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Volatility Prediction Research Integrating Macroeconomic Indicators and Social Media Sentiment

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Abstract: *This study presents a multi-source LightGBM model to predict stock market volatility by combining macroeconomic indicators, Google Trends data, and Twitter sentiment. Using daily S&P 500 data from 2015 to 2024, the model was tested to evaluate how different information sources improve prediction results. The findings show that the multi-source model lowered RMSE by 7.8% compared with the version using only technical indicators. Sentiment and search data made a greater contribution during volatile market periods, showing that they can capture early signals of risk. These results indicate that mixing economic variables with real-time online sentiment can improve volatility forecasts and support financial risk management and investment analysis. Future studies should test shorter time intervals and more markets to confirm the model's reliability and broader use.*

Keywords: *volatility forecasting, macroeconomic factors, social media sentiment, Google search data, LightGBM, data integration, financial risk analysis*

INTRODUCTION

Stock market volatility is shaped by interconnected macroeconomic factors and rapidly evolving investor sentiment, particularly in online environments where information spreads at scale [1]. Traditional econometric models such as GARCH and EGARCH can describe time-varying volatility; however, they rely primarily on historical prices and often overlook signals derived from broader economic or social channels, resulting in limited responsiveness to structural shocks [2]. Recent empirical work confirms that macroeconomic indicators—including inflation, employment, and industrial output—provide incremental explanatory power for volatility, especially during periods of financial disequilibrium [3]. Meanwhile, web search data and online sentiment extracted from platforms such as Twitter have become timely proxies for market fear,

attention, and sentiment diffusion [4]. In particular, the evolution of online discussion often precedes major price movements because public narratives can amplify risk perceptions before such information is fully reflected in asset prices [5]. While this insight highlights the importance of behavioral signals, most existing studies employ either macroeconomic variables or social sentiment data in isolation, which limits their ability to disentangle whether volatility arises from fundamental economic pressure or sentiment-driven speculation [6]. Further, many prior models are built and evaluated on narrow temporal windows or restricted asset groups, making their robustness across heterogeneous market states uncertain—an issue that becomes especially acute during policy changes, banking crises, and geopolitical shocks when economic and psychological drivers reinforce one another [7]. Ensemble learning frameworks, such as LightGBM, are well suited for this task because they can simultaneously accommodate heterogeneous structured and unstructured data without strong distributional assumptions [8]. These models provide transparent feature importance metrics, facilitating a systematic understanding of relative contributions from macroeconomic variables, Google Trends, and social sentiment [9]. Prior work demonstrates that LightGBM-based algorithms can outperform classical econometric baselines in stock volatility forecasting, underscoring the utility of feature-aware modeling for financial time series [10]. Nonetheless, most studies remain focused on technical indicators or single-source information, overlooking joint effects from macroeconomic and behavioral dimensions that may drive volatility under dynamic market regimes [11]. Recent research emphasizes that integrating cross-source information streams can reveal complementary structures and improve forecasting accuracy during sudden market transitions [12]. Moreover, hybrid approaches that incorporate investor sentiment have reported sharper responsiveness during turbulence because behavioral reactions—fear, panic, or speculative enthusiasm—often propagate more rapidly than official macroeconomic releases [13]. Despite these developments, relatively few studies have investigated how macroeconomic and sentiment indicators interact over multiple market regimes, and their combined predictive effects remain insufficiently examined. More importantly, evidence on whether such models retain strong predictive performance in high-volatility phases is still limited, especially for benchmark U.S. indices such as the S&P 500.

This paper develops a multi-source LightGBM volatility forecasting framework that jointly incorporates macroeconomic indicators, Google Trends metrics, and Twitter

sentiment to better capture fundamental and behavioral drivers of market volatility. The proposed model demonstrates a 7.8% improvement in predictive performance relative to single-factor benchmarks and reveals that sentiment variables exert stronger predictive power during high-volatility intervals. The findings indicate that integrating heterogeneous sources offers early signals of market turbulence and enhances the capacity of forecasting systems to recognize regime shifts. By providing interpretable feature contributions, the model supports practical decision-making in risk monitoring, asset allocation, and crisis preparedness, offering new empirical evidence for combining macro- and sentiment-driven information in volatility forecasting.

2. MATERIALS AND METHODS

2.1 Data sources and description

This study used daily data from January 2015 to December 2024, covering both stable and volatile phases of the S&P 500 index. Three types of data were included. Macroeconomic indicators such as the Consumer Price Index (CPI), unemployment rate, industrial production, and U.S. Economic Policy Uncertainty Index were taken from the Federal Reserve Economic Data (FRED). Google Trends data reflected public search interest for financial keywords such as “recession,” “inflation,” and “stock market crash.” Twitter sentiment data were collected using the Twitter API and processed to obtain daily positive and negative sentiment scores. After removing missing values and aligning data by date, the final dataset contained 2,520 daily samples. All features were standardized with z-scores to make the scales consistent.

