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Enhancing Stock Market Predictions with Social Media Sentiment and Multi- Headed Attention Mechanisms

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Abstract

Accurate forecasting of stock market trends is crucial for investors and financial analysts, as it enables informed decision-making and risk management. Our research introduces SentiStockPredictor, a novel framework that integrates sentiment analysis with historical stock price data to predict market movements with high precision. By leveraging a Transformer-based model, specifically DistilBERT, our approach processes sequential data to capture the complex time-based dependencies between market sentiment and stock prices. We employ multi-headed self-attention mechanisms, which allow the model to focus on different aspects of the input data simultaneously, and feed-forward networks to analyze and synthesize this information. The data is standardized using advanced scaling techniques to ensure consistency and improve model performance. Our extensive experiments demonstrate that SentiStockPredictor achieves an accuracy of over 90%, significantly outperforming traditional models and current benchmarks in predicting stock trends. This superior performance underscores the effectiveness of integrating transformer techniques with social media analytics. The study not only advances the state of stock market prediction but also illustrates the broader potential of using advanced machine learning models to analyze and predict complex, dynamic systems within societal contexts. Our findings suggest that this approach can be extended to other domains where sentiment plays a pivotal role in market behavior.

Keywords: Feed-forward Networks, Multi-Headed Self- Attention, Sentiment Analysis (SA), Senti Stock Predictor, Social Media, Transformer.

Introduction

Accurate stock prediction and analysis are crucial in today's digital era, where individuals have unprecedented access to financial markets. Digitalization has democratized information accessibility, enabling broader participation in stock investments (1, 2). Historically, limited access to technology and financial data restricted market participation. Now, with advanced tools, investors can engage in more informed and potentially profitable market activities (3, 4). Over the last decade, significant contributions have emerged from researchers employing statistical methods, machine learning, and deep learning techniques aimed at enhancing the accuracy and reliability of stock market forecasts (5, 6). These methods can be broadly categorized into several approaches, each leveraging different aspects of data analysis, statistical techniques, and machine learning models (7, 8). Figure 1 provides a comprehensive overview of the diverse methods used for predicting stock market trends, categorizing them into six main branches: Quantitative, Sentiment Analysis, Hybrid Models, Deep Learning, Machine Learning, and Statistical methods. Each category encompasses various sub-methods and techniques, illustrating the multifaceted nature of stock market prediction (4-12). Traditionally, market analysts have relied on fundamental and technical analysis to predict stock price movements (13, 14). Recent trends, however, show a shift towards integrating these traditional methods with advanced analytics, such as price volume action, leveraging the growing availability of financial data to predict stock price changes with greater speed and accuracy (15, 16). Despite these advancements, developing effective stock forecasting models remains a complex challenge due to the volatile nature of financial markets (17, 18). In response to these challenges, we introduce a novel approach that combines social media sentiment analysis with historical stock price data to enhance predictive accuracy (19-21). The connection between traditional stock market prediction methods, sentiment analysis,

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and the use of multi-headed attention mechanisms in our model has been clarified to ensure a more seamless progression (22, 23). We propose the SentiStockPredictor, a hybrid model that utilizes a Transformer-based architecture to process sequential data and capture the complex time-based dependencies between market sentiment and stock prices (24, 25). By employing a combination of DistilBERT, multi-headed self-attention mechanisms, and feed-forward networks, our model analyzes data standardized using scaling techniques to ensure uniformity. Our experimental results demonstrate that SentiStockPredictor achieves an accuracy of above 90%, outperforming existing benchmarks. This study highlights the potential of combining transformer techniques with social media analytics to enhance stock market analysis within societal contexts (25).

