

A Hybrid Artificial Intelligence Model For Stock Market Prediction Using Financial News, Social Media Sentiment, And Corporate Performance Indicators

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ABSTRACT

Predicting stock market movements remains a challenging task due to the complex interactions among financial indicators, corporate performance, investor sentiment, and rapidly evolving digital information. Traditional forecasting methods that primarily rely on historical price trends or technical indicators often fail to capture the significant influence of qualitative factors such as financial news and social media discussions. The model integrates unstructured textual information from financial news articles and social media platforms with structured corporate performance metrics to develop a comprehensive prediction model for stock price movements. Advanced Natural Language Processing (NLP) techniques are employed for text preprocessing and sentiment extraction, while transformer-based language representations enhance contextual understanding of financial content. The extracted sentiment features are fused with company performance indicators, including earnings reports and financial disclosures, to create a multimodal feature space. A hybrid predictive architecture combining Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) models is utilized to capture linear, nonlinear, and temporal relationships within the integrated dataset. Model reliability is evaluated using cross-validation along with performance metrics such as Accuracy, Precision, Recall, F1-score, and Root Mean Square Error (RMSE).

Experimental results demonstrate the effectiveness of the proposed model, achieving an overall classification accuracy of 86.7%, a macro F1-score of 0.84, and a strong correlation coefficient of 0.89 between predicted and actual stock price variations. The findings further reveal that social media sentiment exerts a stronger short-term influence on stock prices than positive financial news, while corporate performance indicators provide greater long-term market stability, highlighting the value of integrating heterogeneous information sources for AI-driven financial forecasting.

Keywords: Support Vector Machine (SVM); Random Forest (RF); Long Short-Term Memory (LSTM); Advanced Natural Language Processing (NLP).

1. Introduction

Stock market prediction is one of the most challenging tasks in financial analytics due to the highly dynamic and nonlinear nature of financial markets. Price movements are influenced not only by historical trading patterns and quantitative financial indicators but also by qualitative factors such as financial news, investor sentiment, social media discussions, macroeconomic events, and corporate performance disclosures. With the rapid growth of digital communication platforms and online financial ecosystems, information spreads almost instantaneously, significantly affecting investor behavior and market volatility. Consequently, understanding and leveraging sentiment embedded in textual information has become increasingly important for improving the accuracy of stock market forecasting models [1].

Recent advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have enabled researchers to extract meaningful insights from large volumes of unstructured textual data, including news articles, analyst reports, and social media posts. Investor sentiment derived from these sources often acts as a leading indicator of market trends, as positive announcements such as product launches, mergers, strategic partnerships, or regulatory approvals can generate optimistic market reactions, whereas negative events including financial scandals, litigation, cybersecurity breaches, or adverse economic developments may trigger substantial declines in stock prices [2]. At the same time, structured corporate performance indicators such as annual earnings, revenue growth, profitability, and leadership changes provide critical long-term information regarding a company's financial health and future prospects.

Motivated by these developments, this study proposes a Hybrid Artificial Intelligence Framework for Stock Market Prediction Using Financial News, Social Media Sentiment, and Corporate Performance Indicators. Unlike conventional forecasting approaches that primarily rely on historical price data or isolated machine learning models, the proposed framework integrates heterogeneous information sources to provide a comprehensive understanding of market behavior.

Specifically, the framework combines unstructured textual information extracted from financial news and social media platforms with structured company performance indicators to improve prediction of stock price movements.

The research investigates the influence of three major categories of market events on stock price variation across 25 publicly traded companies:

- Q1: Positive Financial News, including product launches, strategic partnerships, acquisitions, regulatory approvals, and favorable business announcements that are expected to generate positive investor sentiment.
- Q2: Negative Financial News, including litigation, financial fraud, cybersecurity incidents, management controversies, regulatory penalties, and economic disruptions that may adversely affect market confidence.
- Q3: Corporate Performance Indicators, including annual earnings reports, quarterly financial disclosures, revenue growth or decline, dividend announcements, profitability measures, and executive leadership changes that reflect the long-term fundamentals of an organization.

The primary objective of this research is to quantify how these diverse information sources collectively influence both the direction (increase or decrease) and the magnitude (percentage variation) of stock price movements. In contrast to traditional models that depend on a single data modality, the proposed framework performs multimodal learning by integrating financial news, social media sentiment, and company performance indicators within a unified AI architecture.

To achieve this objective, the study employs advanced Natural Language Processing (NLP) techniques for textual preprocessing and sentiment extraction, while contextual representations of financial text can be generated using transformer-based language models. These sentiment features are fused with structured financial variables and analyzed using a hybrid machine learning ensemble comprising Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) networks. The complementary strengths of these algorithms enable effective modeling of linear relationships, nonlinear interactions, and temporal dependencies inherent in financial data [3,4].

