



Stock Market Prediction Using Machine Learning: Techniques, Challenges, and Future Directions

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Abstract

The continuous advancement of machine learning (ML) technologies has significantly transformed the field of financial forecasting, particularly in the area of stock market prediction. The ability to accurately forecast stock price movements and market trends plays a crucial role in supporting informed investment strategies and effective risk management. This paper provides a comprehensive review of recent developments in the application of ML techniques for predicting stock market behavior. It classifies the various ML approaches used in this domain and explores the growing importance of alternative data sources, such as financial news, social media sentiment, and market-related textual information, in enhancing prediction accuracy. In addition, the study presents a comparative assessment of different ML models based on their performance in real-world forecasting scenarios. It highlights several major challenges faced in stock market prediction, including the nonstationary nature of financial data, the risk of model overfitting, limited interpretability of complex algorithms, issues related to data reliability, and practical economic constraints. These factors often limit the effectiveness and applicability of ML models in financial decision-making. The paper concludes by outlining potential future research directions aimed at developing more reliable, interpretable, and economically practical ML models that can better support decision-making processes in the financial sector.

Keywords: Financial time series, machine learning, model interpretability and robustness, sentiment, and alternative data, stock market forecasting

INTRODUCTION

The global stock market is characterized by complexity: high volatility, noisy data, and multiple influencing factors (macro, micro, sentiment, and policy). Traditional statistical and econometric models (ARIMA (Autoregressive integrated moving average), GARCH (Generalized autoregressive conditional heteroskedasticity), etc.) have been successful in modeling trends and volatility; however, they often struggle with nonlinearity, high dimensionality, and rapidly changing conditions.

Machine learning (ML) and deep learning (DL) offer tools to address these issues by learning patterns from large-scale data, automatically extracting features, and integrating varied data sources. Figure 1 shows a survey of alternative data and hybrid approaches.

The objective of this paper is to present a coherent survey of ML methods in stock market forecasting, discuss the latest results and findings, highlight associated challenges, and propose future paths toward more practical and trustworthy systems. While many studies focus on technical indicators and historical prices, this paper focuses on alternative data (sentiment, news) and hybrid approaches.

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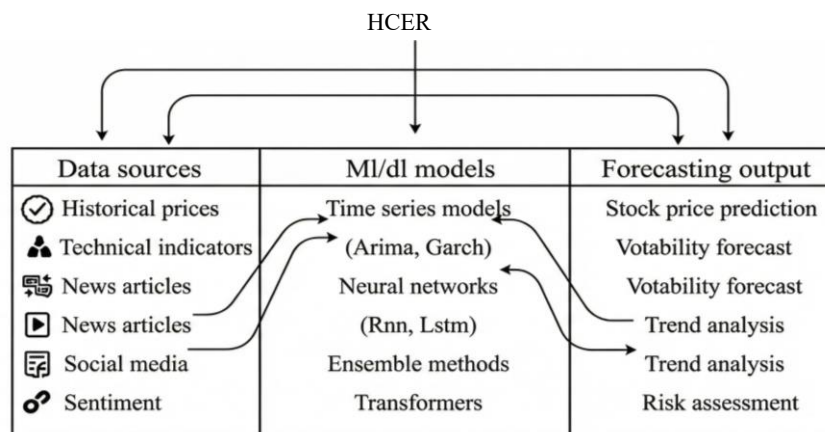


Figure 1. A Survey on alternative data and hybrid approaches.

RELATED WORK AND LITERATURE REVIEW

Reviews and Surveys

A recent review by Saberironaghi, Ren, and Saberironaghi (2025) [1] provides a comprehensive analysis of ML and DL approaches for stock market prediction, focusing on methodology, datasets, and evaluation metrics. Another important work is “Critical Review of Text Mining and Sentiment Analysis for Stock Market Prediction” [2], which analyzed approximately 260 articles and distilled findings about the use of textual data, sentiment extraction methods, and the generalizability of results [3].

Techniques Using Sentiment and Alternative Data

- The HiSA SMFM model integrates historical price data with news-based sentiment, employing long short-term memory (LSTM) architectures to jointly learn temporal and sentiment patterns [4].
- In Stock Price Prediction using Sentiment Analysis and DL for Indian markets, historical price series are used alongside macroeconomic variables (oil, gold, and US dollar exchange rates) and sentiment data to improve predictions [5].
- Indian stock market prediction uses augmented financial intelligence ML test models, including CNN-LSTM, GRU, and bi-LSTM, which are augmented with human superforecaster inputs and natural language processing (NLP) tools [6].