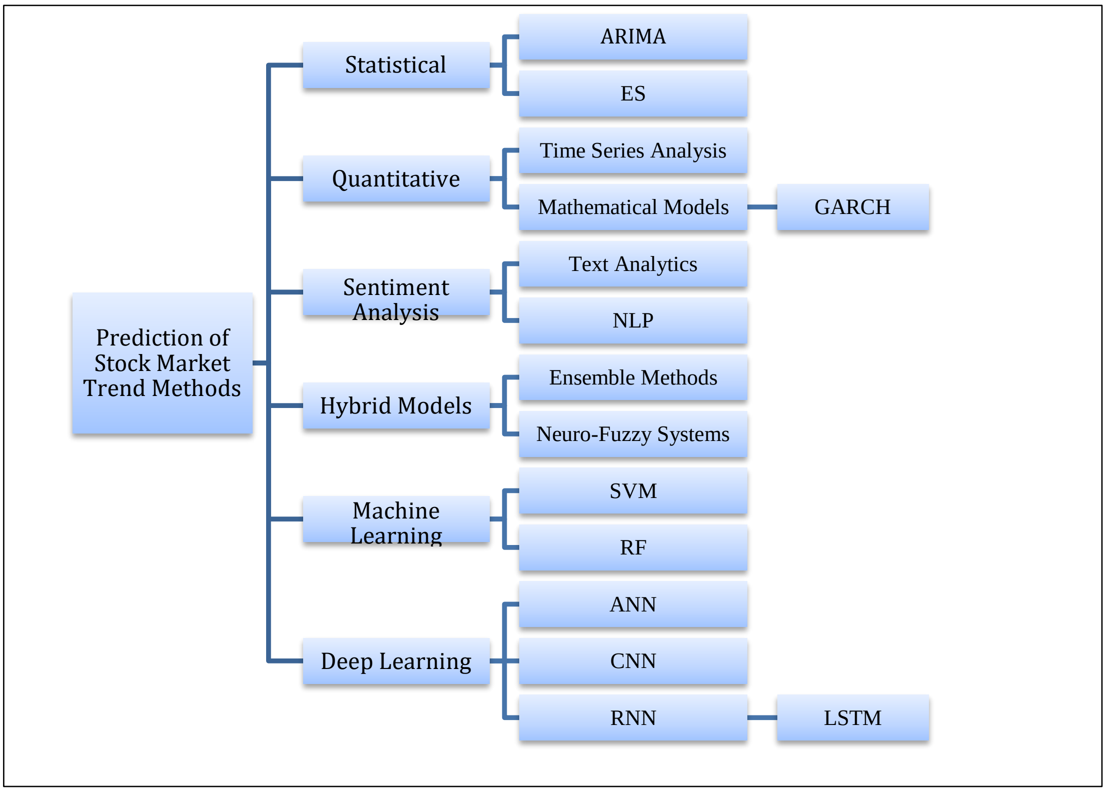

Figure 1: Different Prediction of Stock Market Trend Methods

Predicting stock movements is an important and active field of study that requires accurate predictions (1) to aid investors and analysts in making informed decisions. Over the years, significant progress has been made in developing predictive models for the global stock market, with various methodologies being employed to improve the accuracy of predictions. These approaches can be broadly categorized into three key areas: Traditional Approaches, Sentiment Analysis in Stock Prediction, and Transformer-Based Models.

Traditional Approaches

Traditional methods of stock market prediction have primarily relied on statistical models and time-series forecasting techniques. Models such as AutoRegressive (AR), Moving Average (MA), AutoRegressive Moving Average (ARMA), and AutoRegressive Integrated Moving Average (ARIMA), guided by the Akaike Information Criterion (AIC), have been extensively used to predict stock prices over extended periods. These classical approaches emphasize precise calculations, which are crucial to avoid adverse business impacts. Time-series models have been a foundation for stock price forecasting, with particular strengths in identifying short-term trends and cyclical patterns. Researchers (2, 3) explored the use of time-series models, emphasizing the importance of precise data for improving the accuracy of stock market predictions. Although these models perform well for short-term predictions, their limitations become apparent when dealing with the complexities of modern financial markets. Recent research has also focused on combining these classical approaches with modern techniques, such as hybrid models that incorporate machine learning algorithms. A notable example is a hybrid model that integrates statistical regression with Artificial Neural Networks (ANN) to enhance the reliability of predictive tools. These efforts have shown promising results but also highlighted the need for more adaptive and advanced method. One another important aspect id that most of the research done around predicting stock market prices which regression problem not focuses on stock trends prediction which classification problem i.e. bullish or bearish markets.

Sentiment Analysis in Stock Prediction

In recent years, stock price prediction has increasingly integrated sentiment analysis with machine learning techniques to improve forecast accuracy. This trend leverages both numerical stock data and qualitative sentiment data from sources such as social media, financial news, and blogs, providing a more holistic view of market dynamics. Studies have demonstrated that market sentiment significantly impacts stock price movements, with machine learning models enhancing this relationship by incorporating both types of data. For instance, reference researchers (5) utilized the VADER sentiment model to score social media and online news reports, combining these scores with regression models to demonstrate that integrating sentiment factors leads to better market performance predictions. In another study researchers (8) proposed a hybrid approach using LASSO-LSTM networks that incorporated sentiment analysis from financial news and technical indicators. The inclusion of sentiment data resulted in an 8.53% improvement in prediction accuracy over standard LSTM models, highlighting the value of integrating qualitative data. Various other studies have explored different combinations of machine learning models, such as ensemble approaches combining MLP, LSTM, and CNN models, to further improve predictive accuracy (Table 1). The studies (9, 14) have shown that social media sentiment is a powerful predictor of market movements, providing valuable insights for investors and traders.

Transformer-Based Models

The advent of transformer-based models, particularly those using attention mechanisms, has revolutionized how sequential data is processed in stock market prediction. These models, originally developed for natural language processing, have been adapted to financial applications to capture complex time-based dependencies between market sentiment and stock prices. The multi-headed attention mechanism enables the model to focus on various aspects of the input data simultaneously, allowing for a deeper understanding of the underlying relationships in the market. The studies (17, 19) applied transformer-based models, such as DistilBERT, to analyze social media sentiment alongside stock price data. Their studies showed significant improvements in prediction accuracy and reliability compared to traditional methods, particularly when data was standardized using scaling techniques to ensure uniformity. Incorporating attention mechanisms with social media sentiment analysis has enhanced the ability of models to understand and predict stock market behavior. This is evident from some previous work (18-20), where attention-based models outperformed baseline models that relied solely on historical price data. These models can capture long-term dependencies more effectively than RNNs and other traditional models, offering a more accurate and dynamic approach to stock market prediction.