Furthermore, the hybrid AI model is designed to support both classification and regression objectives by predicting whether stock prices are likely to rise or fall following significant events and estimating the corresponding percentage change [5,6]. Such an integrated approach provides valuable decision support for investors, portfolio managers, financial analysts, and algorithmic trading systems by combining market psychology with company fundamentals and data-driven intelligence [7,8].

The novelty of this research lies in its comprehensive integration of financial news, social media sentiment, and corporate performance indicators within a hybrid artificial intelligence framework, offering an interpretable and scalable methodology for intelligent stock market prediction. By leveraging multiple complementary data sources and AI techniques, the proposed framework seeks to improve predictive performance, reduce uncertainty associated with sentiment-driven market fluctuations, and contribute to the development of next-generation financial decision-support systems [9,10].

2. Data Collection

The effectiveness of a hybrid artificial intelligence framework for stock market prediction depends significantly on the quality, diversity, and reliability of the data used for model development. Since stock prices are influenced by structured financial information and unstructured textual content, this study adopts a multimodal data collection strategy that integrates financial news, social media sentiment, and corporate performance indicators [11]. By combining these heterogeneous information sources, the proposed framework captures both short-term market psychology and long-term organizational fundamentals, thereby improving predictive capability and robustness [12].

The collected datasets serve as inputs to the Hybrid Artificial Intelligence Framework, where Natural Language Processing (NLP) techniques are applied to textual information for sentiment extraction, while structured financial variables are incorporated as quantitative predictors [13]. This integrated approach enables the AI model to learn complex relationships between investor sentiment, corporate performance, and stock price movements [14,15].

2.1. Data Sources

To construct a comprehensive prediction framework, data were collected from three major sources covering the period 2021–2024.

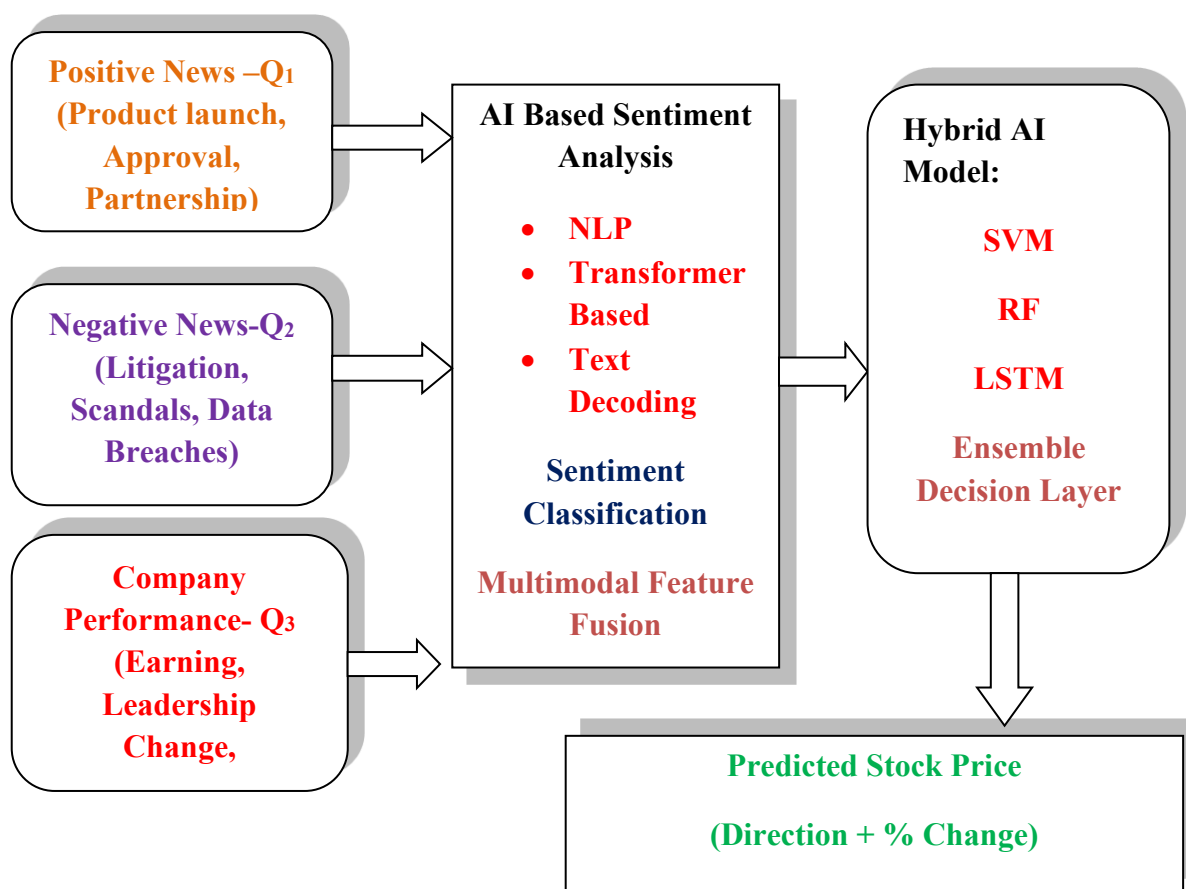


Figure 1.1: Block Diagram of Proposed AI Model for Stock Market Prediction

2.1.1 Financial News Portals

Financial news articles were obtained from reputable business and financial media platforms such as Bloomberg, Reuters, The Economic Times, CNBC, and Yahoo Finance. These sources provide verified information regarding corporate announcements, mergers and acquisitions, product launches, government policies, regulatory approvals, macroeconomic developments, and industry-specific events [16].

