Market resilience in turbulent times: a proactive approach to predicting stock market responses during geopolitical tensions

Srivatsa Maddodi
Department of Computer Science, Srinivas University, Mangaluru, India and Department of Data Engineering, United Airlines Inc, Bengaluru, India, and
Srinivasa Rao Kunte
Department of Computer Science, Srinivas University, Mangaluru, India

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Abstract

Purpose – The Indian stock market can be tricky when there's trouble in the world, like wars or big conflicts. It's like trying to read a secret message. We want to figure out what makes investors nervous or happy, because their feelings often affect how they buy and sell stocks. We're building a tool to make prediction that uses both numbers and people's opinions.

Design/methodology/approach – Hybrid approach leverages Twitter sentiment, market data, volatility index (VIX) and momentum indicators like moving average convergence divergence (MACD) and relative strength index (RSI) to deliver accurate market insights for informed investment decisions during uncertainty.

Findings – Our study reveals that geopolitical tensions' impact on stock markets is fleeting and confined to the short term. Capitalizing on this insight, we built a ground-breaking predictive model with an impressive 98.47% accuracy in forecasting stock market values during such events.

Originality/value – To the best of the authors' knowledge, this model's originality lies in its focus on short-term impact, novel data fusion and high accuracy. Focus on short-term impact: Our model uniquely identifies and quantifies the fleeting effects of geopolitical tensions on market behavior, a previously under-researched area. Novel data fusion: Combining sentiment analysis with established market indicators like VIX and momentum offers a comprehensive and dynamic approach to predicting market movements during volatile periods. Advanced predictive accuracy: Achieving the prediction accuracy (98.47%) sets this model apart from existing solutions, making it a valuable tool for informed decision-making.

Keywords Geopolitical tension, Stock market prediction, Sentiment analysis, Momentum indicator, LSTM

Paper type Technical paper

1. Introduction

The efficient market hypothesis (EMH) suggests that stock prices encapsulate all available information, incorporating historical prices and exchange-based share trades, trading at fair values considering all relevant factors (Fama, 1970, 1991). However, scholarly research over the years has raised questions about whether stock price fluctuations may also be influenced by the behavioral and rational aspects of investors (Shleifer and Summers, 1990). These elements, collectively known as "investor sentiment" or the "mood of the investor," introduce a human element into the market dynamics. The rise of social media platforms such as Twitter, Facebook, YouTube and LinkedIn has provided an instantaneous digital outlet for

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individuals to express opinions and reactions in textual form. Researchers can employ appropriate techniques to analyze these texts and discern the sentiment behind public expressions on these platforms. Geopolitics encompasses a broad spectrum of events with diverse causes and consequences, ranging from terrorist attacks to climate change and from Brexit to the Global Financial Crisis (Bekaert *et al.*, 2014). Such events and threats introduce uncertainties and risks into financial markets, including the stock exchange, giving rise to "geopolitical risk" (GPR), a significant concern for stakeholders such as policymakers, corporations, financial investors and politicians. GPR plays a pivotal role in shaping investor decisions regarding stock transactions. Uncertainty, as emphasized by Campbell *et al.*, is a fundamental aspect in financial economics, influencing investor behavior and market prices (Berk and DeMarzo, 2017). GPRs encompass factors like "geopolitical tensions," "war risk," "terrorist threats" and "trade wars between countries." Historical evidence highlights the negative impact of events such as the September 11, 2001, terrorist attack and the Iraq invasion on global stock exchanges. The annexation of Crimea and Russia's sanctions in 2014 also resulted in significant drops in Russian stock indices. Forecasting stock market behavior during geopolitical tensions presents a formidable challenge due to the volatile nature of the stock market. While news and historical prices are commonly considered influencing factors, recent research emphasizes the strong link between investor sentiment and stock market returns in both the USA and European markets (Baker and Wurgler, 2000; Das and Vasileios, 2014; Lee and Wu, 2016; Shehzad and Malik, 2019). This paper aims to scrutinize the Indian stock market during periods of GPR, specifically focusing on tensions between India and Pakistan following the URI terrorist attack in Pulwama and India's subsequent surgical strike on terrorist camps. Additionally, we examine the ongoing geopolitical tension between Russia and Ukraine, given India's close ties with Russia. Employing analytical approaches, our objective is to provide improved predictions and a deeper understanding of the behavior of the Indian stock market during these critical periods. The analysis concentrates on the National Stock Exchange (NSE), one of India's major stock exchanges, utilizing indexes like the Nifty Next 50 Index and the Nifty Midcap 100 Index, with the flagship Nifty 50 Index comprising 50 companies widely utilized by both Indian and global investors as a barometer of the Indian equity market.

2. Related work

This literature review is divided into two main sections:

Literature related to the substantive issue: This section examines existing research on how geopolitical tensions impact stock markets and the potential for prediction.

Literature related to the theoretical framework: This section explores relevant theories from behavioral finance and network theory that can inform our understanding of how social media sentiment and market indicators might influence investor behavior during geopolitical events.

2.1 Literature related to the substantive issue

Plakandaras *et al.* (2018) explore the use of machine learning, specifically support vector regression (SVR), to predict financial market behavior during periods of geopolitical uncertainty. Their study reveals that SVR offers improved forecasting accuracy over traditional models, especially during market turbulence. However, the effectiveness of SVR varies across different timeframes and sectors, with gold markets showing the strongest response. The authors note that certain sectors, such as technology and tourism, may react differently to geopolitical events. They emphasize the need for further research to refine these models and address limitations for broader applicability.

Alqahtani *et al.* (2020) assess the impact of GPR and crude oil returns on stock market predictability in six Gulf Cooperation Council (GCC) countries, using data from February 2007 to December 2019. They find that while GPR indices show limited ability to predict stock returns within the sample, the global GPR index has some out-of-sample forecasting value for Kuwait and Oman. Crude oil prices generally provide stronger predictive power for GCC stock returns, both within and beyond the sample period. These findings remain robust even when accounting for risk-adjusted returns. The study suggests that while GPR influences GCC stock markets, crude oil prices should be the primary focus for investors seeking short-term forecasts and incorporating additional variables could enhance future prediction models.

Salisu *et al.* (2022a, b) examine the impact of global GPR on the stock markets of advanced economies, including the G7 and Switzerland, over more than a century. They find that GPR significantly predicts stock returns, with the anticipation of geopolitical events often causing more market disruption than the events themselves. Gold proves to be a reliable hedge during geopolitical turbulence, showing a negative correlation with stock market volatility. The study also notes that emerging markets are more sensitive to geopolitical threats, especially when regional trade integration is involved. The research underscores the need to consider GPR sentiment, not just events, for more accurate market predictions and suggests that policymakers could use this understanding to manage risks and enhance stability.