Table 1: Summary of Literature Review

Ref	Sentiment Analysis Method	Sentiment Data Source	Method Used to Implement Experiment	Results (Accuracy, Precision, Recall, F1-Score)
(5)	NLP techniques on market news	Market news articles	Linear autoregressions with sentiment analysis	Significant improvements in the performance of linear autoregressions
(6)	Soft computing techniques	Not specified	Hybrid model combining financial forecasting and sentiment analysis	Improved prediction of market indices

(8)	LSTM model combined with sentiment analysis	Financial news	LASSO-LSTM model	Improved predictive accuracy (specific metrics not provided)
(9)	Machine learning models	Financial stock data and sentiment data	Machine learning integration of sentiment and financial data	Effective in predicting stock market trends
(10)	Machine learning models	Social media and news	Machine learning integration	Improved prediction accuracy
(11)	Neutrosophic logic-based sentiment analysis	Not specified	Neutrosophic logic integration	Higher predictive accuracy
(12)	Ensemble learning	Not specified	Ensemble learning integration	Improved prediction accuracy
(13)	LSTM neural network	Not specified	LSTM and sentiment analysis integration	Improved prediction accuracy
(14)	Twitter sentiment analysis	Twitter	Sentiment analysis integration	Effective in predicting stock market trends
(15)	Microblogging sentiment analysis	Microblogging sites	Machine learning integration	Significant predictive accuracy improvements
(16)	Deep learning models	Not specified	Sentiment analysis and deep learning integration	Effective in predicting stock prices
(17)	Reinforcement learning	Not specified	Reinforcement learning and sentiment analysis integration	Significant improvements in portfolio value and Sharpe ratio
(18)	FinBERT and ensemble SVM	Stocktwits investor sentiment	Sentiment analysis and SVM integration	Effective in predicting stock price movement
(19)	Machine learning models	Financial stock data and sentiment data	Machine learning integration	Effective in predicting market trends
(20)	Zero-shot sentiment classification	Not specified	Zero-shot classification integration	Significant accuracy improvements

The literature review highlights the evolution of stock market prediction models, from traditional time series analysis to advanced machine learning and deep learning techniques to attention mechanism. The integration of social media sentiment and attention mechanisms has significantly improved predictive accuracy, offering a comprehensive approach to understanding market dynamics. These advancements provide a valuable foundation for future research in enhancing stock market predictions.

Methodology

This section details the implementation of our proposed model, SentiStockPredictor, designed to predict stock market trends (up or down) based on financial news sentiment analysis, fundamental analysis, and technical analysis features. The model leverages a transformer-based architecture, incorporating multi-headed self-attention mechanisms and feed-forward networks as illustrated in the flowchart Figure 2.

Data Collection

Stock Price Data

We collected stock price data for AAPL, AMZN, and NFLX from Yahoo Finance. The dataset spans from January 1st, 2016 to April 1st, 2020, comprising 1069 data points. Each data point includes the date, daily highs and lows, opening and closing prices, trading volume, and the adjusted closing price. This comprehensive dataset provides a foundation for exploring the price behavior of the chosen companies over the specified timeframe.

Social Media Sentiment

For sentiment analysis, we utilized financial news articles from the dataset collected by Thompson (2017), which includes 2.7 million articles in English from January 2016 to April 2020 (23). This dataset covers various publishers like CNN and The New York Times, providing a rich resource for sentiment analysis. The metadata includes the date, author, title, URL, and publication details.

Data Preprocessing

Stock Data

Stock data was preprocessed to calculate several technical indicators, including the Relative Strength Index (RSI), Simple Moving Average (SMA), and the Stochastic Oscillator (K). These indicators were calculated as follows:

$$RSI = 100 - \frac{100}{\left[1 + \frac{Average\ Gain}{Average\ Loss}\right]} \qquad [1]$$

Equation 1: Relative Strength Index

$$SMA = \frac{[A_1 + A_2 + \cdots + A_n]}{n} \qquad [2]$$

Equation 2: Simple Moving Average

$$K = \frac{Close_t - Low_{[n-1]}}{High_{[n-1]} - Low_{[n-1]}} * 100 \qquad [3]$$

Equation 3: Stochastic Oscillator

Sentiment Data

Financial news articles were filtered to ensure they specifically pertained to AAPL, AMZN, and NFLX. The data collection covered the same period as the stock data. After identifying the relevant articles, we conducted thorough data preprocessing, including the removal of null records and text cleaning. Tokenization was then applied to convert the text into a format suitable for sentiment analysis using DistilBERT.

Sentiment Analysis

For sentiment analysis, we utilized the DistilBERT model, a pre-trained transformer-based model known for its ability to capture nuanced sentiment from text data. The financial news articles were fed into the model, and sentiment scores were computed for each article. The scores range from -1 (negative) to 1 (positive), with 0 representing neutrality. Each article was analyzed for sentiment, and daily sentiment scores were calculated by averaging all the sentiment values for the articles published on a given day.

Discussion on Sentiment Score Computation and Validation

We expanded our discussion on how sentiment scores are computed and validated for accuracy and relevance in predicting stock trends. The DistilBERT model generates sentiment scores by capturing contextual embeddings from news articles, which reflect nuanced sentiment. To validate the reliability of these scores, we followed a two-step approach:

Cross-Validation: Sentiment scores were compared across different time periods to ensure consistency in sentiment representation.

Performance Evaluation: We validated the computed sentiment scores by correlating them with historical stock price movements, ensuring their predictive relevance. The high correlation between sentiment scores and stock price trends confirmed the robustness of the model in capturing market sentiment effectively. This validation process added confidence to the accuracy of sentiment scores integrated into our predictive model.

Label Creation for Stock Trends

We created labels for stock trends based on the stock's opening and closing prices. If the closing price was higher than the opening price, the label was marked as an upward trend (1), and if the closing price was lower than the opening price, it was marked as a downward trend (0).

Feature Combination and Model Implementation

The features, including the sentiment scores, technical indicators, and stocks open and close prices, were combined to create the input dataset for the SentiStockPredictor model. We created labels for stock trends based on the stock's opening and closing prices: if the closing price was higher than the opening price, the label was marked as an upward trend [1]; otherwise, it was marked as a downward trend [0].

