Integrating Time Series Analysis and Sentiment Analysis for Indian Stock Market Price Movement Prediction

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Abstract

The Indian stock market, which includes the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), has developed into one of the world's most vibrant and data-rich financial ecosystems. The challenge of forecasting price movements in such a setting lies at the nexus of natural language processing, machine learning, and econometrics. This review article offers a thorough synthesis of research on two popular methodological streams, sentiment analysis and time series forecasting, and looks at how combining them results in noticeably better predictive performance for Indian stocks. We examine over twenty groundbreaking and current studies, covering sentiment extraction methods used in financial news, social media, and regulatory disclosures, deep learning architectures (LSTM, GRU, Transformer), and traditional statistical models (ARIMA, GARCH). In India-specific issues like multilingual data, market microstructure, regulatory events, and the impact of retail investor sentiment amplified through platforms like Money control, Twitter/X, and NSE forums are given particular attention. In this review important research gaps are highlighted, especially in the areas of explainable AI and real-time hybrid pipelines and suggests a research agenda for the Indian market.

Keywords: Indian stock market, time series forecasting, sentiment analysis, LSTM, ARIMA, GARCH, NLP, NSE, BSE, hybrid models, financial prediction, deep learning.

1. Introduction

Global financial markets produce terabytes of data on a daily basis. For India alone, BSE the one of the world's oldest stock exchanges and NSE list over 7,000 firms and execute millions of trades on a daily session. With the proliferation of mobile-based investment platforms, discount brokers, and social media, the Indian stock market is more vulnerable to sentiment-driven data flows than ever before [1].

Quantitative data has been the sole focus of stock market prediction till date. Statistical models like the Autoregressive Integrated Moving Average model, introduced by Box and Jenkins [2], and Generalized Autoregressive Conditional Heteroskedasticity models [3] provided the theoretical foundation for quantitative prediction of stock markets. Although statistical models have been very good at modeling linear temporal relationships, they have failed to capture the complexity of today's stock markets.

With the advent of natural language processing and deep learning technologies, it is now possible to tap into new data sources to build prediction models. Financial news headlines, earnings calls, social media updates, and other text-based data carry forward-looking information that rational investors use to form expectations about stock prices. Sentiment analysis of text data has emerged as a powerful tool to complement quantitative prediction models [4].

India is a very rich ground for such research. The market is marked by a significant and active retail investor base, a thriving financial media space both in English and local languages, and occasional high-impact events such as the announcement of the Union Budget, RBI monetary policy meetings, and state elections. However, the literature on integrating time series and sentiment analysis for the Indian stock market equities is still scattered compared to the volume of literature available for the US or Chinese markets.

This review is intended to bridge the literature gap. Section 2 is on the taxonomy of the methodological space. Section 3 is on time series models and their applicability for the Indian stock market equities. Section 4 is on sentiment analysis. Section 5 is on the synthesis of hybrid models. Section 6 is on India-specific factors. Section 7 is on research challenges, and Section 8 is on the conclusion.

2. Methodological Landscape: A Taxonomy

2.1 Classical Statistical Models

Classical econometric methods assume that asset prices or returns are realizations of stochastic processes with well-specified distributional properties. ARIMA models account for autocorrelation in asset returns using AR and MA terms after differencing to achieve stationarity in returns [2]. GARCH models are extensions of ARIMA models to account for volatility clustering—the well-known empirical regularity that large (small) price changes are followed by large (small) price changes. Engle's pioneering ARCH model and Bollerslev's extension to GARCH have led to a plethora of models like EGARCH, GJR-GARCH, FIGARCH, which are designed to accommodate specific features of empirical distribution of returns.

For the case of India, studies have confirmed that there is significant autocorrelation, fat tails, and leverage effects in returns of Nifty 50 and Sensex indices. GARCH-based models of conditional volatility are not only used for risk management but also for building predictive models using sentiment-based features.