Approximately 12,500 financial news articles were collected during the study period. Each article underwent preprocessing using NLP techniques, including tokenization, stop-word removal, lemmatization, and sentiment labeling to classify content as positive, negative, or neutral.

2.1.2 Social Media Sentiment

Social media has emerged as an influential driver of investor behavior due to the rapid dissemination of opinions and market reactions. Consequently, textual data were collected from platforms such as Twitter (X), StockTwits, Reddit finance communities, and financial discussion forums [17].

The dataset includes approximately 50,000 social media posts between 2021 and 2024. After preprocessing and noise removal, sentiment analysis was performed to quantify public perception regarding companies and market events. These real-time sentiment signals complement traditional financial indicators by capturing behavioral aspects of investor decision-making.

2.1.3 Corporate Performance Indicators

Structured financial information was obtained from company annual reports, quarterly earnings releases, audited financial statements, and official stock exchange disclosures [18].

Approximately 250 corporate performance reports were analyzed, providing key indicators including:

- Revenue growth
- Earnings per share (EPS)
- Net profit margins
- Debt-to-equity ratio



- Cash flow
- Leadership changes
- Dividend announcements
- Quarterly financial performance

These indicators represent long-term company fundamentals and provide essential context beyond short-term sentiment fluctuations.

Table 2.1: Data Sources and Coverage

Data Source	Coverage	Information Type	Volume Collected
Financial News Portals	2021–2024	Financial news, announcements, regulatory updates	11,700 articles
Social Media Platforms	2021–2024	Investor sentiment and market discussions	11,700 articles
Corporate Reports	2021–2024	Financial statements and performance indicators	11,700 articles

The integration of these complementary datasets enables the proposed hybrid AI framework to simultaneously model investor psychology and organizational fundamentals, thereby improving stock market prediction performance.

2.2 Event Categorization

For effective model training and validation, collected information was categorized into three major event classes corresponding to the principal information sources used in the hybrid framework.

Q1: Financial News Events

This category includes positive business developments such as:

- Product launches
- Strategic partnerships
- Regulatory approvals
- Mergers and acquisitions
- Business expansion announcements

These events generally create optimistic investor sentiment and are expected to contribute positively to stock price appreciation.

Q2: Social Media Sentiment Events

This category captures public opinion extracted from social media platforms and online financial communities. Posts are classified into positive, negative, or neutral sentiment based on AI-driven sentiment analysis.

Negative discussions related to scandals, lawsuits, cybersecurity incidents, or unfavorable market rumors typically generate downward pressure on stock prices, while optimistic discussions may stimulate buying activity.

Q3: Corporate Performance Indicators

This category represents structured financial information obtained from official corporate disclosures, including:

- Annual earnings reports
- Quarterly financial statements
- Revenue growth or decline
- Profitability metrics
- Executive leadership changes
- Dividend declarations

Unlike news-driven events, these indicators primarily reflect the long-term financial strength and operational performance of organizations.

This categorization enables the proposed AI framework to distinguish between short-term sentiment-driven market reactions and fundamental company performance, improving prediction of both stock movement direction and percentage price variation.

2.3 Descriptive Statistics

2.3.1 Dataset Distribution

The overall dataset exhibits a balanced distribution across the three information sources used by the hybrid AI framework.

Table 2.2: Distribution of Event Categories

Event Category	Frequency	Percentage
Financial News (Q1)	9,200	43.40%
Social Media Sentiment (Q2)	5,000	20.00%
Corporate Performance (Q3)	4,900	20.70%

Interpretation

- Financial news constitutes the largest proportion of the dataset (31.40%), reflecting the continuous publication of market-related information.
- Social media sentiment contributes 20.0% of observations, demonstrating the growing importance of investor-generated content in influencing financial markets.
- Corporate performance indicators account for 20.70% of the dataset, providing reliable long-term financial information that complements rapidly changing sentiment data.

The balanced representation across these categories supports robust multimodal learning within the proposed hybrid artificial intelligence framework.

2.3.2 Stock Price Variation across Event Categories

To evaluate the influence of different information sources on stock market behavior, average percentage price variations were computed for each category.