Triki and Maatoug (2021) investigate the relationship between the USA stock market and gold prices during periods of geopolitical tension and conflict. They find that gold negatively correlates with the Standard & Poor's 500 (S&P 500) Index, serving as a hedge against stock market volatility, especially when GPR is high. The study introduces the GPR index as an effective measure of global political tensions, showing its impact on markets. The correlation between gold and the stock market is dynamic, suggesting the need for adaptable models in response to changing geopolitical conditions. While the study focuses on the USA market, its findings may be relevant to other regions with similar dynamics, and further research is recommended to explore gold's role as a safe haven across different contexts.

Segnon *et al.* (2023) examine the effectiveness of using GPR indicators to predict stock market volatility. Using a robust autoregressive-multivariate-stochastic generalized autoregressive conditional heteroskedasticity mixed data sampling (AR-MSGARCH-MIDAS) model that accounts for structural breaks and both short- and long-term volatility, they find that including GPR variables does not significantly enhance the accuracy of monthly volatility forecasts. The study suggests that the impact of GPR on forecasting may depend on the specific prediction model used. After accounting for non-stationarities, the added information from GPR was not statistically significant, though macroeconomic variables might offer complementary insights in certain cases. Despite using over 122 years of data, the study highlights the challenge of directly capturing the predictive power of geopolitical events on market volatility, suggesting that further research could explore alternative GPR data or model refinements.

Salisu *et al.* (2022a, b) examine the GPRs in emerging markets, finding that stock market volatility in these markets increases in response to geopolitical threats, particularly the anticipation of events rather than the events themselves. The study highlights the potential of machine learning, especially SVR, in forecasting volatility during geopolitical turbulence, with gold being particularly sensitive. It emphasizes the importance of focusing on geopolitical sentiment for better market predictability and notes that emerging markets are more vulnerable to GPR due to trade integration. The findings suggest that different sectors react differently to GPR, with long-term implications for investor confidence and economic growth, underscoring the need for policymakers to understand the GPR–market link to manage risks effectively.

Fiorillo *et al.* (2023) examine the impact of GPR on stock liquidity in international markets, finding that higher GPR leads to decreased liquidity, making it harder to buy and sell shares quickly and at low cost. The study reveals that the anticipation and threat of geopolitical events have a more significant impact on liquidity than the actual events themselves. Stocks in less liquid markets or those issued by financially constrained or less-transparent companies are particularly vulnerable to the negative effects of GPR. These findings suggest that GPR impacts liquidity through increased financing constraints and information asymmetry. The research highlights the importance of understanding the GPR–liquidity link for both investors and policymakers.

Hachicha (2023) examined the GPR during the Russia–Ukraine war, highlighting a strong interdependence between investor sentiment, exchange rates, GPR and developing stock markets across various time horizons. The study finds that investor sentiment often leads to changes in exchange rates, particularly in the short term, and both investor sentiment and GPR significantly influence stock market returns, especially over the long term. Gold is identified as an effective hedge against currency devaluation and stock market instability due to its negative correlation with these variables. Emerging markets are particularly sensitive to fluctuations in GPR and investor sentiment, intensifying the observed co-movements. The study underscores the importance of considering both investor sentiment and GPR when analyzing developing stock markets during periods of geopolitical uncertainty.

Hedström *et al.* (2020) investigate the impact of geopolitical uncertainty on stock market contagion in emerging markets, finding that these markets are more vulnerable to contagion within their regions than from global markets, suggesting potential diversification benefits by investing across different regions. The study reveals that general stock market risk [volatility index (VIX)] is a more significant driver of market volatility than GPR indices, which do not strongly impact return or volatility spillovers between markets. Strong trade integration within regional markets contributes to the heightened regional contagion. Additionally, the study confirms a negative correlation between gold prices and stock market volatility during geopolitical uncertainty. Overall, the findings emphasize the importance of understanding regional trade networks and general market risks in managing contagion in emerging markets.

2.2 Literature related to the theoretical framework

This study utilizes a combined lens from behavioral finance and network theory to understand how social media sentiment and market indicators can influence stock market movements during geopolitical tensions.

Behavioral finance: Prospect theory by Kahneman and Tversky (1979) suggests that investors exhibit loss aversion, potentially leading to risk aversion and selling during periods of uncertainty reflected in negative social media sentiment. Additionally, herd behavior might be amplified by social media, leading to collective overreactions during geopolitical events.

Network theory: The framework of complex adaptive systems can be applied to understand the stock market as a network where individual investor actions based on social media sentiment can have unpredictable collective effects on market behavior. This aligns with the work on market efficiency by Fama (1970), where semi-strong efficiency suggests that public information (including social media) might not be fully priced into the market, offering an opportunity for prediction.

Bollen *et al.* (2011) analyzed Twitter mood and discovered that it can predict stock market movements. They found a correlation between collective mood states on social media and market trends. The study suggests that social media sentiment analysis can be a useful tool for forecasting market behavior, as investors' emotional responses to geopolitical events reflected on social media can impact market dynamics.

Barberis (2013) reviewed the impact of prospect theory on economics over 3 decades, noting its wide applicability in explaining diverse economic behaviors. The key findings emphasize that the prospect theory offers a crucial framework for understanding investor behavior. Integrating behavioral insights from this theory can enhance financial models and improve market predictions.

Shiller (2000) investigated the psychological factors influencing market dynamics, focusing on the roles of irrational exuberance and herd behavior in creating asset bubbles. The key findings highlight that herd behavior can lead to significant market overreactions and that social media can amplify these effects by rapidly and widely spreading sentiments.

Hirshleifer and Teoh (2003) provided a comprehensive review of herding behavior in capital markets, focusing on how information cascades and social learning contribute to this phenomenon. Their key findings emphasize that herd behavior is a significant driver of market volatility. Understanding the influence of social information can improve the ability to predict and interpret market movements.

Banerjee (1992) developed a model to explain herd behavior in economics, demonstrating how individuals often imitate others' actions when they believe others possess better information. The key findings reveal that herd behavior can result in suboptimal decision-making and that during geopolitical crises, market participants may follow prevailing trends rather than making independent assessments.

Ahern and Sosyura (2015) examined the impact of sensationalist media coverage on stock prices, finding that such news significantly affects stock returns and volatility. Their key findings highlight that media, including social media, plays a crucial role in shaping investor perceptions and market reactions. Understanding this media influence is vital for predicting market behavior, especially during geopolitical events.