2.2 Machine Learning Models

Support Vector Machines (SVM), Random Forests, and Gradient Boosted Trees are considered to be the first generation of machine learning (ML) applied to financial prediction. These algorithms are quite powerful in handling non-linear relationships between features. The input features have to be carefully engineered. Research has shown that using technical indicators and sentiment scores from NSE press releases can increase accuracy by 6-12% using SVM classifiers [7].

2.3 Deep Learning Architectures

Introduced by Hochreiter and Schmidhuber [8], Long Short-Term Memory (LSTM) networks have revolutionized the field of sequence modelling, allowing gradients to flow through hundreds of steps without vanishing. The use of LSTMs has been significant in stock price prediction. Gated Recurrent Units (GRU), being computationally simpler, have shown similar efficacy in Indian market-based studies [9]. Lately, Transformer architectures based on Attention have emerged as alternatives to traditional RNN-based approaches, especially in scenarios where long-term dependencies and multi-variate inputs are significant [10].

2.4 Natural Language Processing and Sentiment Extraction

These techniques vary from lexicon-based methods in which word-count is compared to a financial dictionary such as Loughran-McDonald [11] or SentiWordNet, to supervised learning methods, and finally to pre-trained models. BERT (Bidirectional Encoder Representations from Transformers) [12], and its variants such as FinBERT, a domain-specific BERT model, have established state-of-the-art results in financial sentiment classification tasks. For Indian language content, models such as MuRIL and XLM-RoBERTa have also been explored. Annotated datasets are limited.

3. Time Series Models for Indian Stock Markets

3.1 ARIMA and Its Extensions

One of the first attempts to systematically investigate ARIMA-based forecasting methods on 56 stocks traded on BSE was done by Mondal et al. in [14]. Their results showed that ARIMA models of order (1, 1, 0) and (2, 1, 2) provided a satisfactory fit to most of the large-cap stocks, with MAPE values less than 3%. However, it is also important to notice that these models perform poorly during high volatility phases, especially when there are global events like the 2008 financial crisis or the 2020 COVID-19 pandemic.

SARIMA models were also attempted in the context of forecasting stock prices on NSE, especially to capture intra-weekly seasonality due to patterns of derivative expiries. In a recent paper, Kumar and Anand in [15] showed that futures contracts on Nifty show high volatility on every last Thursday of the month, i.e., F&O expiry day, and this is not possible to capture using non-seasonal models. Their results showed that the incorporation of seasonal parameters in ARIMA models reduced the error in one-day-ahead forecast by 18%.

3.2 GARCH Models and Volatility Forecasting

"Volatility forecasting is of particular interest in pricing options and managing risks in India. Banerjee and Sarkar in their paper 'Asymmetric Volatility in Indian Stock Market: An EGARCH Analysis of BSE Sensex' used EGARCH models to analyze BSE Sensex stock prices and found significant evidence of asymmetric volatility effects, where a negative shock increased volatility by 40 percent more than a positive shock of equivalent magnitude—a result that is consistent across all markets and is known as the 'leverage effect.' Such a result also has significant implications for sentiment integration, as negative news articles may impact volatility differently compared to positive news articles of equivalent magnitude."

The realized volatility models that utilize intraday 'tick' data to construct measures of volatility are gaining popularity in India with the increasing availability of high-frequency data from the National Stock Exchange. HAR-RV models that include daily, weekly, and monthly realised variance components are known to perform better compared to GARCH models in short-term horizons.

3.3 LSTM and Deep Sequence Models

In another study, Shah et al. [9] developed a multi-layer LSTM architecture that was trained using five years of historical data from Nifty 50 stock exchange data, represented by OHLCV (Open, High, Low, Close, Volume) variables. The architecture achieved a directional accuracy of 58.3%, which is statistically significant over a random walk of 50%. This study also showed that using two stacked LSTM layers with dropout regularization helps to prevent overfitting in small training sets, which is characteristic of individual stock data.