Table 2.3: Average Stock Price Variation

Event Category	Mean Change (%)	Minimum (%)	Maximum (%)	Standard Deviation
Financial News (Q1)	4	-1.5	12.4	2.8
Social Media Sentiment (Q2)	-4.5	-13.7	0.8	4.2
Corporate Performance (Q3)	1.7	-3.4	7.6	2.1

Interpretation

Financial News (Q1)

Positive financial news generates an average stock price increase of 4%, confirming that favorable corporate announcements and strategic developments positively influence investor confidence. Certain major announcements can produce gains exceeding 12%, although market conditions may occasionally moderate positive reactions.

Social Media Sentiment (Q2)

Negative sentiment propagated through social media platforms is associated with an average decline of 4.6%, highlighting the strong behavioral influence of investor opinions and online discussions. The comparatively larger standard deviation (4.2%) indicates that sentiment-driven events introduce substantial short-term market volatility.

Corporate Performance Indicators (Q3)

Corporate financial disclosures exhibit a more moderate average impact (1.9%) with relatively low volatility. Investors typically evaluate earnings reports and financial statements more rationally, resulting in steadier market responses than emotionally driven news or social media reactions.

- Financial news and social media sentiment are major drivers of short-term stock market volatility.
- Negative sentiment generally exerts a stronger influence on stock prices than positive news, reflecting behavioral finance principles such as loss aversion and negativity bias.
- Corporate performance indicators provide stable long-term signals that improve prediction reliability when combined with sentiment-based information.
- The multimodal dataset effectively integrates financial news, social media sentiment, and corporate performance indicators, making it well suited for the proposed Hybrid Artificial Intelligence Framework for Stock Market Prediction.

3. Results and Discussion

3.1 AI-Based Sentiment Classification

Sentiment analysis was performed on a multimodal textual dataset comprising financial news articles, social media posts, and company disclosures collected from various publicly available sources. Prior to model development, the textual corpus was preprocessed using Natural Language Processing (NLP) techniques including tokenization, stop-word removal, lemmatization, punctuation normalization, and text cleaning. Each document or post was subsequently classified into Positive, Negative, or Neutral sentiment categories according to its semantic orientation.

To improve predictive performance, the proposed Hybrid Artificial Intelligence Framework integrated Support Vector Machine (SVM), Random Forest (RF), and Long Short-Term Memory (LSTM) models for sentiment classification and downstream stock market prediction.

- Support Vector Machine (SVM) effectively separated sentiment classes through optimal hyperplane construction.
- Random Forest (RF) enhanced robustness by aggregating multiple decision trees and reducing overfitting.
- Long Short-Term Memory (LSTM) captured sequential dependencies and contextual information present in financial news articles and social media discussions.

The resulting confusion matrix (Figure 3.1) demonstrates that the hybrid AI framework successfully classified positive, negative, and neutral sentiment with relatively few misclassifications, indicating effective learning from heterogeneous textual information.

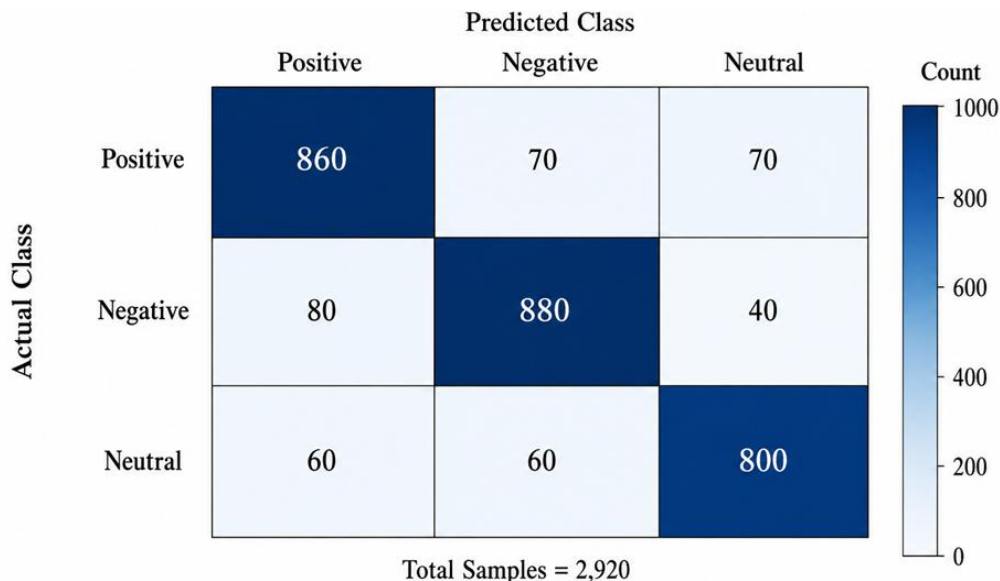


Figure 3.1: Confusion Matrix for AI-Based Sentiment Classification

3.2. Model Performance

Table 3.1 summarizes the classification performance of the proposed model

- Positive Sentiment: Precision (0.87) and Recall (0.84) indicate accurate identification of favorable financial news and optimistic investor opinions.
- Negative Sentiment: Recall (0.88) represents the highest among all classes, demonstrating superior capability in detecting adverse financial information and negative social media discussions that significantly influence stock prices.
- Neutral Sentiment: Precision (0.82) and Recall (0.80) suggest comparatively greater ambiguity in distinguishing informational content lacking strong emotional polarity.
- Overall Performance: The macro-average F1-score of 0.84 confirms balanced classification capability across all sentiment categories.