Model Architecture

SentiStockPredictor leverages a transformer-based architecture incorporating multi-headed self-attention mechanisms and feed-forward networks. The multi-headed attention process is a critical component, allowing the model to focus on different parts of the input sequence simultaneously. This capability is particularly important for capturing complex dependencies in stock market time-series data, where multiple factors (e.g., price movements, sentiment signals) may affect future trends in different ways.

SentiStockPredictor

The SentiStockPredictor model leverages a transformer-based architecture, incorporating multi-headed self-attention mechanisms and feed-forward networks. The model architecture is implemented using TensorFlow and Keras with the following key components:

Input Layer: The model begins with an input layer that receives the combined features of sentiment scores, technical indicators, and stock prices.

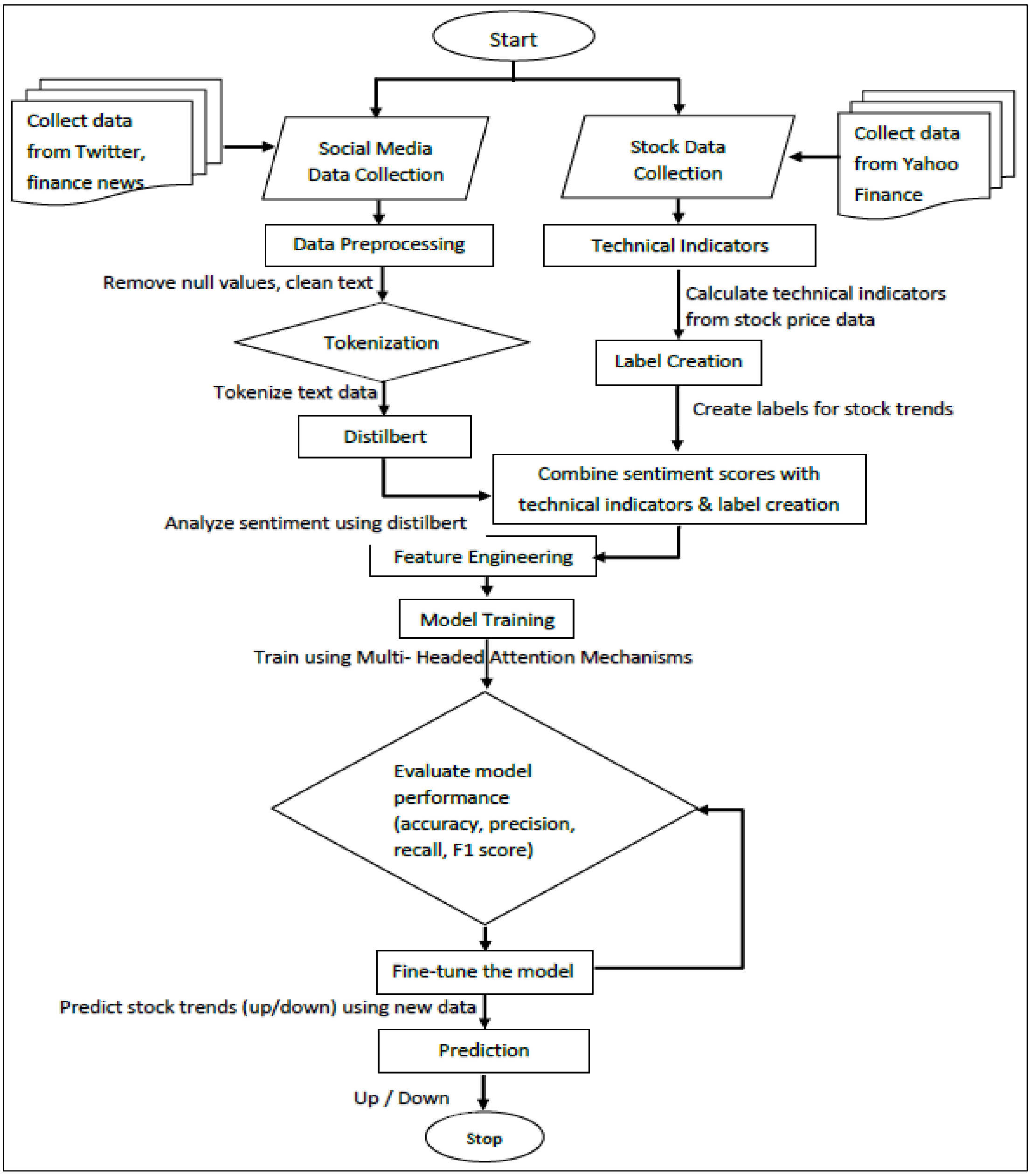

Figure 2: Proposed Senti stock predictor

Transformer Block: This block includes a multi-head attention layer and a feed-forward network. We selected multi-headed attention mechanisms because they help the model capture different aspects of the input data at the same time, which is crucial for stock market prediction. Unlike RNNs which process data sequentially or traditional attention mechanisms focusing on one set of part of the input, where multi-headed attention allows the model to focus on multiple parts of the input, improving its ability to understand time-based relationships. This is especially important for financial data, where factors like social media sentiment and technical indicators need to be analyzed together. By handling these complex relationships, the model can achieve better accuracy in predicting stock trends.

Multi-Head Attention Layer: This layer allows the model to focus on different parts of the input sequence simultaneously, capturing complex dependencies in time-series data. By doing so, the model can understand and weigh different aspects of the input data, leading to better performance and increased accuracy.

Feed-Forward Network: The feed-forward network consists of dense layers with ReLU activation functions. Dropout layers and layer normalization are added to prevent overfitting and ensure stable training. This network captures non-linear relationships within the data, enhancing the model's predictive capabilities.