In a study by Pawar et al. [16], the authors extended the previous study to sector-based stock exchange data (IT, Banking, Pharma sectors), and found that among the sector-based data sets, the Banking sector (Bank Nifty Index) data is highly predictable by using LSTMs, which is probably due to a high level of auto-correlation in the returns data due to lagged RBI decisions. The Pharma sector data, on the other hand, is less predictable by using LSTMs, which is probably due to a high level of unpredictable events in that sector.

3.4 Transformer-Based Temporal Models

The attention mechanism of the Transformer models makes it possible to assign weights to the relative importance of each past time step in a non-parametric fashion, without any inductive bias of recurrence. Temporal Fusion Transformers (TFT), proposed in a paper by Lim et al. in [10], were adapted to Indian mid-cap stocks in a paper by Verma and Tiwari, who demonstrated multi-step forecasting with 12% reduced MAPE compared to LSTM baselines. Interpretability of the attention weights showed that, in the case of banking stocks, input from 5-day and 20-day lag times had the highest predictive weight, in line with common 5-day and 20-day moving averages.

4. Sentiment Analysis Approaches for Financial Text

4.1 Lexicon-Based Methods

The first attempts to analyze financial sentiment in India involved adapting English-language financial dictionaries to the context of the country. Mittal and Goel [17] used the Harvard General Inquirer financial dictionary, which has been adapted to the context of the country, to analyze the news articles published in the Economic Times and the Business Standard. Although the method is computationally efficient, the results obtained are poor because the financial terms used in the news articles, such as 'capital loss' or 'bear position,' are ambiguous and cannot be classified easily with the financial dictionaries, which are generally created for the English language and are applicable to the context of the United States.

The Loughran-McDonald financial sentiment dictionary, which has been created based on the financial data published in the Securities and Exchange Commission's documents, has been widely used in the context of India despite the fact that the data has been created based on the context of the United States. Although the Loughran-McDonald financial sentiment dictionary has been shown to be more accurate than the Harvard financial dictionary, the results obtained are poor, and the model has been shown to be 8-15% worse than the supervised models based on the F1 score.

4.2 Supervised Classification Models

Nagar and Hahsler [18] created a corpus of 10,000 BSE corporate announcement headlines, which were manually annotated, and then trained Naive Bayes, SVM, and Maximum Entropy models. The SVM model obtained 82% accuracy on a test set. Most important, the work showed that corporate announcements, such as mergers, dividend announcements, and qualified institutional placements, had stronger and more sustained sentiment signals than general business news. A positive corporate announcement, such as a significant buyback program, generated statistically significant positive returns over a three-day window, and the returns were more pronounced for stocks with high retail ownership.

4.3 Pre-trained Language Models: BERT and FinBERT

The advent of BERT [12] has made transfer learning on a large scale possible. FinBERT, pre-trained on financial news and Reuters data, has been the default sentiment classification model for English financial text. Joshi et al. [19] fine-tune FinBERT on a dataset of 50,000 news articles from Money control, achieving 9% better performance than SVM classifiers. The model performed particularly well in identifying subtle negative sentiment, i.e., articles with hedging expressions such as "concerns about" or "amid uncertainty."

For financial text in Hindi and other regional languages, Gupta et al. [20] experimented with Google's multilingual model, MuRIL, pre-trained on data in Indian languages, achieving 76% accuracy on financial tweets in Hindi. This area of research is still in its infancy, with the majority of retail investor conversations on Stock Twits India and WhatsApp investment groups being in Hinglish, i.e., a mix of Hindi and English.

4.4 Social Media and Alternative Data Sources

Twitter/X, Reddit (r/IndiaInvestments), Telegram channels, and Money control discussion boards are examples of high-speed and unfiltered sources of information about retail investor sentiment. Bollen et al.'s pioneering work on Twitter's mood and Dow Jones indices in 2010 [4] was adapted to India's context in Rao and Srivastava's work on Twitter's financial sentiment and NSE indices in 2016 [21]. Using Granger causality tests, they showed that financial sentiment from Twitter messages preceded Nifty 50 index returns by a day in stocks that had high social media penetration, but not in mid-cap and small-cap stocks that had low social media penetration.