Watts (2002) developed a model to explain global cascades on random networks, demonstrating how small initial shocks can trigger widespread effects throughout a network. The key findings suggest that financial markets can undergo significant changes from minor events due to network effects, and social media can act as a catalyst for such cascades, particularly during periods of geopolitical uncertainty.

Tetlock (2007) analyzed how media content influences investor sentiment and market outcomes, finding that a negative media tone tends to predict downward pressure on stock prices. The key takeaways are that media sentiment analysis is essential for anticipating market movements and that investors' responses to geopolitical news can be significantly shaped by the media's tone and framing.

Cookson *et al.* (2020) investigated how social media amplifies political extremism, revealing that echo chambers contribute to polarized opinions and behavior. Their findings highlight that social media can enhance investor biases and lead to extreme market reactions. Monitoring social media sentiment is, therefore, crucial for predicting market responses, particularly during geopolitical crises.

Li *et al.* (2019) examined the impact of social media on the financial performance of initial public offerings (IPOs), finding that positive social media sentiment significantly boosts IPO performance. The key takeaways are that favorable social media sentiment can enhance investor confidence and improve market performance. Additionally, analyzing social media trends can offer valuable insights into market dynamics, especially during geopolitical events.

Loughran and McDonald (2011) developed a method for textual analysis of financial disclosures, identifying that specific words and phrases correlate with market performance. Their key findings suggest that textual analysis of social media can be a powerful tool for predicting market movements. Understanding the language used in social media posts can help gauge investor sentiment and anticipate potential market reactions.

2.3 Research gap

While a substantial amount of research explores the link between geopolitical tensions and stock market movements, existing studies often rely solely on public sentiment analysis from social media. The literature highlights several areas for further investigation:

(1) *Limited integration of sentiment analysis and market indicators:* While sentiment analysis and traditional indicators like the VIX and momentum indicators (MACD and RSI) have been explored separately, there is a lack of studies integrating these approaches to enhance stock market predictions during geopolitical events.

(2) *Dynamic and multifaceted models:* Many studies focus on static models or single indicators. There is a need for dynamic, multifaceted models that adapt to changing geopolitical conditions and integrate various types of data (e.g. investor sentiment, public sentiment and traditional indicators).

To address these gaps, we propose a more comprehensive approach that incorporates both investor and public sentiment analysis, alongside traditional market indicators like the VIX and momentum indicators (MACD, RSI, etc.). This multifaceted approach offers distinct advantages for stock market prediction:

2.4 Enhanced accuracy through a multi-layered lens

(1) *Gauging market mood:* Sentiment analysis helps capture the emotional state of investors and the general public, which can significantly influence market movements. Optimistic sentiment may lead to buying sprees, while fear can trigger selloffs.

(2) *Capturing broader trends and investor insights:* Investor sentiment analysis, in particular, can reveal investors' perceptions of specific companies or industries, potentially impacting their stock prices.

(1) *Improving prediction capabilities:*

- *Identifying early trends:* By analyzing sentiment trends alongside traditional indicators like the VIX, investors can potentially identify potential shifts in market sentiment before they are fully reflected in stock prices.
- *Mitigating risk:* During periods of high volatility (reflected by the VIX), understanding investor sentiment can help investors make informed decisions and potentially reduce risk.

2.5 Leveraging the power of traditional indicators

(1) *VIX as a volatility gauge:* The VIX, often referred to as the "fear gauge," provides valuable insights into market sentiment during periods of uncertainty. Integrating these data alongside sentiment analysis can offer a more complete understanding of market psychology.

(2) *Momentum indicators for market dynamics:* Momentum indicators like MACD and RSI can capture the direction and strength of price movements. This information, combined with sentiment analysis, can help predict short-term market trends, particularly during geopolitical events.

2.6 Limitations and the importance of a balanced approach

(1) *Market noise:* Sentiment analysis can be influenced by irrelevant information online. Filtering and interpreting the data accurately is crucial.

(2) *Self-fulfilling prophecies:* Negative sentiment can potentially lead to market downturns, creating a self-fulfilling prophecy. It's important to consider this possibility when using sentiment analysis.

Overall, analyzing both investor and public sentiment alongside traditional market indicators offers valuable insights for stock market forecasting, particularly during periods of geopolitical instability. This comprehensive approach can potentially improve the accuracy of short-term prediction models by providing a deeper understanding of the psychological and social factors influencing investor behavior.

2.7 Research objectives and questions

This research aims to develop a novel approach for the Indian stock market:

2.8 Objectives

(1) Develop a hybrid model combining social media sentiment analysis with market indicators;

(2) Assess the short-term impact of geopolitical tensions on the Indian stock market and

(3) Evaluate the model's effectiveness in predicting stock market movements during such events.

2.9 Research questions

RQ1. Can social media sentiment analysis identify investor nervousness or confidence during geopolitical tensions?

RQ2. How effectively do traditional market indicators (VIX, MACD and RSI) capture the market's response to geopolitical events?

RQ3. How accurately can a hybrid model predict short-term stock market movements during geopolitical tensions?

2.10 Hypothesis

A hybrid model incorporating social media sentiment analysis with traditional market indicators will outperform existing models in predicting short-term stock market movements during geopolitical tensions.

3. Methodology

This section provides a comprehensive overview of the key theoretical concepts utilized in the present research endeavor.

Sentiment analysis is a widely recognized approach in data science, a field that integrates various algorithms, machine learning theories and tools to extract valuable insights from raw data. Currently, data science approaches are extensively applied in domains such as stock market movement prediction and analysis. The movement of market prices is influenced by a myriad of online factors, including social media comments, financial news and stock-related news. Natural language processing (NLP) is employed to handle unstructured online data, transforming it into a structured format that computers can use in conjunction with stock data to predict market movements (Mehta *et al.*, 2021; Sidogi *et al.*, 2021; Ardyanta and Sari, 2021).

Our proposed model represents an innovative approach that combines sentiment analysis, traditional market indicators like momentum and VIX and advanced machine learning techniques like long short-term memory (LSTM) to forecast movements in the Nifty 50 Index. Sentiment analysis plays a pivotal role by extracting valuable insights from social media to gauge investor and public sentiment. This aspect allows us to capture the nuanced emotional responses of market participants, which often influence trading decisions and market trends.

In parallel, traditional market indicators such as momentum and the VIX provide foundational metrics that reflect market dynamics and risk levels. These indicators are crucial in understanding the current state of the market and its potential directions.

