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A Comprehensive Review and Empirical Results on News Sentiment–Driven Machine Learning Models for Stock Market Price Prediction

Mohd Rashid
Research Scholar, Department of Computer Science, Malwanchal University, Indore
Dr. Sharad Patil
Supervisor, Department of Computer Science, Malwanchal University, Indore

Abstract
This paper presents a comprehensive review and empirical evaluation of news sentiment–driven machine learning models for stock market price prediction. The study synthesizes existing research on financial sentiment analysis, highlighting the growing relevance of textual signals derived from news headlines and articles in forecasting short-term market movements. Leveraging multiple sentiment extraction techniques—including lexicon-based approaches, machine learning classifiers, and transformer-based models such as FinBERT—the research integrates sentiment with historical price data to assess predictive accuracy across various model classes. Empirical experiments compare baseline statistical models, traditional ML algorithms, and deep learning architectures, revealing that sentiment-augmented models consistently outperform price-only approaches, particularly for short-horizon predictions. Results from robustness checks and backtesting further demonstrate the practical value of sentiment-enhanced forecasting in real trading environments. The study contributes a unified framework, benchmark results, and insights that advance sentiment-aware financial prediction research.
Keywords: News Sentiment, Stock Market Prediction, Machine Learning Models, Financial Text Analysis, Deep Learning

Introduction

The integration of news sentiment into stock market prediction has emerged as a significant advancement in financial analytics, driven by the understanding that market movements are not solely dependent on historical price patterns but are also influenced by the emotional and informational content disseminated through news media. Traditional forecasting models often fall short in capturing the qualitative dimensions of market behavior, especially during periods of heightened uncertainty when investor reactions to news become more pronounced. With the rapid development of natural language processing (NLP) and machine learning, sentiment extracted from financial news now provides an enriched feature set capable of enhancing predictive performance. Existing studies reveal that positive and negative news signals can

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meaningfully affect stock returns, volatility, and investor expectations, indicating that sentiment-driven models may outperform conventional quantitative approaches. However, despite notable progress, the literature remains fragmented, with considerable variation in methodologies, sentiment extraction techniques, and model architectures, resulting in inconsistent conclusions regarding overall effectiveness. This paper addresses these gaps by offering a comprehensive review of news sentiment–driven predictive models and presenting empirical findings comparing lexicon-based, machine learning–based, and transformer-based sentiment extraction techniques integrated with various forecasting algorithms. By evaluating the performance of hybrid models that combine sentiment with historical price data, the study aims to determine the extent to which sentiment contributes to improved short-term market prediction accuracy. Furthermore, this research investigates the robustness of sentiment-enhanced models across different prediction horizons and market conditions, providing insights into their real-world applicability for traders, analysts, and financial institutions. Ultimately, this work contributes a unified perspective on the role of news sentiment in financial forecasting, highlights the strengths and limitations of existing approaches, and establishes an empirical benchmark for future innovations in sentiment-aware stock prediction systems.

Significance of the Study

This study holds substantial significance as it contributes both theoretically and practically to the evolving field of financial machine learning by rigorously evaluating how news sentiment can enhance stock market prediction models. From an academic standpoint, the research advances financial ML by integrating diverse sentiment extraction techniques—ranging from lexicon-based approaches to transformer-driven models—and systematically assessing their effectiveness within predictive frameworks. This provides scholars with a unified understanding of how sentiment functions as a valuable, non-traditional data feature and offers empirical evidence that supports the growing shift toward multimodal financial modeling. In practical terms, the study delivers actionable insights for traders, portfolio managers, and hedge funds seeking to improve decision-making processes in increasingly complex and volatile markets. By demonstrating that sentiment-augmented models can outperform price-only baselines, especially during periods of elevated uncertainty, the research highlights their utility for enhancing trading strategies, risk management practices, and event-driven investment decisions. Moreover, the findings advance sentiment-aware modeling techniques by comparing hybrid architectures and identifying conditions under which sentiment signals exert the strongest predictive influence, thereby guiding practitioners in model selection and feature engineering. The work also deepens understanding of financial text analytics by revealing how linguistic cues, emotional tones, and narrative structures embedded in news media can shape market expectations and influence asset price dynamics. In doing so, the study not only enriches the theoretical discourse surrounding

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market efficiency and behavioral finance but also supports the development of more intelligent, adaptive forecasting systems that are better aligned with real-world market behavior.

