparison of JP Morgan Chase Stock Price Prediction.

Table 4. Prediction Results for Stocks With and Without Sentiment Score

Predicted Stock	**Without Sentiment Score**			**With Sentiment Score**		
	MSE	MAPE	Accuracy	MSE	MAPE	Accuracy
Microsoft	146.21	0.039	96.10%	144.69	0.039	96.13%
Visa	52.78	0.029	97.09%	44.45	0.027	97.35%
Citi Bank	10.61	0.059	94.07%	7.70	0.050	95.04%
Meta	138.53	0.029	97.13%	100.02	0.024	97.58%
Autodesk	144.37	0.034	96.63%	211.38	0.049	95.06%
JP Morgan Chase	96.63	0.072	92.76%	128.85	0.085	91.51%

5 Conclusion

This research introduces a novel hybrid approach combining FinBERT sentiment analysis of earnings conference calls with LSTM-based stock price prediction. While previous studies have explored stock price prediction using historical closing prices and sentiment analysis of news and social media content, our work specifically examines the predictive value of earnings call sentiment in the context of stock price movements. Our experimental analysis, conducted on six US stocks from the Financial and Technology sectors, reveals compelling but nuanced results. Four companies—Citibank, Meta, Visa, and Microsoft—demonstrated improved prediction accuracy when incorporating earnings call sentiment scores. This finding suggests that the linguistic content and tone of earnings calls contain valuable predictive information for certain stocks. However, the divergent results observed with JP Morgan Chase and Autodesk, where the traditional LSTM model outperformed our hybrid approach, indicate that the relationship between earnings call sentiment and stock price movements may be influenced by additional factors not captured in our current model.

The findings of this study open several promising avenues for future research. A systematic investigation into the characteristics of companies where sentiment-enhanced prediction proves most effective could provide valuable insights for both retail and institutional investors. Understanding these patterns could help develop more targeted application strategies for sentiment-based prediction models. The varying performance across different stocks suggests the need to identify and incorporate additional parameters that could improve the model's robustness and generalizability. Future work should explore expanding the model's scope to a broader range of stocks while considering factors such as market capitalization, trading volume, sector-specific economic indicators, broader market sentiment metrics, and company-specific financial fundamentals. These factors could be particularly relevant in cases where the current model shows limited predictive power. The integration of these research directions could significantly advance our understanding of how textual sentiment from corporate communications influences stock price movements. Such advancement would contribute to the development of more sophisticated investment decision-making tools, potentially benefiting both academic research and practical applications in financial markets. As the field of natural language processing continues to evolve, particularly in the context of financial text analysis, future improvements in sentiment extraction techniques may further enhance the model's predictive capabilities.

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