The integration of machine learning techniques further enhances our model's capabilities. Machine learning algorithms, known for their ability to learn from data and adapt over time, enable us to identify complex patterns and relationships within vast datasets. By incorporating these adaptive capabilities, our model not only improves prediction accuracy but also adapts to evolving market conditions and unforeseen events.

The synergy between sentiment analysis, traditional market indicators and machine learning creates a comprehensive framework that addresses both the qualitative and quantitative aspects of market forecasting. This holistic approach aims to provide deeper insights into market behavior during unprecedented periods of uncertainty and volatility, facilitating more informed decision-making for investors and stakeholders alike.

Overall, our model represents a step forward in predictive analytics for financial markets, leveraging the power of data-driven insights and advanced technology to navigate the complexities of today's dynamic market environment effectively.

3.1 Sentiment analysis

Natural language processing (NLP), a branch of artificial intelligence, excels at analyzing text data to extract valuable insights (Lin and Nuha, 2023). Within this realm, sentiment analysis emerges as a powerful tool for mining public data and uncovering underlying opinions and emotions. Leveraging NLP methods, it classifies the sentiment of a text as positive, negative or neutral (Shah *et al.*, 2019). Among the available tools, VADER stands out as a free and open-source option that combines dictionary and rule-driven approaches to analyze sentiment and quantify its intensity word by word. This makes it particularly adept at handling social media data, where its polarity score function calculates the emotional leaning of each word (Hutto and Gilbert, 2014; Bonta *et al.*, 2019).

Below are the steps carried out for sentiment analysis.

(1) To analyze the sentiment of Twitter data, we leverage natural language processing techniques like Vader, enabling us to detect the emotional tone expressed in tweets.

(2) Classify the sentiment into two types. Type 1: public sentiment and Type 2: investor sentiment.

- Tweets related to the general topic relating to events are classified as public tweets, and sentiment analysis is performed on these tweets to determine the public sentiment.

- Tweets related to the stock market (Nifty 50) are classified as investor tweets, and sentiment analysis is performed on these tweets to determine the investor sentiment.

(3) Determine whether a tweet conveys a positive, negative or neutral sentiment.

(4) Calculate public and investor sentiment indexes.

3.2 Efficient market hypothesis (EMH) and sentiment analysis

The EMH posits that markets are perfectly efficient, meaning all available information is fully reflected in stock prices, leaving little room for sentiment analysis to impact predictions significantly. According to EMH, since prices should incorporate all relevant data, investor sentiment, as captured through sentiment analysis, should not affect price movements in a meaningful way. However, sentiment analysis, which quantifies opinions and emotions from textual data, can challenge this assumption. It demonstrates that investor sentiment – often conveyed through social media – can indeed influence market prices. This implies that market behavior may deviate from the strict efficiency predicted by EMH, particularly in the short term. Psychological factors and emotional biases captured through sentiment analysis can reveal temporary inefficiencies, leading to price movements that diverge from what would be expected under the EMH framework.

Psychological factors and investor behavior: Sentiment analysis helps understanding how psychological factors and market sentiment influence investor behavior, potentially leading to temporary inefficiencies and deviations from EMH predictions.

(1) *Emotional reactions:* Investors' decisions are often influenced by emotions such as fear, greed and optimism. For example, during periods of market uncertainty or geopolitical tension, sentiment analysis can reveal heightened anxiety or panic among investors, which may lead to selloffs or increased volatility. Conversely, periods of positive sentiment might lead to overoptimism and inflated asset prices.

(2) *Herd behavior:* Sentiment analysis can uncover patterns of herd behavior, where investors collectively move in the same direction based on shared sentiments. This behavior can exacerbate market swings and create price movements that deviate from fundamental values. For instance, a surge of positive sentiment on social media about a particular stock can lead to a buying frenzy, driving up the stock price temporarily beyond its intrinsic value.

3.3 Machine learning

Predicting future Nifty 50 movements can be crucial for investors navigating the volatile Indian stock market. This research explores the potential of LSTM, a powerful neural network architecture, to improve upon existing prediction methods. LSTMs excel at analyzing sequential data, making them ideal for processing and forecasting time-series data like stock prices (Manurung *et al.*, 2018).

(1) National Stock Exchange of India (NSE) data consisting of Nifty 50 index and Sentiment Index output of sentiment analysis and momentum data are passed as input for LSTM architecture neural network for predicting the index value.

3.4 Dataset

To investigate the impact of geopolitical tensions on the Indian stock market, we selected three distinct events encompassing border disputes and terrorist attacks: the India–Pakistan tensions following the URI attack and surgical strike (2016), the Pulwama attack and response (2019) and the ongoing Russia–Ukraine conflict (2022–2023). For each event, we collected comprehensive datasets spanning the period of immediate tension and market repercussions. Nifty 50 index data, VIX volatility readings, were sourced from reliable financial databases like https://www.nseindia.com/

Three distinct datasets were selected for analysis, each corresponding to a specific geopolitical event:

(1) EVENT-1: Tension between Pakistan and India during URI Terrorist Attack and Surgical Strike

Dataset-1: URI Terrorist Attack and Surgical Strike

Duration: 16.09.2016 to 30.10.2016

(2) EVENT-2: Tension between Pakistan and India during Pulwama Terrorist Attack and Surgical Strike

Dataset-2: Pulwama Terrorist Attack and Surgical Strike

Duration: 12.02.2019 to 30.03.2019

(3) EVENT-3: Tension between Russia and Ukraine due to Invasion of Ukraine

Dataset-3: Invasion of Ukraine

Duration: 01.02.2022 to 21.10.2023

Twitter data set for sentiment analysis: Tweets data with respect to the specific events are extracted. These tweets belong to two different category.

- Data related to general Tweets during URI terrorist attack and surgical strike with hashtags.

Uri Attack: #Uriattack OR #surgicalstrike OR #indianarmy OR #Uriattacks OR #UnitedAgainstPak OR #TerrorFactory_Pak OR #TerrorStatePak OR #ActAgainstPak OR #WakeUpModi OR #MaunModiSarkar.

Pulwama Attack: #pulwamaattack OR #surgicalstrike OR #indianarmy OR #indiastrikesback OR #bringbackabhinandan OR #indiastrikespakistan.

Russia and Ukraine: #russia or #ukraine or #putin or #nato or #zelensky or #russiaukrainewar or #russiaukraineconflict or #biden or #russian or #ukranian.

- Tweets related to Nifty 50 with hashtag #nifty50 OR #nse.

4. Proposed model

In this section, we discuss the tools used and the proposed model for predicting stock market in the event of geopolitical tensions.

The proposed model of stock market prediction is indicated in Figure 1.