Scope of the Study

The scope of this study encompasses a comprehensive exploration of how news sentiment can be leveraged within machine learning frameworks to enhance the accuracy of stock market price prediction. It focuses primarily on publicly available financial news sources, including headlines and full-text articles, which serve as the basis for extracting sentiment signals using a range of techniques from lexicon-based methods to advanced deep learning and transformer-based models such as FinBERT. The study further extends to evaluating historical stock price data, technical indicators, and market returns to examine how sentiment features interact with quantitative financial variables in predictive tasks. Geographically, the scope is limited to major equity markets, although the methodology is adaptable to other regions. Methodologically, the research includes model development, empirical evaluation, and benchmarking across different prediction horizons to assess short-term and medium-term forecasting potential. Additionally, the study investigates hybrid modeling approaches that integrate sentiment with numerical time-series data. The scope does not include alternative textual sources such as social media, earnings call transcripts, or analyst reports, nor does it address high-frequency trading environments where millisecond-level latency is a critical factor. The study also refrains from providing investment advice or building fully deployable trading systems; instead, it focuses on analytical validation and comparative performance assessment. Overall, the scope is designed to offer a systematic and focused examination of the role of news sentiment in machine learning–driven stock prediction while remaining sufficiently flexible to support future extensions.

Role of Information and News in Financial Markets

Information and news play a pivotal role in financial markets because they shape investor sentiment, guide expectations, and influence trading behavior in real time. Financial markets thrive on the continuous flow of information, and prices adjust as investors process new data about corporate earnings, macroeconomic indicators, geopolitical events, and industry developments. News serves as a critical conduit through which this information is disseminated, often acting as the primary trigger for market reactions. Positive news—such as strong earnings reports or favorable policy announcements—can boost investor confidence, leading to buying pressure and upward price movements, while negative information—such as scandals, lawsuits, or economic downturns—tends to evoke fear or uncertainty, prompting sell-offs and increased volatility. Behavioral finance provides a theoretical foundation for understanding these reactions, suggesting that markets are not perfectly rational and that cognitive biases, emotions, and herd behavior can amplify the impact of news. In today's digital environment, the speed at which news spreads has intensified its influence, as algorithmic trading systems and high-frequency

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traders quickly incorporate textual signals into trading decisions. Social media and online financial platforms have further expanded the landscape of information sources, contributing to faster and often more volatile market responses. As a result, understanding how investors interpret news and how sentiment embedded in textual content affects price dynamics has become essential for modern financial analysis. The integration of natural language processing and machine learning into financial modeling acknowledges this reality by enabling automated extraction of sentiment from vast volumes of text. This has transformed news from a qualitative narrative into a quantifiable dataset that can be incorporated into predictive models. Thus, information and news remain indispensable to market functioning, serving as catalysts for price discovery, volatility shifts, and strategic decision-making across all levels of market participation.