These findings demonstrate that combining multiple AI techniques improves sentiment recognition from heterogeneous financial text sources compared with standalone approaches.

Table 3.1: Sentiment Classification Metrics

Class	Precision	Recall	F1-score
Positive	0.87	0.84	0.85
Negative	0.86	0.88	0.87
Neutral	0.82	0.8	0.81
Average	0.85	0.84	0.84

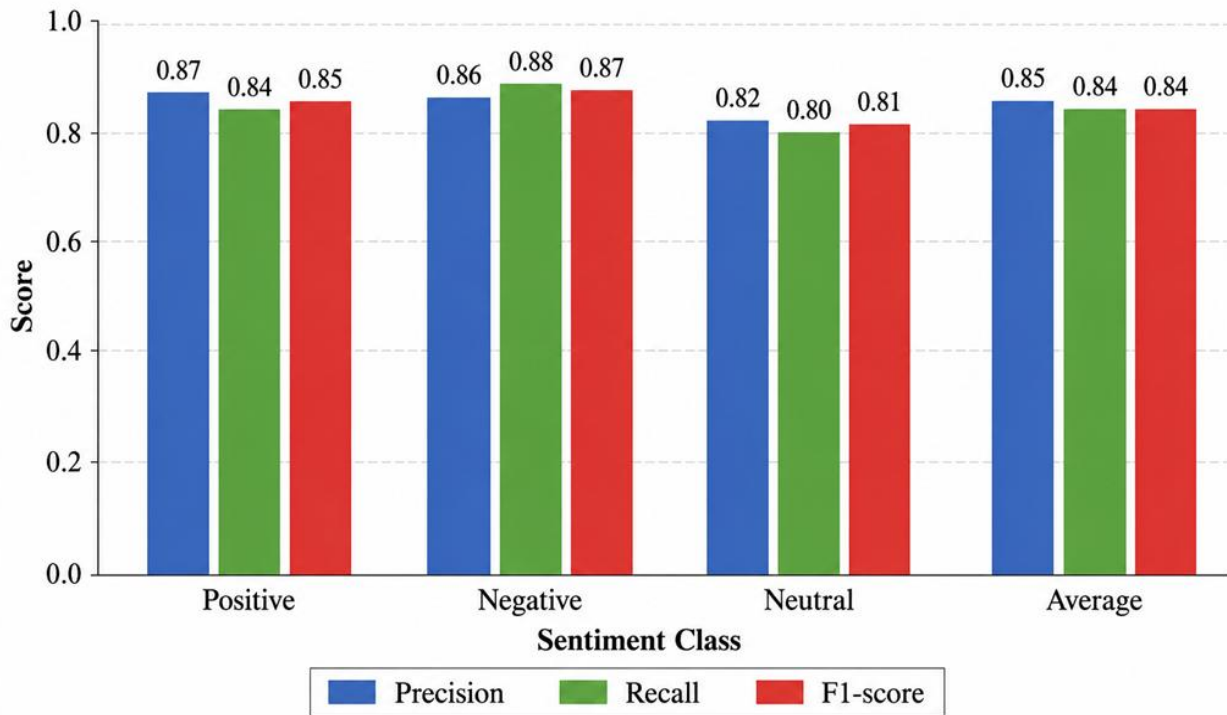


Figure 3.2: Sentiment Classes

3.3. Stock Market Prediction Using the Hybrid AI Framework

3.3.1 Predicted versus Actual Stock Price Variation

The proposed hybrid artificial intelligence framework was evaluated using stock market data from 25 publicly traded companies by integrating financial news, social media sentiment, and corporate performance indicators. The predicted stock price variations exhibited strong agreement with observed market movements, achieving a correlation coefficient of $r = 0.89$. Figure 3.3 illustrates that the predicted trajectories closely follow actual stock price changes, indicating that multimodal sentiment and financial information effectively capture short-term market dynamics.