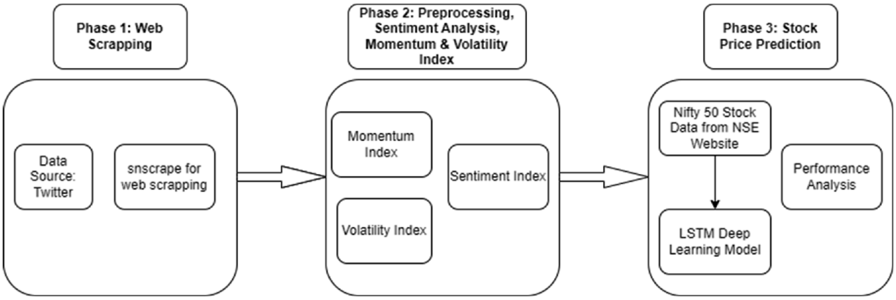
4.1 Phase-1 – web scraping

To capture sentiment during the chosen geopolitical events, we utilized web scraping techniques to gather user data from Twitter. We employed the robust “snscrape” library to efficiently extract tweets relevant to each event based on targeted keywords, hashtags and location filters. This approach allowed us to gather a large and diverse dataset of tweets of around one million, offering valuable insights into public opinion and emotional responses during periods of geopolitical uncertainty. By analyzing these Twitter data alongside market data, we aim to shed light on the complex interplay between sentiment and stock market fluctuations in the Indian context.

4.2 Phase-2

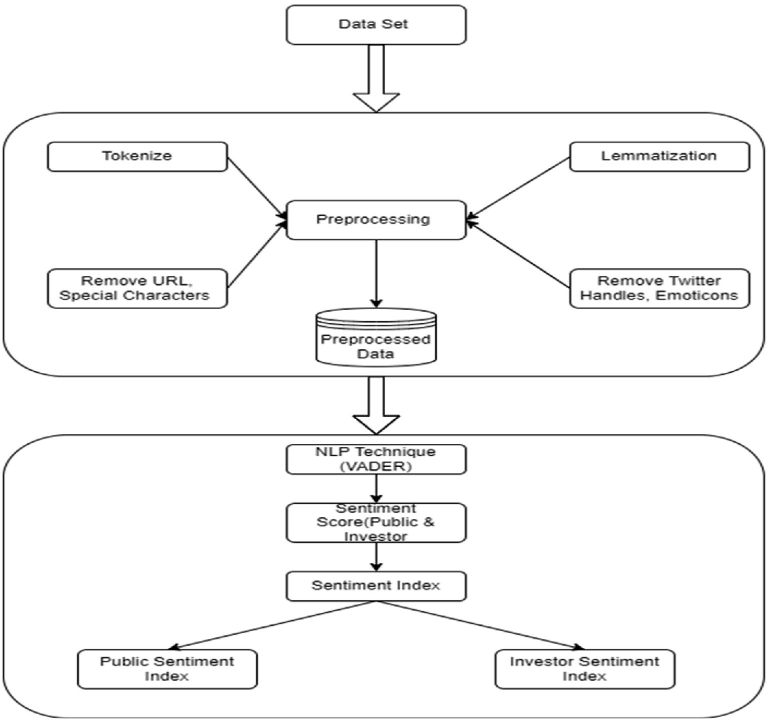
In this phase, we perform data preprocessing of raw data and sentiment analysis of preprocessed data. The framework used for this is shown in Figure 2.

4.2.1 Data preprocessing. Preprocessing our Twitter data before sentiment analysis was crucial to extract meaningful insights from the emotional response to the chosen geopolitical events. While standard techniques like text cleaning, tokenization and stemming and/or lemmatization were employed (Figure 2), we placed particular emphasis on removing noise specific to social media content, such as uniform resource locators (URLs), hashtags and



Source(s): Authors' own work

Figure 1. Proposed model of stock market prediction



Source(s): Authors' own work

Figure 2. Proposed framework for sentiment analysis

Twitter handles. This addressed the potential for irrelevant information and biases to skew the sentiment analysis results. Additionally, utilizing a sentiment lexicon tailored to online language allowed us to capture the nuanced emotional expressions often used in Twitter communication. These rigorous preprocessing steps laid the foundation for accurate and reliable sentiment analysis, ensuring our research findings truly reflect the public's emotional response to the specific geopolitical events under investigation.

4.2.2 Sentiment analysis. To effectively analyze sentiment from diverse tweet sources, we categorized them into two segments (Figure 2). Public sentiment focused on broader hashtags related to the specific geopolitical events (#Uriattack, #Pulwamaattack, etc.), capturing the public's emotional response. Investor sentiment, on the other hand, targeted tweets referencing the Nifty 50 index (#nifty50, #nse), aiming to gauge market participants' sentiment towards the events' potential economic impact. We employed a VADER sentiment dictionary, considering the nuances of online language and event-specific keywords. While acknowledging potential limitations of hashtag-based sentiment analysis, we implemented careful data preprocessing and analysis techniques to mitigate biases and enhance the accuracy of our findings. Our commitment to ethical research practices emphasizes responsible data handling and respect for user privacy.

4.2.3 Sentiment score and sentiment index. To quantify the emotional response to the chosen geopolitical events, we leveraged sentiment analysis to calculate sentiment scores for both public and investor tweets using Equation (1). These scores were further aggregated into the "Sentiment Index," a dynamic metric incorporating daily sentiment averages while accounting for the diminishing impact of older information through a carefully chosen decay factor as per Equation (2). This approach allowed us to track the evolving trends in public and investor sentiment over time, shedding light on how emotional responses potentially influenced market behavior during periods of geopolitical uncertainty. By analyzing the differences in public and investor sentiment trends, we aim to provide valuable insights for businesses, investors and policymakers navigating the complex interplay between public opinion and market dynamics.

$$Avg\ Score_d = \frac{\sum_{d=1}^{N} SS}{\sum_{d=1}^{N} TT} \tag{1}$$

where:

$AvgScore_d$ = average sentiment score per day.

N = number of days in dataset;

TT = total number of tweets and

SS= sentiment score of each tweet.

$$Sentiment\ Index = \sum_{d=1}^{N} AvgScore_d * W_d \tag{2}$$

where:

$\mathrm{AvgScore_d}$ = average sentiment score per day.

N = number of days in dataset.