ML/DL Models in Use

Common models across literature include:

- *Tree-based and ensemble methods*: Random Forests, XGBoost.
- *Recurrent neural networks (RNNs)*: LSTM, GRU.
- *Hybrid models*: combining LSTM (or other DL) with sentiment or other external features.
- *Deep architectures*: CNN-LSTM, attention-based networks, and transformer models.
- *Nontraditional inputs*: textual data (news, social media), macroeconomic indicators, sentiment, and events.

Figure 2 shows the models used for stock price forecasting.

Metrics and Datasets

Key evaluation metrics:

- *Regression metrics*: RMSE (root mean square error), MAE (mean absolute error), MAPE.
- *Classification metrics (if predicting direction)*: Accuracy, precision, recall, and F1 score.
- *Economic/trading metrics*: Sharpe ratio, cumulative return, and maximum drawdown.
- Time horizon is important (1-day ahead, 5-day ahead, longer).

Datasets

Most studies use historical daily price data; many also collect news headlines, tweets, and macroeconomic variables. Studies are often region specific (e.g., India and the US) (Table 1).

TAXONOMY OF METHODS

To structure the landscape, the methods can be grouped as follows in Table 2.

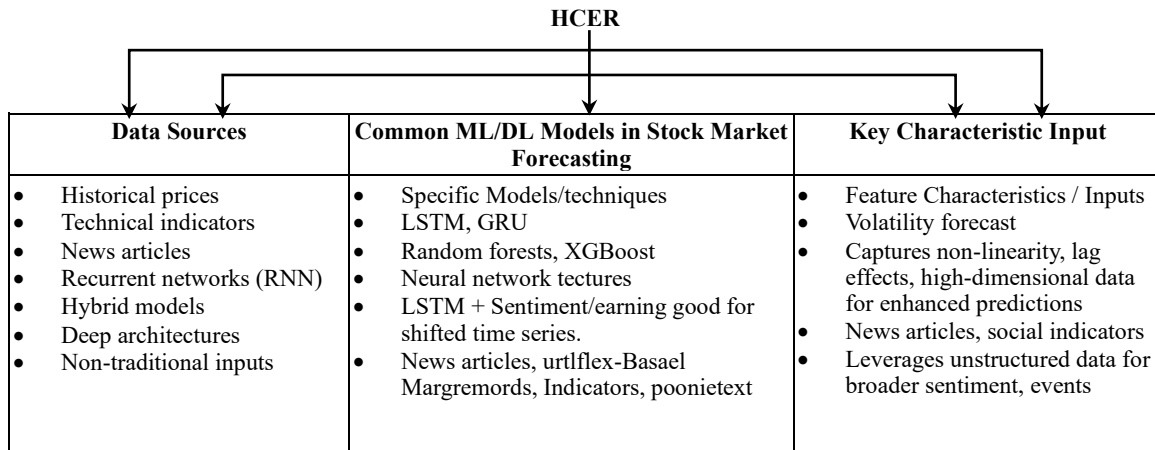


Figure 2. Models used for stock price forecasting.

Table 1. Matrix and dataset.

Evaluation metrics	Common datasets
Regression metrics <ul style="list-style-type: none"> RMSE MAPE 	<ul style="list-style-type: none"> Historical daily prices (OHLCV) News headlines
Classification metrics (direction) <ul style="list-style-type: none"> Accuracy PE Ratio Executive return Economic/trading metrics 	<ul style="list-style-type: none"> Social media posts Macroeconomic variables Events data
<i>Time horizon:</i> 1-day, longer	<i>Region specific:</i> India, US, etc.

Table 2. Taxonomy of methods.