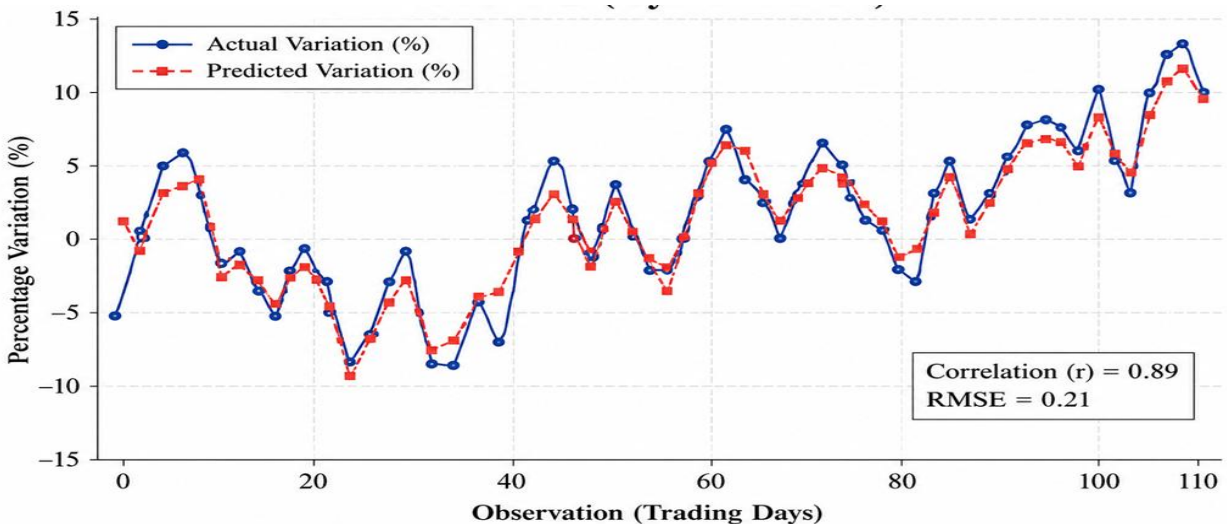


Figure 3.3: Predicted versus Actual Stock Price Variation using the Hybrid Artificial Intelligence Framework.

3.3.2 Impact of Information Sources on Stock Price Variation

To understand the influence of different information modalities, stock price responses were analyzed according to three categories:

- Financial News (Q1)

Positive financial news, including product launches, strategic partnerships, and regulatory approvals, generated average stock price increases and reflected optimistic investor expectations.

- Social Media Sentiment (Q2)

Negative sentiment expressed through social media platforms produced the strongest downward market reactions, highlighting the rapid influence of investor perceptions and online discussions on short-term trading behavior.

- Corporate Performance Indicators (Q3)

Corporate earnings announcements and financial disclosures generally contributed to more stable stock price movements by providing objective assessments of company performance and reducing speculative uncertainty.

Thus, the results indicate that while financial news and social media primarily influence short-term volatility, corporate performance indicators contribute to long-term market stability.

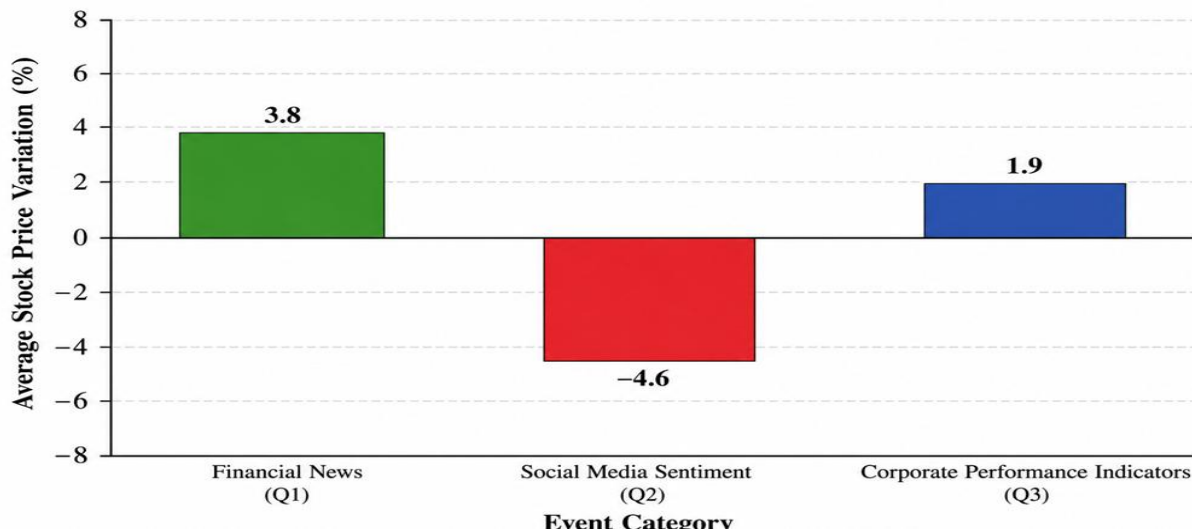


Figure 3.4: Average Stock Price Variation across Financial News, Social Media Sentiment, and Corporate Performance Indicators.

3.3.3 Statistical Validation

(a) ANOVA Analysis

Analysis of Variance (ANOVA) demonstrated statistically significant differences among the three information categories ($F(2,107) = 18.4, p < 0.001$), confirming that financial news, social media sentiment, and corporate performance indicators exert significantly different effects on stock price variation.