W_d = Weight of day d and is calculated as follows:

$W_d = \lambda^{N-d}$

λ = decay factor. The value is set as 90%

4.2.4 Momentum index. To gain insights into the interplay between sentiment and market dynamics during the chosen geopolitical events, we employed a combined momentum index incorporating two popular technical indicators: MACD and RSI. MACD, calculated by subtracting two exponential moving averages, provides a signal of price momentum and identifies potential overbought or oversold zones. RSI, focusing on recent price movements, further strengthens the momentum analysis. By integrating this combined momentum index with our sentiment index derived from Twitter data, we aimed to uncover potential correlations between emotional responses and market behavior. This approach allowed us to gain a more nuanced understanding of how investor psychology and sentiment interact with technical market indicators during periods of geopolitical uncertainty.

MACD: It is calculated by subtracting 26 period exponential moving average (EMA) from 12 period EMA.

MACD is calculated as per below Equation (3).

$$\text{MACD} = \text{12Period EMA} - \text{26Period EMA} \tag{3}$$

where:

EMA gives higher weight to recent prices.
EMA is calculated as per below Equation (4).

$$\text{EMA}_t = \left[V_t * \left(\frac{S}{1+d}\right)\right] + \text{EMA}_y * \left[1 - \left(\frac{S}{1+d}\right)\right] \tag{4}$$

where:

EMA_t = EMA Today

V_t = Value Today

s = smoothing

EMA_y = EMA yesterday

d = Number of days

4.2.5 Smoothing factor is calculated as [2/(selected period +1)]. If we are calculating 26 day moving average, then smoothing factor would be [2/(26 + 1)] = 0.074

RSI: Step 1 of the RSI calculation involves transforming average gains and losses into relative percentage changes as per Equation (5). This is achieved by dividing the average gain and average loss, calculated over a 14-day period, by the closing price of the stock. This step allows us to express the average price movements as ratios, facilitating comparison between different market conditions and aiding in the identification of potential overbought or oversold zones, which are key aspects of our analysis of market behavior during geopolitical events.

$$\mathrm{RSI}_{\text{step one}} = 100 - \left[\frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}} \right] \tag{5}$$

Step 2 of the RSI calculation employs the Wilder smoothing ratio technique to smooth the percentage changes obtained in Step 1 as per Equation (6). This smoothing process helps to reduce volatility and noise in the data, ensuring the RSI values oscillate between 0 and 100 in a well-functioning market. This characteristic is crucial for our analysis, as it allows us to identify potential overbought or oversold zones, which can be indicative of investor sentiment and potentially influence market behavior during the chosen geopolitical events.

$$\mathrm{RSI}_{\text{step two}} = 100 - \left[\frac{100}{1 + \frac{((\text{Previous Average Gain} * 13) + \text{Current Gain})}{((\text{Previous Average Loss} * 13) + \text{Current Loss})}} \right] \tag{6}$$

4.2.6 Volatility index. The VIX is a real-time market indicator reflecting investors' expectations of future market volatility over the next 30 days. It generally tends to increase when the market falls, as investors anticipate further price swings and uncertainty. Conversely, VIX values tend to decrease during periods of market stability. In our research on the impact of geopolitical tensions on the Indian stock market, we anticipate VIX to rise in response to these events as investors react to potential disruptions and increased risk. Analyzing VIX alongside other technical indicators and sentiment data will help us gain a nuanced understanding of how market dynamics and investor psychology interact during periods of geopolitical uncertainty.

4.3 Phase-3 – prediction of stock market index value

To predict the stock market index values during the chosen geopolitical events, we employed a LSTM neural network architecture. LSTM's ability to capture long-term dependencies in time series data makes it particularly well suited for analyzing stock prices. We used a combination of past stock prices, VIX data and momentum indicators as input features for the LSTM model. Training was conducted with 80% of each dataset, while the remaining 20% was used for validation. This split allows for robust model evaluation while ensuring sufficient data for training. Our LSTM predictions aim to shed light on how market dynamics respond to geopolitical tensions, offering insights into investor behavior and potential market trends. While we acknowledge limitations in data availability and potential model biases, our research provides a valuable framework for further exploring the complex interplay between geopolitical events and stock market behavior.

5. Results and discussions

To investigate the impact of different features on predicting the stock market index during geopolitical tensions, we conducted seven experiments using varying combinations of data inputs. We compared the effectiveness of models trained with:

(1) Only Nifty 50 data (Exp-1);

(2) Nifty 50 and public sentiment (Exp-2);

(3) Nifty 50 and investor sentiment (Exp-3);

(4) Nifty 50, both public and investor sentiment (Exp-4);

(5) Nifty 50, public sentiment, investor sentiment and VIX (Exp-5);

(6) Nifty 50, public sentiment, investor sentiment and momentum index (Exp-6) and

(7) All features (Exp-7).

This approach allowed us to assess the incremental value of each feature and identify the combination that best captures the market dynamics during these events. We evaluated the performance of each model using classification and regression metrics. We expect that incorporating sentiment analysis, volatility data and momentum indicators alongside historical stock prices will lead to improved prediction accuracy, reflecting the influence of public and investor psychology on market behavior during periods of uncertainty.

Table 1 shows results obtained for all the seven different experimental trained model with respect to regression metrics: R-squared, mean squared error (MSE) and mean absolute error (MAE), and Table 2 shows the results with respect to classification metrics: accuracy, recall and F1 score.

Geopolitical events can significantly impact the Indian stock market, a major emerging economy highly integrated with the global financial system. This paper examines the impact of specific events like the Uri/Pulwama attacks and the Russia–Ukraine war on the Nifty 50 index, analyzing both immediate and sustained effects. While the Uri/Pulwama attacks triggered a temporary decline followed by a swift rebound (Nifty 50 down 2.2% followed by a 1.7% rise) as observed in Figures 3 and 4, the ongoing Russia–Ukraine war

Events	Metric	Exp-1	Exp-2	Exp-3	Exp-4	Exp-5	Exp-6	Exp-7
Event-I	*R*-squared	0.2567	0.2723	0.2763	0.3079	0.3263	0.3263	0.3482
	MSE	0.0379	0.0351	0.0304	0.0268	0.0252	0.0248	0.0198
	MAE	0.0968	0.0897	0.0875	0.0817	0.0810	0.0804	0.0782
Event-II	*R*-squared	0.2487	0.2789	0.2772	0.3051	0.3229	0.3229	0.3471
	MSE	0.0381	0.0343	0.0364	0.0282	0.0259	0.0251	0.0154
	MAE	0.0951	0.0862	0.0875	0.0809	0.0804	0.0812	0.0759
Event-III	*R*-squared	0.2515	0.2759	0.2763	0.3084	0.3259	0.3239	0.3391
	MSE	0.0363	0.0351	0.0304	0.0289	0.0272	0.0260	0.0102
	MAE	0.0942	0.0847	0.0855	0.0814	0.0815	0.0809	0.0759