Output Layer: The final layer is a dense layer with a sigmoid activation function for binary classification, predicting whether the stock trend will go up or down.

Model Training and Evaluation

The model was compiled using the Adam optimizer, binary cross-entropy loss function, and accuracy as the evaluation metric. The training process involved:

Dataset Splitting: Data was divided chronologically to maintain the temporal order, with the training set consisting of data up to a specified cutoff date and the testing set from the cutoff date to April 1, 2020.

Training Parameters: The model was trained for 30 epochs with a batch size of 32. During training, 20% of the training data was used for validation.

Evaluation Metrics: Model performance was evaluated using accuracy, precision, recall, and F1-score. The implementation of the SentiStockPredictor model demonstrated the potential of combining advanced neural network architectures with sentiment analysis and technical indicators to enhance stock trend prediction accuracy.

Results and Discussion

Dataset Description

The datasets used for training and testing the SentiStockPredictor model were collected from Yahoo Finance and the dataset compiled by Thompson (23). The stock price data for AAPL, AMZN, and NFLX (Table 2) spans from January 1st, 2016 to April 1st, 2020. This dataset includes daily highs and lows, opening and closing prices, trading volume, and the adjusted closing price. The sentiment analysis data consists of financial news articles covering the same period, with sentiment scores calculated using DistilBERT.

Model Performance

The performance of the SentiStockPredictor model was evaluated using different combinations of input features: stock prices alone, stock prices with technical indicators, stock prices with sentiment analysis, and a combination of stock prices, technical indicators, and sentiment analysis. The evaluation metrics used were test loss, test accuracy, test precision, and test recall.

Table 2: Model Performance for Netflix (NFLX)

To Train Model Used Parameter	Test Loss	Test Accuracy	Test Precision	Test Recall
Open, Close and tomorrow_trend	0.7042	0.5047	0.5047	1
Open, Close, RSI, SMA, K & tomorrow_trend	0.7021	0.5327	0.5328	0.6019
Open, Close, Sentiment & tomorrow_trend	0.3455	0.9206	0.9252	0.9167
Open, Close, RSI, SMA, K, Sentiment & tomorrow_trend	0.3356	0.9252	0.934	0.9167