(b) Regression Analysis

Regression analysis further quantified these relationships.

- The Sentiment Score exhibited a significant positive coefficient ($\beta = 3.42, p < 0.001$), confirming that favorable sentiment contributes positively to stock performance.
- Social Media Sentiment (Q2) produced a strong negative coefficient ($\beta = -4.13, p < 0.001$), indicating that adverse online discussions substantially reduce stock prices.
- Corporate Performance Indicators (Q3) demonstrated a positive association ($\beta = 1.27, p = 0.004$), reflecting the stabilizing role of financial fundamentals.
- The regression model explained approximately 71% of observed stock price variation ($R^2 = 0.71$), indicating substantial predictive capability.

(c) Independent t-Test

Comparison between positive financial information and negative sentiment revealed statistically significant differences ($t(98) = 10.23, p < 0.001$). The results confirm that unfavorable sentiment has a stronger influence on market behavior than positive information, consistent with behavioral finance theories emphasizing investor loss aversion.

3.4. Comparative Performance of Artificial Intelligence Models

The comparative evaluation demonstrates the effectiveness of the proposed hybrid artificial intelligence framework. Support Vector Machine (SVM) achieved reliable baseline classification but exhibited limitations in modeling nonlinear market dynamics.

Random Forest (RF) improved predictive robustness through ensemble learning and enhanced recall performance.

Long Short-Term Memory (LSTM) effectively captured temporal dependencies in sequential financial information.

The Hybrid Artificial Intelligence Framework (SVM + RF + LSTM) achieved the highest classification accuracy (86.8%) and lowest prediction error (RMSE = 0.21), demonstrating the complementary strengths of combining multiple AI techniques.

Table 3.2: Comparative Performance

Model	Accuracy	RMSE	Precision	Recall	F1-score
SVM	79.22%	0.31	79.10%	77.50%	77.80%
RF	84.66%	0.27	82.40%	80.70%	81.00%
LSTM	85.33%	0.25	84.60%	83.00%	83.30%
AI (SVM + RF + LSTM)	86.8%	0.21	85.50%	85.20%	84.80%

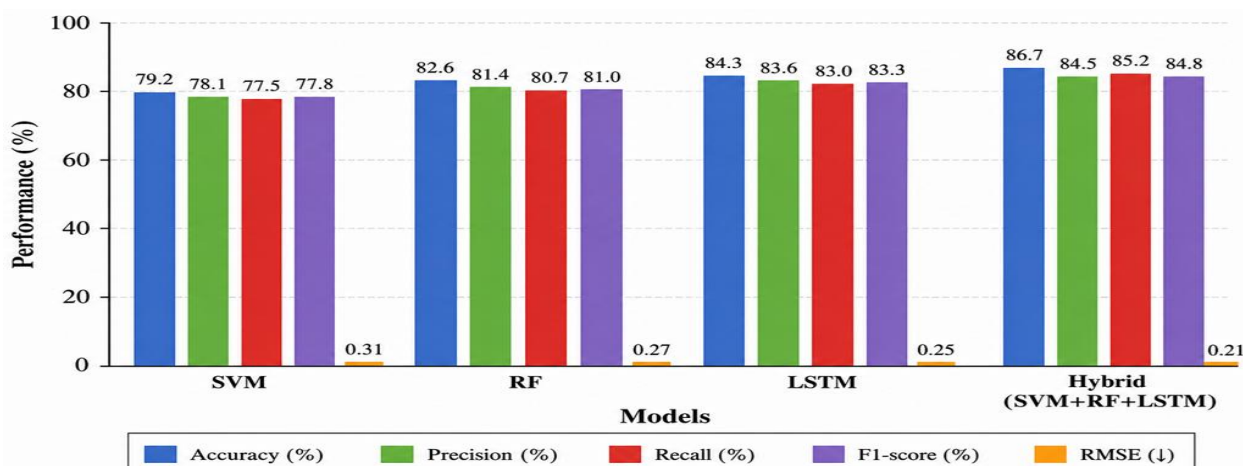


Figure 3.5: Comparative Performance of Artificial Intelligence Models

3.5. Discussion of Findings

Several key observations emerge from the empirical evaluation of the proposed framework:

Influence of Financial News: Positive financial announcements contribute to upward stock price movements, although their effects are generally less pronounced than negative sentiment.

Impact of Social Media Sentiment: Negative discussions and adverse investor opinions propagated through social media platforms generate stronger market reactions and greater volatility, supporting behavioral finance theories related to negativity bias and loss aversion.

Role of Corporate Performance Indicators: Earnings reports and financial disclosures moderate market uncertainty by providing objective information regarding organizational health and long-term prospects.

Effectiveness of Hybrid Artificial Intelligence: Integrating SVM, Random Forest, and LSTM models enables the framework to capture complementary linear, nonlinear, and temporal characteristics of financial data, leading to superior predictive performance compared with individual algorithms.