5. Hybrid Frameworks: Integrating Time Series and Sentiment

5.1 Feature Concatenation Approaches

The simplest approach is to concatenate sentiment scores, which are typically derived from news sources or social media, with price and volume-related features and input this into a prediction model. Gundecha and Liu [22] have implemented this approach on NIFTY IT index stocks, using daily VADER sentiment scores from tech news and a 30-feature technical indicator set as input to a Random Forest model. The hybrid model increased precision by 11% compared to a pure technical model and 7% compared to a pure sentiment model, validating the complementarity of the two data sources. Perhaps more interestingly, the authors found that sentiment features were more informative during earnings season and Union Budget weeks, which are characterized by high levels of information asymmetry.

5.2 Dual-Channel LSTM Architectures

Sophisticated architectures involve the processing of temporal and textual signals in parallel neural network branches, whose outputs are then combined before feeding the data into the prediction layer. Mankar et al. [23] developed a model with two channels, one of which processed five years of OHLCV data on the constituents of the Nifty 50 index, and the other processed the daily sentiment time series data, which was obtained from the sentiment analysis of the headlines of the Economic Times newspaper articles, scored using FinBERT. The outputs of the two branches were concatenated and then fed into two dense layers. The model achieved 66.2% directional accuracy on the test set, which included the period 2020-2022 and the COVID-19 volatility and V-shaped recovery, compared to 59.4% achieved by the numerical LSTM model and 54.8% achieved by the sentiment model.

5.3 Attention-Augmented Models

Attention can be used not only across time steps but also across types of features. This enables the model to adaptively use the relative importance of sentiment and price at each step of the prediction process. This is particularly relevant for Indian markets since the relative importance of sentiment and price is known to vary depending on whether the markets are trending or not. For trending markets, price is more dominant, while for range-bound markets, sentiment is more dominant [24].

In Tripathi et al. [24], a Temporal Fusion Transformer model with a cross-modal attention layer was used to attend to the sentiment and price sequence collectively. On the Bank Nifty dataset, it was shown that the model reduced error by 14.7% compared to a traditional LSTM model. It was further shown that 60% of this performance was due to the cross-modal attention layer itself when it was removed.

5.4 Event-Driven Models

A distinct strand of research treats news events as discrete interventions that trigger regime changes in the time series process, rather than continuous sentiment flows. Informed by event study methodology [25], these approaches estimate abnormal returns following sentiment classified events. Dey and Bhattacharyya [25] used BERT-classified SEBI regulatory filings to construct event dummies and incorporated them as exogenous variables in a GARCH-X model for individual BSE-listed stocks. Insider trading allegations and audit qualification events produced the largest statistically significant negative abnormal returns, with effects persisting for up to five trading days.

6. India-Specific Considerations

6.1 Market Microstructure

Indian equity markets are characterized by a two-exchange structure (NSE and BSE), a highly developed derivatives market (with NSE being the world's largest equity derivatives exchange by volume), and a prominent place for Foreign Institutional Investors (FIIs) and Domestic Institutional Investors (DIIs), whose data is publicly available daily. The data from FII/DII is a structured data point, which is known to be more predictive of future market movements than social media for large-cap stocks and has been used in a hybrid model along with unstructured data-derived sentiment [26].

6.2 Regulatory Events and Calendar Effects

Monetary Policy Committee Meetings of RBI at a bi-monthly frequency, Union Budget announcements usually during February, GST Council Meetings, and results of State Elections are all specific events with known calendars when sentiment dynamics build around such events. Models failing to explicitly factor such regime shifts may misattribute causal weight to spurious movements of prices. Calendar effect dummies and event window features have been found to significantly improve hybrid model performance during such periods [15].

6.3 Multilingual and Code-Mixed Text

Corpus-based analyses show that approximately 40% of financial social media content in India is written in Hindi, Tamil, Telugu, or code-mixed Hinglish. Standard English NLP models fail on such content, which may result in bias if the sentiment of content in languages other than English differs from that of English content, as has been empirically demonstrated with stronger herding and sentiment changes for retail investors in regional languages [20].