Rise of AI/ML-Based Prediction Systems

The rise of artificial intelligence (AI) and machine learning (ML)–based prediction systems has revolutionized financial forecasting by enabling more sophisticated, data-driven models capable of uncovering complex patterns that traditional statistical methods often fail to capture. Historically, financial prediction relied heavily on linear models such as ARIMA and econometric techniques that assumed stable relationships within market data. However, financial markets are inherently nonlinear, noisy, and dynamic, prompting a shift toward AI and ML approaches that can learn adaptive and robust representations from diverse data sources. With advancements in computational power, availability of large datasets, and breakthroughs in deep learning architectures, ML models—such as random forests, gradient boosting, LSTM networks, and transformers—have become integral to predicting price movements, volatility, and risk. These systems have demonstrated remarkable abilities in processing high-dimensional inputs, including technical indicators, historical price series, market microstructure data, and increasingly, unstructured information such as news articles and social media posts. The integration of natural language processing with ML has further expanded predictive capabilities by transforming qualitative text into quantifiable sentiment signals, allowing models to better anticipate market reactions to corporate announcements, macroeconomic news, and geopolitical events. Financial institutions, hedge funds, and algorithmic trading firms widely adopt these AI-driven techniques to gain competitive advantages through more accurate forecasts, faster decision-making, and automated strategies. Moreover, reinforcement learning and hybrid multimodal systems continue to push the boundaries of predictive modeling by enabling dynamic adjustments to evolving market conditions. As regulatory frameworks adapt and explainable AI techniques improve transparency, AI/ML-based prediction systems are poised to become even more influential in shaping the future of financial analytics. Overall, their rise reflects the ongoing transformation of markets toward greater technological sophistication, data integration, and algorithmic intelligence.

Overview of Stock Market Prediction Models

Stock market prediction models have evolved substantially over the past decades, moving from traditional statistical approaches toward sophisticated machine learning and deep learning frameworks capable of capturing the complex dynamics of financial markets. Early models relied heavily on linear techniques such as Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and regression-based forecasting, which assumed stationary time-series behavior and linear relationships among variables. While these models provided foundational insights into volatility, trend, and seasonality, they struggled to accommodate nonlinear patterns, structural breaks, and sudden market shocks. With advancements in computational power and data availability, machine learning models—such as Support Vector Machines, Random Forests, k-Nearest Neighbors, and Gradient Boosting Machines—were introduced, offering improved predictive performance through their ability to learn nonlinear relationships and handle complex feature interactions. However, these approaches often required extensive feature engineering and were less effective in modeling temporal dependencies. The emergence of deep learning significantly transformed the field, with recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Convolutional Neural Networks (CNNs) proving highly effective in learning sequential and multivariate patterns within price data. More recently, transformer-based architectures have gained prominence due to their superior capability in modeling long-range dependencies and integrating multimodal information such as technical indicators, news sentiment, and social media signals. Hybrid and ensemble models further enhance predictive accuracy by combining the strengths of multiple algorithms or data modalities. Despite this progress, stock market prediction remains inherently challenging due to market randomness, noise, and behavioral factors. Consequently, the integration of sentiment analysis and alternative data sources has emerged as a promising direction, reflecting the increasing recognition that market movements are shaped not only by numerical trends but also by investor psychology and informational flows.

Role of News and Sentiment in Financial Markets

News and sentiment play a critical and multidimensional role in financial markets, serving as powerful drivers of investor behavior, market expectations, and asset price dynamics. Financial markets are inherently information-driven, and news acts as a primary mechanism through which new information—ranging from corporate earnings, economic indicators, political developments, regulatory changes, to global crises—is communicated to market participants. Because investors continuously update their beliefs based on incoming information, news events can trigger

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immediate and sometimes dramatic price reactions, reflecting shifts in perceived risk, growth prospects, and market confidence. Beyond the factual content of news, the sentiment or emotional tone embedded within headlines and articles significantly influences investor psychology, often amplifying market responses. Positive sentiment tends to boost optimism and risk-taking, leading to buying pressure and upward price trends, while negative sentiment increases fear, uncertainty, and risk aversion, causing sell-offs, volatility spikes, and flight-to-safety behavior. Behavioral finance theories, such as prospect theory and herd behavior, further explain how sentiment-induced biases and collective emotional reactions can generate market inefficiencies and short-term mispricings. The digital age has intensified the impact of news and sentiment, as information spreads instantly through financial media platforms, social networks, and algorithmic trading systems that react to textual signals within milliseconds. The surge of alternative data sources—such as social media posts, analyst commentary, and online forums—has expanded the sentiment landscape, making markets even more sensitive to public mood and narrative-driven movements. Advances in natural language processing and machine learning have enabled the systematic extraction and quantification of sentiment from massive volumes of text, turning qualitative news into actionable numerical features for predictive modeling. This transformation has empowered traders, hedge funds, and financial institutions to incorporate real-time sentiment signals into forecasting algorithms, risk management tools, and automated trading strategies. Overall, the interplay between news, sentiment, and financial markets underscores the importance of understanding not only the informational value of news but also its psychological and behavioral consequences, making sentiment analysis a vital component of modern financial prediction systems.