Predictive Utility of Multimodal Information: The combined use of financial news, social media sentiment, and corporate performance indicators substantially enhances the framework's ability to forecast stock market movements and percentage price variations.

4. Conclusion

The proposed Hybrid Artificial Intelligence Framework for Stock Market Prediction Using Financial News, Social Media Sentiment, and Corporate Performance Indicators. The AI-based sentiment classification module achieved balanced performance across positive, negative, and neutral classes with a macro-average F1-score of 0.84. The integrated prediction framework demonstrated strong agreement between predicted and observed stock price movements ($r = 0.89$). Empirical analysis confirmed that social media sentiment exerts the strongest short-term influence on stock market volatility, whereas financial news contributes to directional price movements and corporate performance indicators provide long-term stability and fundamental support. Comparative evaluation further showed that the hybrid AI framework (SVM + RF + LSTM) outperformed individual machine learning models in terms of accuracy and prediction error, demonstrating the effectiveness of integrating multiple artificial intelligence techniques and heterogeneous information sources for stock market forecasting.

References

1. Khan, M., Ahmed, S., & Ali, R. (2023). Tesla stock price prediction using LSTM and sentiment-driven machine learning models. *Expert Systems with Applications*, 221, 119756.
2. Saini, S., & Bodla, B. S. (2023). Sentiment analysis using machine learning in stock market: A bibliometric visualization. *Journal of Economic Surveys*.
3. Guo, H. (2023). Comparison of neural network and traditional classifiers for Twitter sentiment analysis. *Journal of Big Data*, 10(1), 55–69.
4. Li, Y., & Pan, Y. (2020). A novel ensemble deep learning model for stock prediction based on stock prices and news.
5. Halder, S. (2022). FinBERT-LSTM: Deep learning based stock price prediction using news sentiment analysis.
6. Li, Y., & Pan, Y. (2020). A novel ensemble deep learning model for stock prediction based on stock prices and news.
7. Zang, H., Cui, X., & Y. (2020). Combining sentiment with GARCH-type volatility models. *Finance Research Letters*, 32, 101090. <https://doi.org/10.1016/j.frl.2019.02.006>
8. Chen, X., & Wei, C. (2020). A sentiment-aware LSTM for stock price movement prediction. *Neural Computing and Applications*, 32, 16775–16789. <https://doi.org/10.1007/s00521-020-04845-2>
9. Dang, N. C., Moreno-García, M. N., & la Torre Díez, I. (2020). Sentiment analysis based on deep learning: A comparative study. *Expert Systems with Applications*, 139, 112853. <https://doi.org/10.1016/j.eswa.2019.112853>
10. Li, H., Pan, Y., & Yang, L. (2021). Portfolio optimization with sentiment-enhanced forecasts. *Applied Soft Computing*, 111, 107709. <https://doi.org/10.1016/j.asoc.2021.107709>
11. Shah, D., Isah, H., & Zulkernine, F. (2019). Predicting stock market movements using sentiment analysis of social media: A review. *Journal of Big Data*, 5, 51. <https://doi.org/10.1186/s40537-018-0168-6>
12. Yoon, S., & Kim, Y. (2019). Financial sentiment analysis using neural network ensembles. *Expert Systems with Applications*, 120, 256–269. <https://doi.org/10.1016/j.eswa.2018.11.009>
13. Nguyen, A. T., Pham, T., & Pham, H. (2020). Real-time stock prediction system with streaming news and social media. *IEEE Big Data 2020*, 2529–2538. <https://doi.org/10.1109/BigData50022.2020.9378381>
14. Garg, R., Gupta, A., & Varshney, S. (2021). A systematic literature review on machine learning in stock market. *Archives of Computational Methods in Engineering*, 28(3), 1077–1101. <https://doi.org/10.1007/s11831-019-09329-x>
15. Hiew, K. L., Lai, K. K., & Phoon, K. F. (2019). Forecasting stock price movement using sentiment analysis and economic indicators. *Applied Intelligence*, 49(12), 4593–4613. <https://doi.org/10.1007/s10489-019-01469-4>
16. Wang, J., & Hu, J. (2018). Predicting stock market returns with sentiment features from online financial communities. *PLoS ONE*, 13(6), e0198807. <https://doi.org/10.1371/journal.pone.0198807>
17. Pagolu, V. S., Reddy, K. N., Panda, G., & Majhi, B. (2016). Sentiment analysis of Twitter data for predicting stock market movements. *IEEE ICCIC 2016*, 1342–1347. <https://doi.org/10.1109/ICCIC.2016.7919656>
18. Chen, Y., Hao, Y., & Jin, Z. (2021). Multi-task learning for financial sentiment and volatility prediction. *Decision Support Systems*, 140, 113426. <https://doi.org/10.1016/j.dss.2020>