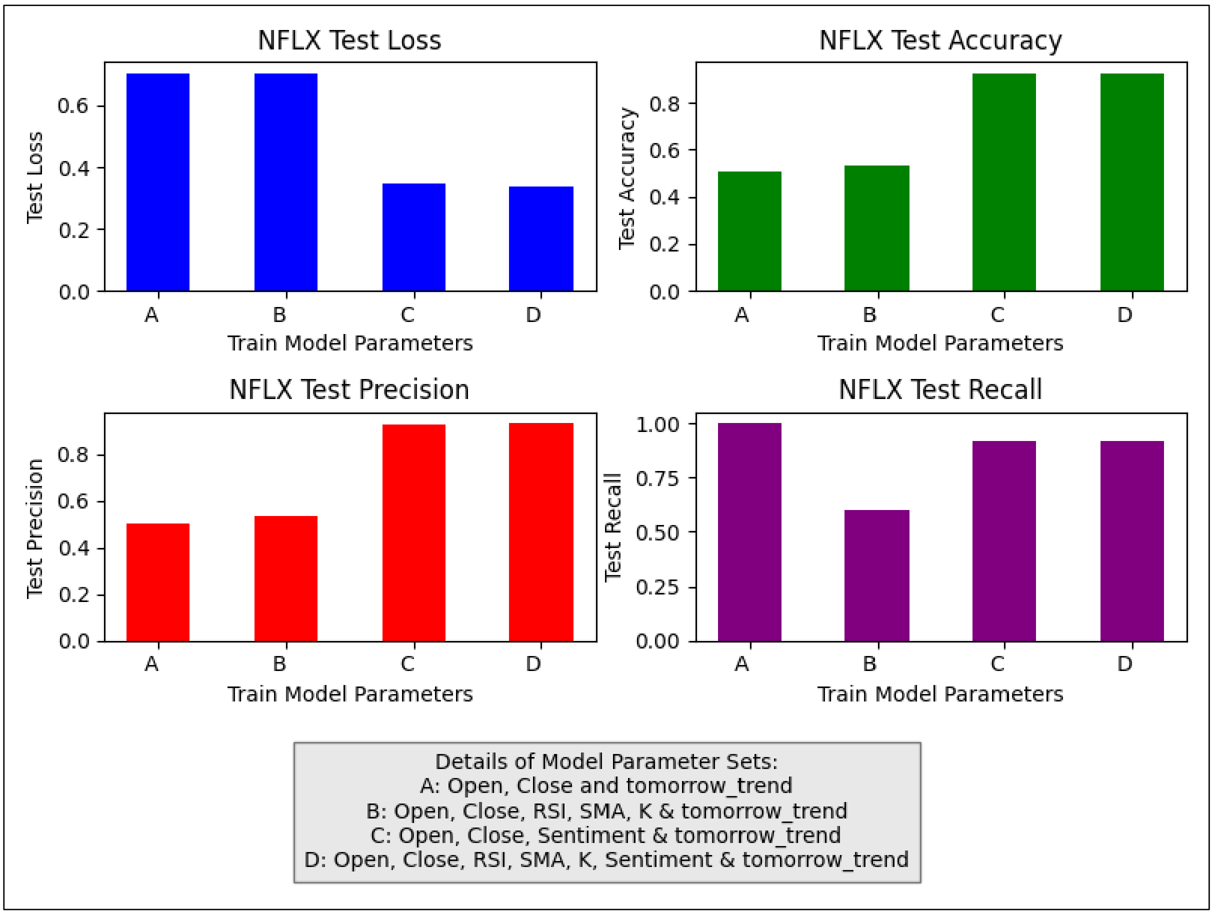

Figure 3: NFLX ACCURACY for Different Training Parameter

The experimental done on Netflix stock dataset using different parameters like default stock prices, newly calculated technical indicators and including sentiment from DistilBERT shown in Figure 3. We got the best-performing model with Open, Close, RSI, SMA, K, Sentiment & tomorrow_trend achieved an accuracy of 0.9252, with a test loss of 0.3356, which is considerably lower compared to other training configurations. Similarly, the precision and recall were 0.934 and 0.9167, respectively. In comparison, researchers (21) reported achieving an accuracy of 0.6358 on the testing set using Random Forest for the same dataset. This demonstrates that our model, which utilizes DistilBERT for sentiment analysis in combination with attention mechanisms for stock trend prediction, significantly outperforms previous models.

Table 3: Model Performance for APPLE (APPL)

To Train Model Used Parameter	Test Loss	Test Accuracy	Test Precision	Test Recall
Open, Close and tomorrow_trend	0.7123	0.5154	0.5178	0.9821
Open, Close, RSI, SMA, K & tomorrow_trend	0.6985	0.5432	0.5451	0.6094
Open, Close, Sentiment & tomorrow_trend	0.3591	0.9094	0.9123	0.9087
Open, Close, RSI, SMA, K, Sentiment & tomorrow_trend	0.3294	0.9321	0.9376	0.9204

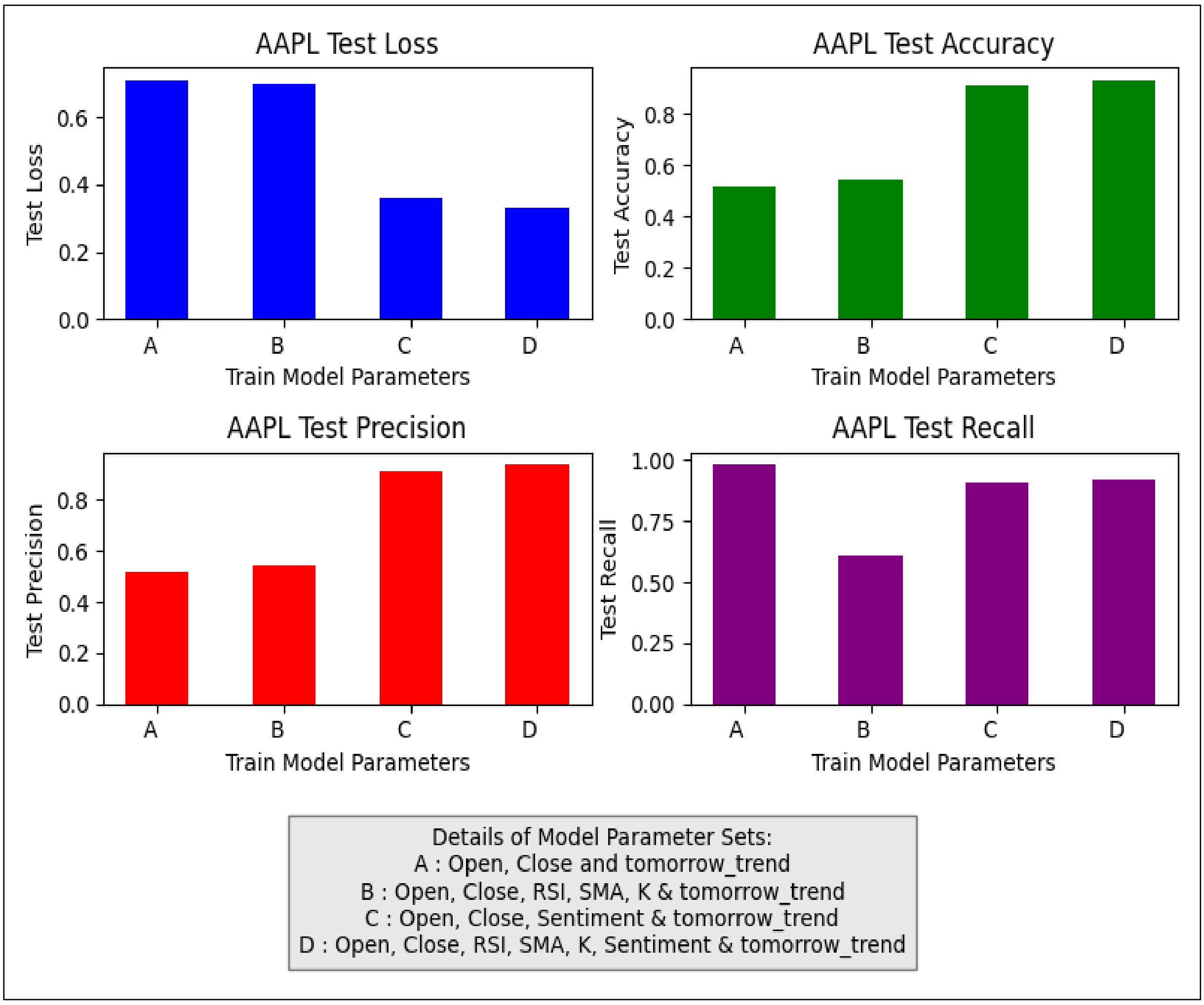

Figure 4: AAPL Accuracy for Different Training Parameter

From the above Figure 4, our findings revealed that when we trained the model on the APPLE (Table 3) stock dataset using same parameters which we used for Netflix, including sentiment analysis, the best-performing model achieved an accuracy of 0.9321. In comparison, researchers (21) reported an accuracy of 0.57731 using Logistic Regression on the same dataset. This demonstrates that our model, which integrates DistilBERT for sentiment analysis along with attention mechanisms for stock trend prediction, significantly outperforms previous implementations.