Source(s): Authors' own work

Table 1. Experimental results in terms of regression metrics

Events	Metric	Exp-1	Exp-2	Exp-3	Exp-4	Exp-5	Exp-6	Exp-7
Event-I	Accuracy	84.51%	87.24%	91.25%	95.01%	97.15%	96.73%	97.99%
	Recall	72.18%	75.21%	78.91%	82.49%	83.71%	83.46%	87.92%
	F1 Score	80.12%	81.27%	84.62%	89.12%	91.83%	90.04%	91.41%
Event-II	Accuracy	85.01%	86.98%	91.72%	95.49%	96.72%	97.38%	98.63%
	Recall	72.51%	76.12%	78.43%	82.46%	83.01%	89.85%	89.21%
	F1 Score	80.82%	81.74%	85.01%	89.47%	90.15%	91.89%	92.35%
Event-III	Accuracy	84.78%	90.21%	91.93%	95.97%	96.83%	97.62%	98.79%
	Recall	72.36%	76.06%	78.31%	82.42%	83.45%	89.01%	90.12%
	F1 Score	80.36%	85.32%	81.09%	89.73%	90.78%	91.14%	95.68%

Source(s): Authors' own work

Table 2. Experimental results in terms of classification metrics

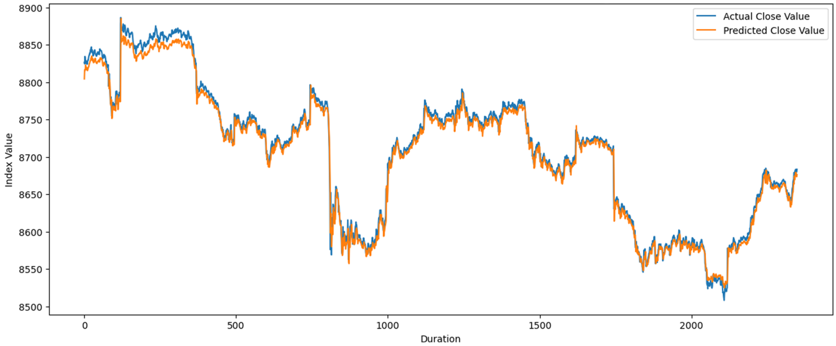


Figure 3.
Actual vs predicted value graph for event-1

Source(s): Authors' own work

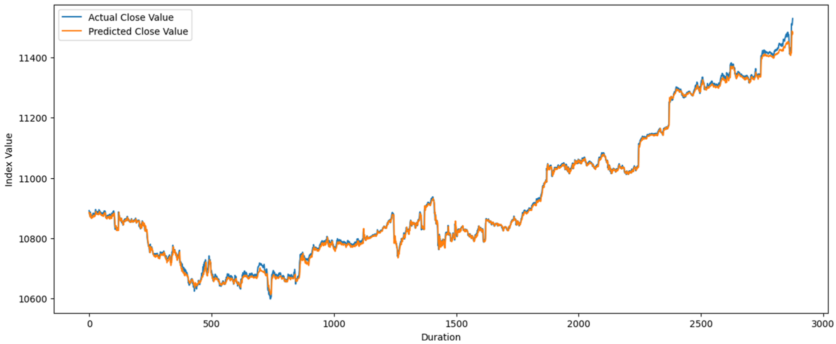


Figure 4.
Actual vs predicted value graph for event-2

Source(s): Authors' own work

has caused a much more prolonged downturn (Nifty 50 down 815 points, exceeding 7% decline within the first two months), as observed in Figure 5. This disparity highlights the influence of event scale, economic impact and global uncertainty on market behavior. Potential moderating factors like government response and investor confidence should

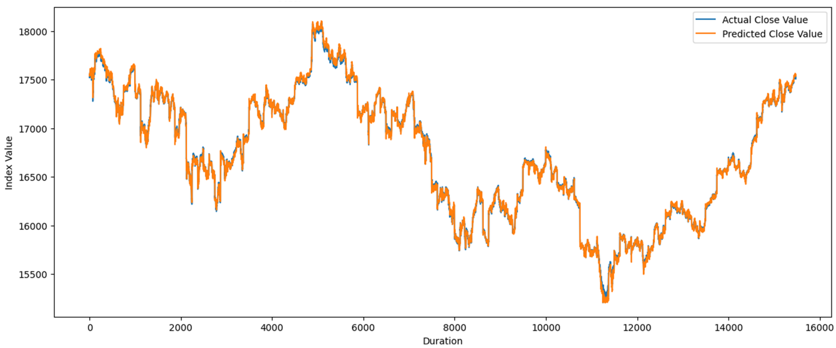


Figure 5.
Actual vs predicted value graph for event-3

Source(s): Authors' own work

also be considered for a comprehensive understanding of market dynamics during such events. Integrating sentiment analysis alongside this data-driven approach can further illuminate the complex interplay between public emotions, news narratives and investor decisions. Ultimately, understanding the nuanced relationship between geopolitical events, investor sentiment and market behavior is crucial for informed decision-making by investors, policymakers and all stakeholders navigating the ever-changing global landscape.

5.1 Key findings

Sentiment analysis boosts accuracy: Adding public sentiment analysis to stock data (Exp-2) increased prediction accuracy by 3% compared to just using Nifty-50 data (Exp-1). This benefit grew to 3% when investor sentiment was included (Exp-3) and 10% when combining both public and investor sentiment (Exp-4). This highlights the value of sentiment analysis in capturing market trends.

VIX matter: Including the VIX in Exp-5 further improved accuracy by 2% over Exp-4. This suggests its effectiveness in gauging market sentiment, as shown in Table 2.

Momentum indicators shine together: Integrating all momentum indicators in Exp-6 yielded an additional 2% accuracy gain over Exp-4. This demonstrates the synergy of these indicators in capturing market dynamics during uncertainty.

Combined power: These findings showcase the potential of leveraging sentiment analysis, VIXs and momentum indicators together (Exp-7). Combining these techniques can significantly improve stock prediction accuracy by 14% compared to just using Nifty-50 data (Exp-1).

5.2 Implications of findings

5.2.1 Sentiment analysis captures investor psychology (RQ1). The study successfully addressed the role of sentiment analysis in identifying investor behavior during geopolitical tensions (RQ1). Public sentiment analysis alone improved prediction accuracy by 3% (Exp-2 vs Exp-1), demonstrating its ability to capture broad market trends. Notably, including investor sentiment analysis yielded an additional boost of 3% (Exp-3 vs Exp-1). This finding directly supports the objective of developing a hybrid model that leverages social media analysis to understand investor confidence or nervousness during such events. The greatest improvement (10%, Exp-4 vs Exp-1) came from combining both public and investor sentiment, highlighting the synergy achieved by incorporating these complementary sources.