Category	Inputs/features	Models used	Strengths	Weaknesses
Historical/technical Only	Past prices, technical indicators (RSI, MACD, MA, volume, etc.)	ARIMA, SVR, Random Forest, LSTM, GRU	Simpler, less data requirement; moderate performance in stable regimes	Fails when market dynamics change; lag in reaction; often misses external shocks
Sentiment/news enhanced	Sentiment from news, social media, and macro indicators	LSTM with sentiment, Random Forest + news, hybrid architectures	Can incorporate market sentiment, sometimes earlier signals; better adaptation	Noisy, subjectivity in sentiment extraction; lag between event and impact; difficulty aligning sentiment with price moves
Hybrid/ensemble	Technical + Sentiment possibly human-expert inputs	Model stacking, ensemble (RF + DL), CNN+LSTM, attention models	Leverage complementary strengths; often best empirical accuracy	Complexity, risk of overfitting, interpretability suffer, and computation cost
Advanced architectures/latest trends	Alternative data (events, graph relationships), sentiment aspects, news event extraction	Attention networks; Transformers; Graph Neural Networks; aspect-based sentiment models	Better at capturing long contexts, capable of richer relationships, promising recent results arXiv+2MDPI+2	Require large data, computational resources; harder to deploy; risk of overparameterization

COMPARATIVE PERFORMANCE AND EMPIRICAL FINDINGS

Based on recent literature, here are some comparative observations.

Sentiment Improves Performance Conditionally

Several studies (HiSA SMFM, Stock Price Prediction with Sentiment for Indian Markets) have shown that adding sentiment features improves forecast errors (lower RMSE/MAE), especially for short-term horizons. Sentimental information improves ML performance only under specific conditions.

Its contribution is strongest during high-information periods, such as earnings announcements or major news events. In stable markets, sentiment signals add limited value and may introduce noise. Effective integration and timing determine whether sentiment enhances predictive accuracy [7].

DL Models Outperform Classical Methods When Data Volume is Sufficient

RNN variants (LSTM/GRU) often perform better than ARIMA or simple regression. Hybrid models combining DL with external features often yield the best results in many recent studies. DL models outperform classical ML and statistical methods when trained on large, high-quality datasets. With sufficient data volume, DL architecture effectively captures complex nonlinear relationships and long-term dependencies. In contrast, limited data often leads to overfitting, reducing the benefits of DL, and favoring simpler traditional models [8].

Diminishing Returns and Overfitting Risk

In some datasets, complex models show only marginal gains over simpler approaches. In addition, models trained on historical data may fail in new market regimes. As model complexity and data volume increase, performance gains in ML often exhibit diminishing returns. Beyond a certain point, additional features or layers contribute to marginal improvements while increasing the risk of overfitting. Overly complex models may capture noise instead of meaningful patterns, thereby reducing generalization on unseen data [9].

Geographical/Regional Sensitivity

Models trained on US markets may not perform similarly on Indian markets, among others, because of differences in volatility, liquidity, market behavior, and regulatory influences. ML models exhibit strong geographical and regional sensitivity because market behavior, regulations, and investor sentiment vary across locations. Models trained in one region often fail to generalize to others. Incorporating region specific features and localized training data improves robustness and predictive reliability [10].

Time Horizon Matters

Prediction accuracy tends to degrade for longer forecast horizons. Short-term (1-day ahead) forecasts are often more accurate; however, longer forecasting is more difficult to generalize. Hybrid models mitigate this effect somewhat. The time horizon significantly influences ML prediction performance. Short-term forecasts typically achieve higher accuracy because of stronger temporal dependencies and stable patterns. As the forecast horizon extends, uncertainty, noise, and structural changes increase, reducing model generalization and reliability for longer-term predictions. Table 3 presents comparative performance and empirical findings.

CHALLENGES

Although ML has shown promise, many obstacles remain before models can be reliably used in real-world trading settings.

Non-Stationarity and Regime Shifts

Stock markets change over time: new regulations, economic shocks, pandemics, and geopolitical events. Models trained on past data may not adapt quickly to new regimes.

Table 3. Comparative performance and empirical findings.

Finding	Observation/details	Key references
Sentiment improves performance	Lower RMSE/MAE for short-term forecasts	IDEAS/RePEc +1
DL outperforms classical methods	RNNs (LSTM/GRU) models are often the best performing	IDEAS/RePEc +3; arXiv +3
Diminishing returns and overfitting	RNNs (LSTM/GRU) outperform ARIMA; hybrid models are often best	PubMed +2; JEST.VGTU.It +2
Geographical sensitivity	Performance varies (US: marginal gains; failure in bear markets due to regional differences)	PubMed/RePEc +2; arXiv +2
Time horizon matters	Short-term (1-day) forecasts are more accurate; hybrid models improve performance	IDEAS/RePEc +2; arXiv +2

Data Quality, Availability, and Lag

- Sentiment or news data may be noisy, ambiguous, or misaligned with the actual effect on prices.
- The delay between news publication and market reaction complicates alignment.
- Alternative data sources may have biases and missing values.