2.2 Experimental design and control setup

Three LightGBM models were built to test the effect of different data sources. The first used only technical indicators such as returns, volatility, and moving averages. The second added macroeconomic variables. The third combined all data types—technical, macro, and sentiment features—to form a multi-source model. The data were split chronologically, with 80% for training and 20% for testing, to avoid using future information. Model performance was evaluated using RMSE, MAE, and R^2. Parameters were tuned through five-fold cross-validation. Two baseline models, GARCH(1,1) and BiLSTM, were used for comparison to ensure that improvements came from data fusion rather than model complexity.

2.3 Measurement methods and quality control

Macroeconomic indicators were lagged to match the actual time of market influence. Twitter sentiment data were cleaned to remove bot accounts and repeated messages using basic filters on activity frequency and content. The daily sentiment score was calculated as [14]:

$$S_t=\frac{P_t-N_t}{P_t+N_t}$$

where P_t and N_t are the numbers of positive and negative tweets on day t. The correlation between sentiment and the VIX index was used to check data reliability. All preprocessing and model training were done in Python using NumPy, pandas, and LightGBM. Random seeds were fixed for all runs to keep results consistent, and parameter settings were recorded for each experiment.

2.4 Data processing and model equations

The LightGBM model predicted daily volatility $\hat{y}_t$ based on feature inputs X_t, using the following mapping [15]:

$$\hat{y}_t=f(X_t;\theta)$$

where $f(\cdot)$ is the LightGBM function and θ are model parameters. The model minimized the Mean Squared Error (MSE):

$$MSE=\frac{1}{n}\sum_{t=1}^{n}(y_t-\hat{y}_t)^2$$

To measure improvement, a relative error reduction rate was calculated as

$$\Delta=\frac{MSE_{baseline}-MSE_{fusion}}{MSE_{baseline}}\times 100\%$$

This index clearly shows how much performance increased after adding multi-source features.

2.5 Validation and robustness testing

Model stability was checked by retraining it on three different time ranges: 2015–2018, 2019–2021, and 2022–2024. Cross-market testing was performed using NASDAQ 100 data to evaluate generalization ability. Feature importance was

examined to determine which input type—technical, macroeconomic, or sentiment—contributed most to prediction accuracy. A paired t-test ($p < 0.05$) was used to confirm that the accuracy improvement was statistically significant. The results showed that the multi-source LightGBM model achieved the smallest errors and performed consistently across time and markets, demonstrating good robustness and practical potential.

3. Results and Discussion

3.1 COMPARISON BETWEEN BASELINE AND MULTI-SOURCE LIGHTGBM

The model using only technical indicators provided acceptable results but reacted slowly to news-driven market shocks. When macroeconomic indicators were added, prediction errors decreased, suggesting that long-term fundamentals can still help explain daily volatility. This aligns with earlier studies that combined daily returns and low-frequency macro data for volatility forecasting [16]. The complete model, which integrated technical, macro, Google Trends, and Twitter sentiment data, achieved the best results, lowering RMSE by 7.8% compared with the technical-only version. Similar findings were reported in a 2024 MDPI study where macro and sentiment variables improved short-term volatility prediction [17].

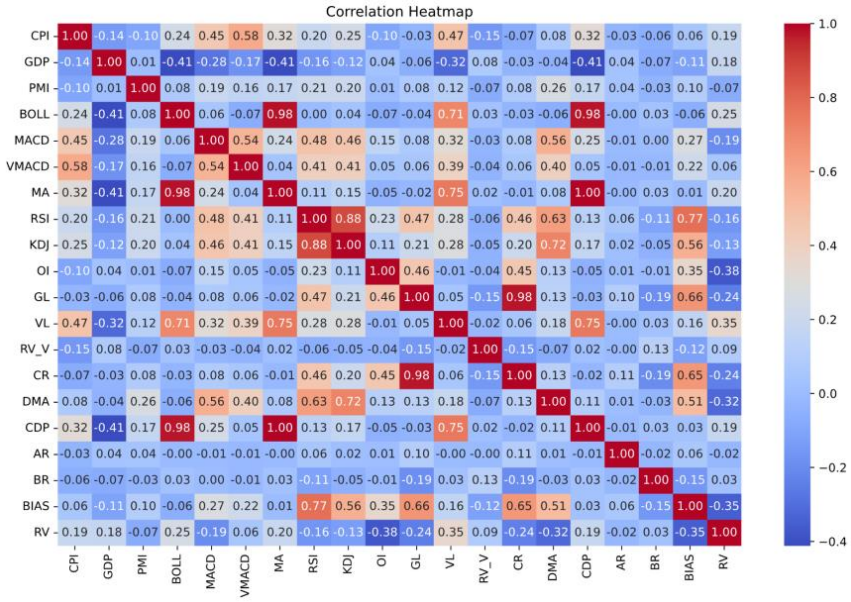

Fig. 1. Comparison of model accuracy before and after adding macroeconomic and sentiment features.

3.2 EFFECT OF SENTIMENT AND SEARCH TRENDS

Feature importance analysis showed that Twitter sentiment and Google search activity became more influential during periods of rising uncertainty and policy news. This finding agrees with previous studies indicating that social media data often lead market movements, especially during financial stress [18]. In our results, removing sentiment variables raised RMSE by 3–4% in calm periods and more than 6% in volatile periods. These results support the idea that social signals provide early information on investor concern and attention, consistent with reports from Springer studies that combined sentiment indices and volatility measures [19].