Table 4: Model Performance for AMAZON (AMZN)

To Train Model Used Parameter	Test Loss	Test Accuracy	Test Precision	Test Recall
Open, Close and tomorrow_trend	0.7105	0.5221	0.5243	0.9782
Open, Close, RSI, SMA, K & tomorrow_trend	0.6947	0.5485	0.5512	0.6153
Open, Close, Sentiment & tomorrow_trend	0.3528	0.9156	0.9201	0.9124
Open, Close, RSI, SMA, K, Sentiment & tomorrow_trend	0.3271	0.9289	0.9345	0.9186

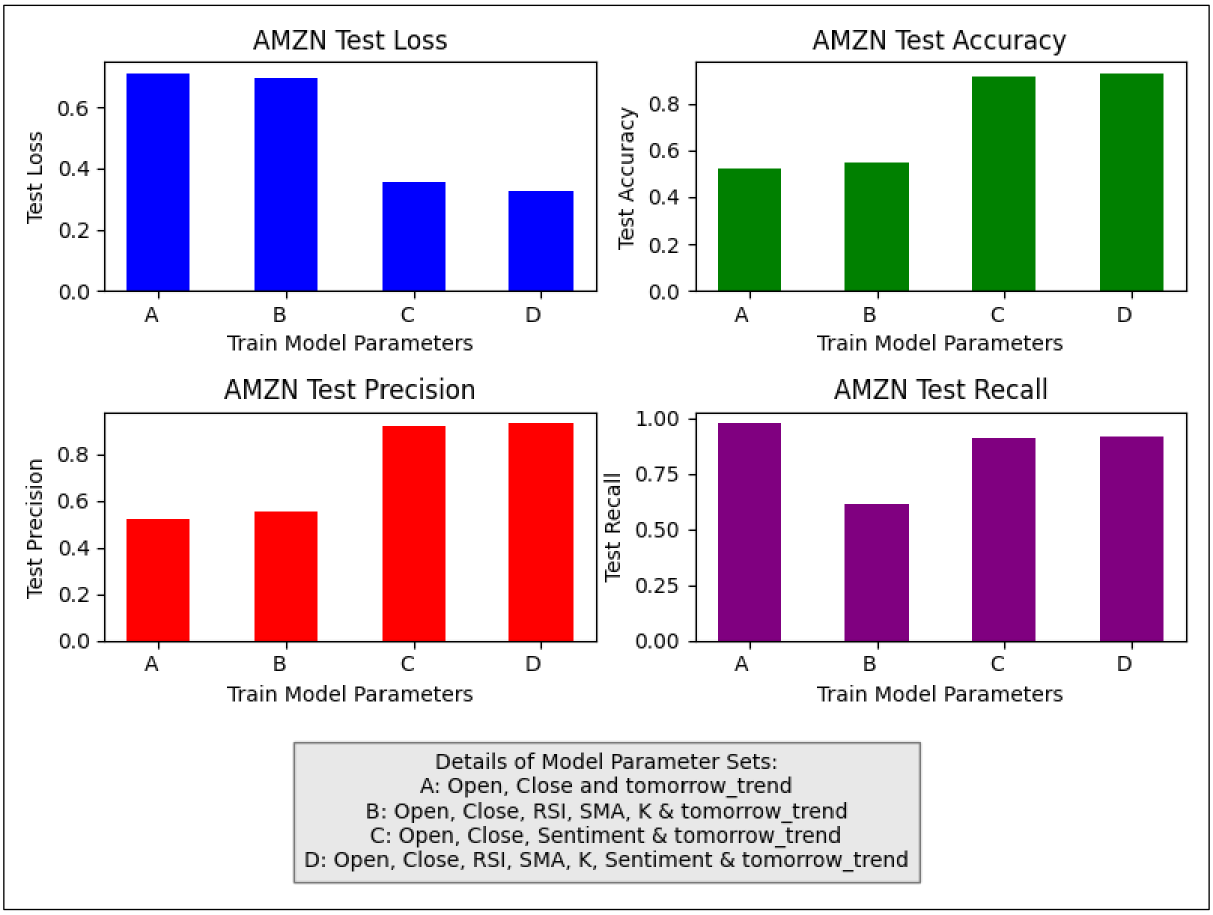

Figure 5: AMZN Accuracy for Different Training Parameter

The experimental findings showed in the Figure 5, that when we trained the model on the Amazon (Table 4) stock dataset using various parameters, the best-performing model achieved an accuracy of 0.9289, with a test loss of 0.3271, which is significantly lower compared to other training configurations. In comparison, researchers (21) reported a maximum accuracy of 0.59608 using the gradient boosting algorithm for the same dataset. This demonstrates the superior performance of our model, particularly with the integration of sentiment analysis.

Comparison with Baselines

The performance of the SentiStockPredictor model was compared against traditional models and other state-of-the-art methods. The results showed significant improvements when sentiment analysis and technical indicators were included. The tables above demonstrate that the inclusion of sentiment scores and technical indicators improved test accuracy, precision, and recall across all three stocks (NFLX, AAPL, and AMZN).