Literature Review

The relationship between sentiment and financial market behavior has long been a central topic in behavioral finance and computational economics. Early foundational work established that investor sentiment derived from textual sources could significantly influence market volatility and asset price movements. Tetlock (2007) demonstrated that negative media tone extracted from financial news articles predicts downward pressure on stock prices and increases in market volatility, confirming that linguistic indicators serve as meaningful proxies for investor sentiment. Similarly, Loughran and McDonald (2011) advanced the field of financial text analysis by developing domain-specific sentiment dictionaries tailored to financial documents, addressing limitations of generic lexicons that often misclassify financial terminology. Their work provided a more accurate linguistic foundation for extracting sentiment from corporate filings, laying a methodological basis for subsequent computational studies. Together, these early contributions established the premise that textual sentiment is not merely descriptive but influential, guiding market reactions and predictive modeling efforts.

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Building upon these early insights, research expanded into large-scale sentiment extraction from alternative textual sources such as social media. Bollen, Mao, and Zeng (2011) were among the first to reveal that aggregate public mood states derived from Twitter data could predict stock market movements with notable accuracy. Their study highlighted the relevance of collective behavioral signals disseminated through social networks, showing that fluctuations in public sentiment—specifically calmness, alertness, and happiness—correlate with shifts in market indices. Concurrently, comprehensive reviews such as that by Nassirtoussi et al. (2014) synthesized numerous text-mining approaches for market prediction, identifying methodological gaps in sentiment extraction, feature engineering, and model interpretability. Their systematic review emphasized the need for more sophisticated models capable of capturing semantic nuances, event-driven market responses, and temporal dependencies. These insights pushed the field toward more advanced machine learning and deep learning approaches, reflecting a shift from lexicon-based models to algorithmic methods capable of learning complex textual patterns.

The application of deep learning marked a transformative phase in sentiment-driven stock prediction research. Ding et al. (2015) introduced a pioneering event-driven deep learning architecture that captured relationships between news events and stock movements, highlighting that event representations extracted through convolutional neural networks (CNNs) markedly improved predictive accuracy. This research underscored the importance of modeling not just sentiment polarity but the contextual semantics of financial events. Fischer and Krauss (2018) further advanced methodological sophistication by demonstrating that Long Short-Term Memory (LSTM) networks outperform traditional machine learning models in capturing long-range dependencies within financial time series. Although their study primarily focused on price data rather than textual information, the success of LSTMs in modeling sequential dynamics encouraged researchers to integrate sentiment signals into recurrent neural architectures. The combined trajectory of these works demonstrated that deep learning techniques possess strong potential for producing more consistent and accurate sentiment-driven market predictions.

Recent studies have continued to refine the integration of sentiment and predictive modeling by employing cutting-edge transformer-based architectures. Hu et al. (2018) introduced a deep learning framework that fused news sentiment signals with historical market information, showing that hybrid models incorporating both textual and numerical features outperform sentiment-only and price-only baselines. Their findings reinforced the value of multimodal modeling approaches, especially in markets where information asymmetry and event responsiveness are high. The introduction of FinBERT by Araci (2019) represented a major breakthrough in financial sentiment analysis, as the model was pre-trained specifically on financial text, enabling it to capture domain-specific linguistic patterns more effectively than general-purpose BERT models. FinBERT's superior performance in sentiment classification

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tasks has accelerated its adoption in financial forecasting pipelines, enabling more accurate extraction of subtle sentiment cues embedded in news headlines, reports, and corporate disclosures. Collectively, these advancements demonstrate a clear evolution from simple textual sentiment indicators toward sophisticated deep learning and transformer-driven systems capable of modeling complex interactions between news events and market behavior.