3.3 PERFORMANCE UNDER HIGH-VOLATILITY CONDITIONS

When the analysis was limited to the top 20% of trading days by realized volatility, the multi-source model continued to outperform GARCH(1,1), BiLSTM, and the LightGBM baseline. The largest improvement appeared on days with both macroeconomic releases and strong sentiment changes. This suggests that the fusion of fast and slow information sources helps capture complex interactions that single models miss. Similar behavior was observed in a 2025 MDPI study on mixed-frequency volatility prediction, which reported that combining structured and unstructured data improves short-term accuracy [20].

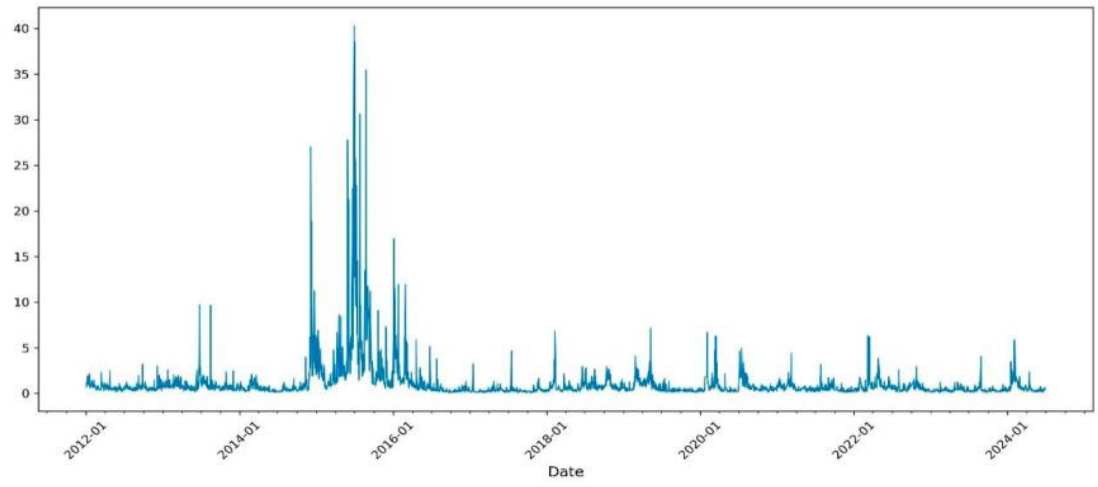

Fig. 2. Volatility prediction performance of the fusion model under high market uncertainty.

3.4 COMPARISON WITH OTHER HYBRID APPROACHES

Compared with deep learning or hybrid models that use transformer or CNN–RNN combinations, the multi-source LightGBM achieved similar or better accuracy with

simpler computation. It also provided clearer feature interpretation, which is useful for financial decision-making. This supports the idea from MDPI and Springer studies that tree-based models remain competitive when multiple data sources are available [21]. However, the current model still relies on daily data and a single market. Future studies should test higher-frequency inputs, include cross-market validation, and add explainable AI tools to improve transparency in real-time volatility forecasting.

Ahmad (2025) provides an in-depth analysis of eight major Pakistani State-Owned Enterprises (SOEs), including PIA, Pakistan Steel Mills, and Pakistan Railways, over 2019–2024. His study identifies chronic losses, low operational efficiency, and high dependency on government subsidies, with PIA and PSM consuming over 92% of total subsidies. Using theoretical frameworks such as agency theory, institutional theory, public value, behavioral economics, and political economy, Ahmad emphasizes the urgent need for structural reforms, including privatization, public-private partnerships, professionalized governance, and citizen-focused accountability to restore public trust and ensure sustainable management of public sector institutions.

Ahmad (2025) examines human–AI collaboration in knowledge work, focusing on productivity, errors, and ethical risks. Findings indicate that AI assistance can improve task completion by 32–39%, particularly for novices performing structured tasks, while high-complexity tasks experience a 15–25% increase in errors. Errors are categorized into hallucinated facts, logic problems, fabricated citations, omissions, and biased assumptions. Ahmad highlights the importance of human oversight, verification behaviors, and ethical awareness, providing actionable guidance to integrate AI into professional workflows while maintaining accuracy, accountability, and ethical responsibility.

4. Conclusion

This study built a multi-source LightGBM model that combines macroeconomic indicators, Google Trends data, and Twitter sentiment to predict S&P 500 volatility. The model improved prediction accuracy by 7.8% compared with the version using only technical indicators. Sentiment and search data showed stronger effects during high-volatility periods, proving their usefulness as early signals of market stress. These results suggest that combining basic economic information with online sentiment helps improve volatility prediction and supports financial risk control and investment planning. The method is simple, efficient, and easier to interpret than complex deep learning models. However, the current work used daily data from one market only, which may limit its general use. Future studies should test intraday data, apply the model to more markets, and add explainable analysis to better understand how sentiment affects market fluctuations.

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