5.2.2 Market indicators enhance model performance (RQ2). The research also investigated the effectiveness of traditional market indicators in capturing the market's response to geopolitical tensions (RQ2). The VIX proved valuable, increasing prediction accuracy by 2% (Exp-5 vs Exp-4). This suggests that incorporating volatility data are effective in gauging market sentiment during periods of uncertainty. Additionally, integrating all momentum indicators (MACD, RSI, etc.) resulted in a further 2% accuracy gain (Exp-6 vs Exp-4). This finding aligns with the objective of using market indicators to understand market dynamics during these events.

5.2.3 Hybrid model delivers enhanced prediction accuracy (RQ3). The core outcome of the research directly addresses RQ3. The significant 14% improvement in prediction accuracy achieved by the combined model (Exp-7) compared to the baseline model using only Nifty-50 data (Exp-1) provides a clear answer. This finding demonstrates that the hybrid model, incorporating sentiment analysis and market indicators, is demonstrably more accurate in predicting short-term stock market movements during geopolitical tensions.

By quantifying the improvement (14%), the research directly addresses the question of how accurately the model predicts these movements. This outcome validates the objective of evaluating the model's effectiveness and supports the hypothesis that the hybrid approach outperforms existing models in such situations.

5.3 Comparison with existing work

We have compared our prediction results with the following two of the latest published related works.

Wang *et al.* (2020) discussed regarding the investor sentiment and stock price movement. The authors have used East Money, the most popular online forum of China for Stocks, for analyzing the investor sentiment, on the stock movements of CSI300 Index which is traded in major stock exchanges of China. The authors have analyzed the effect of investor sentiment on trading volume, stock price, order imbalance of big trade etc. We have considered this for comparison as the authors used the sentiment analysis for online investor sentiment with LSTM is used as sentiment classifier.

Das *et al.* (2022) considered four different news sources like Facebook comments, financial news and stock-related articles from *Economic Times* and Twitter data and seven different techniques like VADER, Logistic Regression, Loughran–McDonald, Henry, TextBlob, Linear SVC and Stanford are used for sentiment analysis. Sentiment analysis was performed on individual data source as well as the combination of the different data sources. We have considered this for comparison as the authors used multiple sentiment analysis techniques across multiple data sources for prediction.

Table 3 shows the comparison of this proposed research work with two of the latest published related works. From the comparison with the related works, it is evident that the proposed work achieves higher accuracy in prediction as it uses multiple parameters like sentiment analysis, momentum indicator and VIX data along with the stock data.

Work done	Data sources	Stock data	Tool for sentiment analysis	Prediction method	Accuracy
Wang *et al*	Online Forum	CSI 300	LSTM	Machine Learning Algorithms	Avg: 77.83%
Das *et al*	Stock-related articles headlines from "Economic Times," Tweets from Twitter, Financial news from "Economic Times" and Facebook comments	Nifty 50	VADER, Logistic Regression, Loughran–McDonald, Henry, TextBlob, Linear SVC and Stanford	LSTM	Linear SVC: 98.32% Logistic Regression: 97.67% VADER: 96.85% Loughran–McDonald: 94.78% Henry: 96.36% TextBlob: 96.48% Stanford: 96.57%
Proposed work	Twitter, VIX and Momentum	Nifty 50	VADER	CNN-BDLSTM	Avg: 98.47%

Source(s): Authors' own work

Table 3.
Comparison with existing work

6. Conclusion and practical implications

In conclusion, this paper has not only confirmed the significant impact of geopolitical tensions on the Indian stock market but also demonstrated the crucial role of sentiment analysis in understanding investor behavior during these events. By analyzing social media sentiment data, we developed a novel prediction model that incorporates sentiment alongside volatility and momentum indicators for improved accuracy.

We successfully developed a predictive model that utilizes sentiment analysis, VIX and momentum indicator to forecast stock market values during geopolitical tensions with an accuracy of 98.47%. Our research shows that including more than just historical Nifty 50 data significantly improves our model's ability to predict stock movements during geopolitical tensions. By incorporating public and investor sentiment analysis with stock data (Exp-4), we achieved a 10% accuracy boost compared to using only Nifty 50 data (Exp-1). Adding the VIX and momentum indicators (Exp-7) further improved accuracy by 4%. This highlights the valuable role these factors play in capturing market sentiment and dynamics during uncertain times.

6.1 Limitations

While our current research demonstrates substantial accuracy of prediction of the stock market during geopolitical events, future iterations will explore expanding the model's capabilities:

(1) *Data diversification:* Integrating additional data sources like news articles, official reports and broader social media platforms can offer a more comprehensive view of public and expert sentiment, potentially enhancing forecasting accuracy.

(2) *Technical indicator expansion:* Including metrics like market breadth and foreign investor activity can provide deeper insights into market internals and investor behavior, improving the model's ability to capture the nuanced dynamics of geopolitical tension-driven market fluctuations.

(3) *Addressing limitations:* Optimizing indicator settings and using these indicators in conjunction with other technical and fundamental analysis tools can provide a more comprehensive view of the market and reduce the risk of relying on few indicators.

6.2 Recommendations

6.2.1 For researchers.

(1) Integrate sentiment analysis data into forecasting models to gain deeper insights into societal influences on economic activity and

(2) Develop more accurate forecasting models leading to better predictions of future economic trends.

6.2.2 For investors.

(1) Utilize sentiment analysis tools to gain a broader understanding of public interest and make more informed investment decisions, especially during periods of high market volatility.

6.2.3 For policymakers.

(1) Leverage models informed by sentiment analysis data to understand societal concerns more effectively and

(2) Craft better response strategies and measures to stabilize financial markets during times of unrest.

6.2.4 Investor benefits.

(1) *Precise stock selection and risk reduction:* This model offers a valuable edge to investors, especially during market turbulence. By combining sentiment analysis with momentum indicators, it provides a comprehensive view of potential stock movements. This allows for more accurate stock selection, earlier identification of trends and, ultimately, reduced investment risk.

(2) *Future-proofing the model:* The model's success paves the way for exciting advancements. This includes integration into automated trading strategies and attracting partnerships or investments to expand its application. These developments hold the potential to significantly improve stock prediction accuracy and market sentiment insights. Ultimately, this translates to better investment decisions and potentially higher returns for investors.

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Corresponding author
Srivatsa Maddodi can be contacted at: srivatsa.maddodi@gmail.com