Overfitting and Generalization

High-capacity models (deep networks and ensembles) can overfit training data. Without proper regularization, validation, and out-of-sample testing, the results may look good in research but fail in practice.

Interpretability and Transparency

Regulators, investors, and institutions often require explanations of model decisions. Black-box models (DL and ensembles) can be difficult to interpret. Explainable AI (XAI) methods (SHAP, LIME (Local interpretable model-agnostic explanations), and attention visualization) are less common in published works.

Economic Practicalities

- *Transaction costs, slippage, taxes:* Many studies assume ideal trading with no friction, which overstates potential returns.
- *Latency:* real-time prediction and execution constraints.
- *Risk management:* Drawdowns and tail risks are often not sufficiently addressed.

PROPOSED FRAMEWORK AND EXPERIMENTAL DESIGN (SUGGESTED FOR FUTURE WORK)

To achieve robust, publishable contributions, the following experimental framework is recommended.

Data Collection

- *Historical data:* daily price OHLCV for multiple stocks/indices, over 5–10 years.
- *Alternative data:* news headlines/articles; social media (Twitter, Reddit, etc.); macroeconomic indicators; and event databases.
- *Time alignment:* ensures that sentiment/news data timestamps align with market data (e.g., intraday or daily, depending on the model horizon).

Feature Engineering

- Technical indicators (moving averages, RSI, MACD, Bollinger Bands, etc.).
- Lagged returns and volatility measures.
- Sentiment features: polarity, subjectivity, aspect-based sentiment, event extraction, and trend in sentiment.

- Macroeconomic features if relevant (interest rates, inflation, currency rates).
- Dimensionality reduction or feature selection (PCA (Principal component analysis), Lasso, or feature importance) to avoid overfitting.

Model Selection

- *Baseline models*: ARIMA, SVR, Random Forest.
- *Deep models*: LSTM, GRU, Transformer-based models.
- *Hybrid/Ensemble models*: stacking combinations of models or blending decisions.

Experiment with attention mechanisms and graph-based models to model relationships among stocks or sectors.

Training and Validation Strategy

- Use rolling-window backtesting to simulate real forecasting (train on past periods and test on unseen future data).
- Apply cross-validation techniques adapted for time series (time-series cross-validation).
- Use regularization, dropout, and early stopping for neural network models.

Evaluation Metrics

- *Standard statistical metrics*: RMSE, MAE, MAPE.
- Directional accuracy/classification metrics for predicting up/down trends.
- *Economic metrics*: Sharpe ratio, cumulative return, and maximum drawdown.
- *Robustness metrics*: stability over different time periods and stress periods (e.g., financial crises, high volatility windows).

FUTURE DIRECTIONS

Several promising research directions emerge from reviewing recent literature and considering challenges:

1. *Explainable and transparent ML*: More work is needed to integrate XAI techniques, aspect-based sentiment, and interpretable hybrid models.
2. *Multimodal learning*: Combining various data types, such as numerical, textual, event, and image/chart data, to better model market dynamics.
3. *Graph neural networks and relationships*: Modeling relationships among stocks, sectors, and companies via graphs to capture co-movement and contagion.
4. *Adaptive/online learning*: Methods that update with new data, handle non-stationarity, and detect regime shifts.
5. *Real-world constraints*: Incorporating transaction costs, latency, risk measures, and portfolio optimization in evaluation, in addition to statistical accuracy.
6. *Event detection and causality*: Using causality analysis (e.g., Granger causality) to understand which inputs actually cause price movements, rather than merely correlating with them.
7. *Models*: Incorporating expert predictions and forecasts (as in some recent work) to combine domain knowledge with ML.

CONCLUSION

ML methods have made significant inroads into stock market forecasting; with many studies showing that integrating historical price data with sentiment and external indicators yields more accurate forecasts than using technical data alone.

However, challenges remain, especially in ensuring that models generalize, remain robust over time, and produce outputs that are interpretable and financially meaningful. Future research that focuses not only on prediction performance but also on transparency, economic realism, and adaptability will likely have the greatest impact.

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