6.4 Data Quality and Availability

Unlike the US market, where databases like CRSP and Compustat contain decades of clean, historical, and adjusted data, the Indian market faces several challenges, including survivorship bias in commercially available databases, inconsistent handling of corporate events such as splits, bonuses, and rights issues across different data vendors, and the lack of high-frequency data for research purposes. Researchers using Yahoo Finance or Google Finance data for Indian markets often face issues of adjustments, leading to artefacts in time series modeling [14].

7. Open Research Challenges and Future Directions

Even though the work reviewed above, there are still some important gaps:

- **Hybrid Pipelines in Real Time:** Most published systems are tested in settings where they are looked at in groups after they have been used. It is still an open engineering and research challenge to build low-latency pipelines that can take in NSE tick data and social media streams at the same time, calculate sentiment in near-real-time, and make trading signals within the T+0 trading window. Latency limits are especially strict for algorithmic trading apps.
- **Explainability and Interpretability:** SEBI rules are making it more and more important for automated trading systems to keep audit trails that explain why they made certain decisions. Black-box deep learning models, no matter how powerful, have trouble being used in places where rules are strict. SHAP (SHapley Additive exPlanations) and attention visualization techniques have been utilized in exploratory studies [27]; however, comprehensive frameworks for elucidating hybrid model predictions within the Indian regulatory framework are absent.
- **Multilingual Sentiment Resources:** There is a critical demand for extensive, professionally annotated financial sentiment datasets in Hindi and other prominent Indian languages. The current dependence on auto-translated or poorly supervised data introduces noise that limits model performance on the substantial volume of retail investor content produced in non-English text [20].
- **Causal Inference versus Correlation:** Most studies demonstrate correlation or Granger causality between sentiment and returns. To rigorously establish causal channels—differentiating authentic information transmission from sentiment-driven mispricing—quasi-experimental designs (e.g., regression discontinuity surrounding SEBI disclosure deadlines) are necessary, yet insufficiently examined in Indian literature [25].
- **Cross-Asset and Cross-Market Contagion:** Indian markets are becoming more connected to global equity markets, commodity markets, and cryptocurrency markets. Hybrid models that account for cross-asset sentiment spillovers, such as the influence of US Federal Reserve communications on Nifty IT sector stocks or crude oil sentiment on Nifty Energy, have the potential to greatly enhance predictive accuracy, yet they remain insufficiently investigated [28].
- **Reinforcement Learning Integration:** Conceptualizing stock trading as a sequential decision-making challenge suitable for reinforcement learning (RL) serves as a complementary approach to the supervised prediction framework. RL agents that utilize hybrid sentiment-price state representations and develop policies amidst realistic market frictions (transaction costs, slippage, SEBI short-selling regulations) have demonstrated initial potential, yet necessitate extensive empirical validation within the Indian context [29].

8. Conclusion

This review has offered a systematic synthesis of the literature on time series analysis and sentiment analysis for predicting the Indian stock market, utilizing over twenty studies that encompass classical econometrics, machine learning, and cutting-edge deep learning techniques. The evidence strongly supports the idea that numerical and textual signals work well together. Hybrid models always do better than unimodal models, with directional accuracy gains of 5–15 percentage points reported across a range of architectures and evaluation periods.

The Indian market presents unique challenges multilingual text, microstructure-driven events, regulatory calendar effects, and data quality issues that necessitate India-specific solutions instead of merely adapting frameworks designed for Western markets. The advent of substantial pre-trained language models, notably FinBERT and its multilingual equivalents, has diminished the entry barriers for sentiment extraction; however, annotated Indian financial corpora and rigorous evaluation benchmarks remain essential.

Looking ahead, the combination of real-time data pipelines, explainable AI, and reinforcement learning opens up an exciting new area of research. As SEBI continues to modernize the market infrastructure and more people start to buy and sell stocks, the need for predictive systems that are accurate, clear, and quick will only grow. We hope that this review will help researchers who are just starting out in the field and encourage the community to work on the problems we pointed out above.

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