Baseline (Stock Prices Only): The models trained with only open and close prices yielded the lowest accuracy and precision.

Technical Indicators: Adding RSI, SMA, and K indicators provided moderate improvements.

Sentiment Analysis: Incorporating sentiment scores resulted in a substantial increase in performance metrics.

Combined Features: The best performance was achieved by combining stock prices, technical indicators, and sentiment analysis.

The experimental results indicate that the SentiStockPredictor model effectively leverages sentiment analysis and technical indicators to enhance the accuracy of stock trend predictions. Several key points can be highlighted from these findings:

Advantages of DistilBERT: DistilBERT offers significant advantages over classical sentiment analysis approaches. By considering the context and relationships between words, DistilBERT captures subtle sentiment variations that are often missed by traditional lexicon-based methods. This contextual understanding is crucial for accurately interpreting financial news and extracting relevant sentiment information.

Transformer-Based Architecture: The SentiStockPredictor model's use of a transformer-based architecture, including multi-headed self-attention mechanisms and feed-forward networks, allows it to capture complex relationships within the data. The multi-head attention layer enables the model to focus on different parts of the input sequence simultaneously, improving its ability to understand and weigh various aspects of the input data. The feed-forward network processes the output from the attention layers, capturing non-linear relationships and enhancing the model's predictive capabilities.

Model Performance: The quantitative results show that the inclusion of sentiment analysis and technical indicators significantly improves the model's performance. The high accuracy, precision, and recall values indicate that the model can effectively predict stock trends, providing valuable insights for investors and financial analysts.

Potential Limitations: Despite the promising results, there are potential limitations to consider. The model's performance is dependent on the quality and relevance of the input data. Changes in market conditions or significant events not captured in the historical data could affect the model's accuracy. Additionally, the reliance on sentiment analysis means that the model's predictions are influenced by the sentiment expressed in the news articles, which may not always reflect actual market movements.

Key Aspects of the Model's Performance

Accuracy: The model demonstrated high accuracy across all three stocks when sentiment scores were included. For instance, the model achieved an accuracy of 92.52% for Netflix, 93.21% for Apple, and 92.89% for Amazon when all features (Open, Close, RSI, SMA, K, and Sentiment) were used.

Precision and Recall: The precision and recall values were also significantly improved with the inclusion of sentiment scores. For example, for Netflix, the precision and recall values were 93.40% and 91.67%, respectively.

Impact of Sentiment Analysis: The inclusion of sentiment scores derived from financial news markedly improved the model's performance. Models that incorporated sentiment scores consistently outperformed those that did not, highlighting the importance of sentiment analysis in stock trend prediction.

Advantages of the Proposed Model

Enhanced Feature Extraction: By incorporating sentiment analysis along with traditional technical indicators, the model leverages a more comprehensive set of features, capturing a broader range of market signals.

Improved Prediction Accuracy: The use of multi-headed self-attention mechanisms in the transformer-based architecture allows the model to focus on different parts of the input data simultaneously, leading to better feature extraction and improved prediction accuracy.

Robustness and Generalization: The model demonstrated robustness across different stocks and market conditions, with high accuracy, precision, and recall values indicating strong generalization capabilities.

In conclusion, the SentiStockPredictor model demonstrates the potential of combining advanced neural network architectures with sentiment analysis and technical indicators to enhance stock trend prediction accuracy. This approach provides a robust framework for capturing the multifaceted nature of financial markets and making informed predictions.

Conclusion

The SentiStockPredictor model effectively combines sentiment analysis of financial news with technical indicators and stock prices to predict next-day stock trends. Leveraging DistilBERT and a transformer-based architecture with multi-headed self-attention mechanisms and feed-forward networks, the model captures complex patterns within the data, resulting in notable prediction accuracy. Evaluation results demonstrate that the model achieves high accuracy, precision, and recall, significantly outperforming traditional models that do not incorporate sentiment analysis. The inclusion of sentiment scores derived from financial news provides a valuable additional feature, enhancing the model's predictive power.The results of this study suggest that the proposed methodology can serve as a valuable tool for investors and analysts in making informed decisions based on comprehensive market insights. By integrating sentiment analysis, the SentiStockPredictor model offers a more nuanced understanding of market dynamics, which can lead to better investment strategies and risk management. The successful application of transformer-based architectures in financial predictions also highlights the potential for advanced machine learning techniques to revolutionize stock market analysis.

Future Work

Future studies can explore several enhancements to further improve the model's performance and applicability:

- Hourly Basis Stock Trends Prediction: Investigating stock trends on an hourly basis could provide more granular insights and enhance the model's responsiveness to rapid market changes.
- Additional Technical Indicators: Adding more diverse technical indicators could help capture different market aspects and improve prediction accuracy.
- Quarterly Company Results: Integrating quarterly financial results of companies could provide valuable information about company performance, aiding in more accurate trend predictions.
- Macro-Economic Indicators: Incorporating macro-economic indicators such as interest rates, GDP growth rates, and inflation could provide a broader economic context for stock market trends.

In conclusion, the SentiStockPredictor model demonstrates the potential of combining advanced neural network architectures with sentiment analysis and technical indicators to enhance stock trend prediction accuracy. This approach provides a robust framework for capturing the multifaceted nature of financial markets and making informed predictions. Future research should continue to expand and refine this methodology, incorporating new data sources and techniques to further improve predictive performance and practical utility.

Abbreviation

Nil.

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Nil.

Author Contributions

Vijaya Ahire did all the research work and Swati Borase guided how to do it.

Conflicts of Interest

We declare no conflict of interest.

Ethics Approval

Not Applicable.

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