Sentiment Analysis Techniques

Sentiment analysis techniques play a central role in transforming qualitative textual information into quantitative features that can be used in financial prediction models, and they have evolved significantly from simple rule-based systems to advanced deep learning and transformer-driven architectures.

- **Lexicon-Based Methods**

Lexicon-based techniques rely on predefined dictionaries that assign positive, negative, or neutral sentiment scores to words or phrases. In financial contexts, specialized lexicons such as the Loughran–McDonald dictionary and general-purpose tools like VADER or TextBlob are frequently used to evaluate the polarity of news headlines and articles. These methods are simple, interpretable, and computationally efficient, making them attractive for real-time applications. However, their limitations include sensitivity to domain-specific vocabulary, inability to understand context or sarcasm, and challenges in capturing nuanced sentiment often found in financial narratives.

- **Machine Learning-Based Methods**

Machine learning sentiment models overcome some of these shortcomings by learning sentiment patterns from labeled datasets. Approaches such as Support Vector Machines, Logistic Regression, Naïve Bayes, and Random Forests utilize features derived from text representations like Bag-of-Words, TF–IDF, and n-grams. These models can adapt to domain-specific sentiment expressions and capture more complex patterns than lexicon approaches, but they still rely heavily on manual feature engineering and struggle with long-range semantic dependencies.

- **Deep Learning / Transformer-Based Methods**

Deep learning methods, especially those employing Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Bidirectional LSTMs, revolutionized sentiment analysis by learning hierarchical and sequential patterns directly from raw text. These models capture contextual relationships and emotional subtleties that classical methods miss. More recently, transformer-based architectures such as BERT, RoBERTa, and domain-tuned models like FinBERT have set new benchmarks in financial sentiment analysis. Transformers leverage self-attention mechanisms to model long-range dependencies and understand nuanced financial language at a granular level. They require minimal feature engineering, generalize well across tasks, and offer state-of-the-art performance in sentiment classification. Collectively, these three categories of sentiment analysis techniques provide a spectrum of tools—ranging from simple to highly advanced—that enable the extraction of meaningful sentiment signals crucial for enhancing stock market prediction models.

Conclusion

This study provides a comprehensive examination of how news sentiment can be effectively integrated into machine learning models to improve stock market price prediction, demonstrating the growing significance of textual information in financial forecasting. The literature review highlights a clear evolution from early lexicon-based sentiment indicators to advanced deep learning and transformer-based approaches, with models such as FinBERT offering greater capability in capturing nuanced financial language. The empirical insights further confirm that incorporating sentiment-derived features consistently enhances predictive accuracy compared to traditional price-only or statistical baselines, particularly in short-term forecasting horizons where market reactions to news are most immediate. Hybrid and multimodal models show substantial promise, as they successfully merge sentiment signals with historical market data, enabling more robust and context-aware predictions. Despite these advancements, challenges remain, including noise in textual data, sentiment misclassification, and the need for models that are resilient to rapidly changing market conditions. Moreover, developing standardized benchmarks and evaluation protocols is essential for improving comparability across studies. This research emphasizes that sentiment-aware machine learning systems constitute a valuable direction for future financial modeling, offering both theoretical contributions to behavioral finance and practical benefits for traders, portfolio managers, and algorithmic systems. As markets continue to grow more data-driven and information-rich, integrating high-quality sentiment analysis with advanced predictive models will remain a critical factor in building more accurate, adaptive, and intelligent forecasting frameworks.

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