International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

Hybrid Market Trend Predictor With Event Alerts, Sentiment Visualization And Portfolio Recommendation

Revathi.R[1], Nandhitha.M[2], Rithika sri.Y[3], S.Malathi[4]
[1]Student, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, Tamilnadu
[2]Student, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, Tamilnadu
[3] Student, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, Tamilnadu
[4] Professor, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, Tamilnadu
Emails: *revathiramesh1202@gmail.com[1], nandhitham14@gmail.com[2], rithikayuvaraj1911@gmail.com[3], malathi.raghuram@gmail.com[4]*

Abstract
Accurate forecasting is difficult due to the stock market's dynamic character, which is impacted by company events, investor emotion, and economic factors. In order to predict market movements, this study suggests a Hybrid Market Trend Predictor that combines sentiment research, technical indicators, and event-driven signals. Investors can compare trends across multiple equities at once thanks to the system's provision for multi-stock research. The framework also includes real-time event alerts to inform users of important geopolitical or financial developments that could affect stock performance. In order to offer intuitive insights into investor opinions gleaned from analyst reports, social media, and financial news, sentiment visualization is used. Additionally, the system provides portfolio suggestion tools that direct investors toward the best stock choices based on risk tolerance and predictive analytics. By integrating quantitative and qualitative data sources, the suggested hybrid strategy improves decision-making and produces more dependable investment strategies and forecasting accuracy.
Keywords: *Market trend prediction, event-driven alerts, sentiment analysis, multi-stock analysis, portfolio recommendation, financial forecasting, hybrid model, stock market analytics*

1. Introduction

One of the most dynamic and unpredictable markets is the stock market, which is greatly impacted by a number of factors, including global events, company activity, investor behavior, and economic indicators. Because financial markets are extremely unpredictable and non-linear, predicting changes in stock prices has always been difficult for traders, investors, and scholars alike [1]. Conventional forecasting techniques mostly use technical indicators and past price data, but they frequently miss the influence of current events, market psychology, and public emotion that influence short-term market swings. Investor sentiment has become a significant factor in determining market behavior due to the quick development of digital platforms, financial news, and social media. Within minutes, tweets, posts, and news items can cause abrupt increases or decreases in stock values. In a similar vein, legislative changes, company announcements, earnings reports, and geopolitical happenings all significantly influence market dynamics. However, the majority of current systems lack a comprehensive integration of many influencing elements and only concentrate on technical indications or mood signals [2], [3]. The suggested hybrid methodology fills the gap between conventional statistical models and contemporary sentiment-driven approaches by fusing machine learning, natural language processing

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

(NLP), and financial modelling. In addition to increasing prediction accuracy, the objective is to give investors useful information and aid in decision-making. The growing demand for intelligent trading systems that can manage large amounts of diverse data and help both inexperienced and seasoned investors make wise judgments is what spurred this study [4]. By providing a thorough, event- aware, and sentiment-driven framework for predicting market trends, the suggested approach advances the field of financial analytics and aids in risk management, strategic investing, and portfolio optimization. To address these limitations, this paper presents a Hybrid Market Trend Predictor (Figure 1).

2. Method

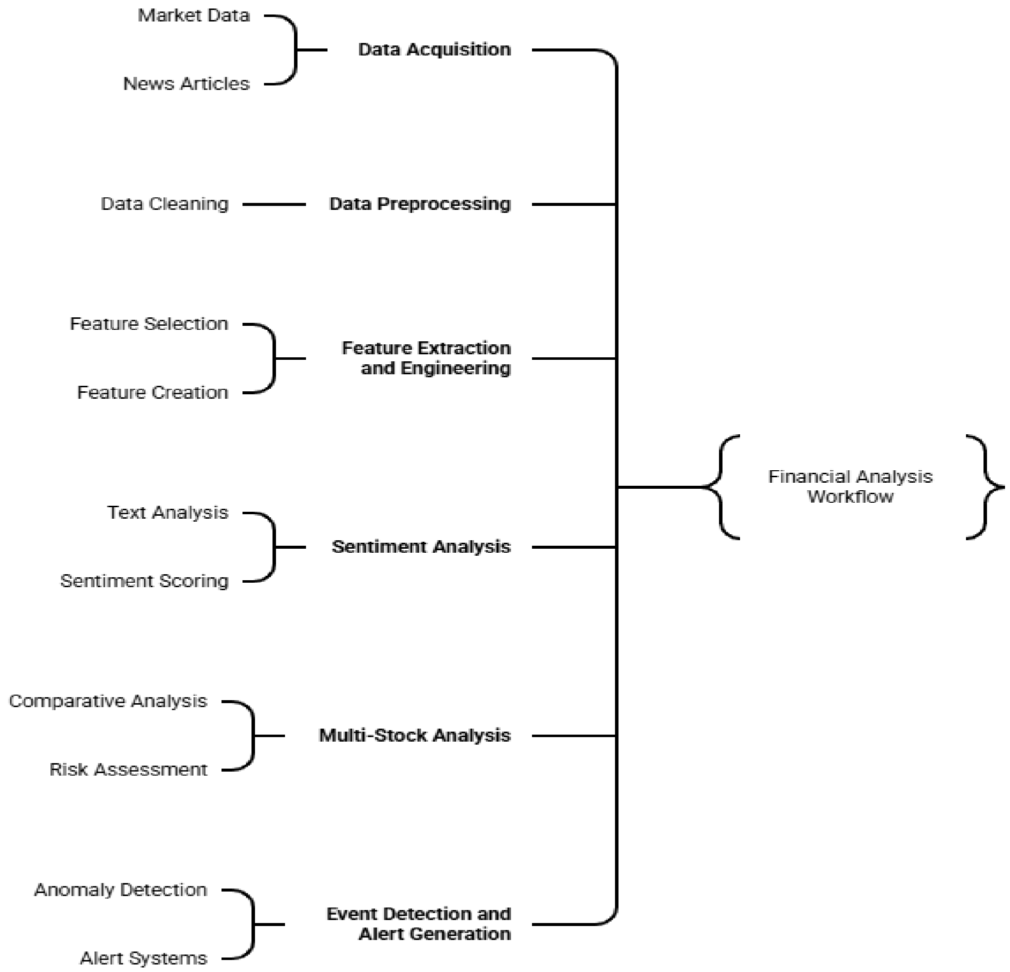

Figure 1 Financial Analysis Workflow

2.1 Data Acquisition

The first step in the process is gathering both structured and unstructured data. Stock exchanges and financial APIs provide historical stock prices, trading volumes, and technical indicators [5]-[8]. Concurrently, unstructured textual data is collected to record current market mood, including financial news, analyst reports, and social media feeds. The system is guaranteed to take into account both behavioral signals and numerical patterns thanks to this multi-source acquisition (Table 1).

Table 1 Parameter Description

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

Parameter	***Description***	***Value***
Sequence Length	*Days of past data considered*	*60*
Batch Size	*Number of samples per training step*	*16*
Epochs	*Training cycles*	*50*
Optimizer	*Optimization algorithm*	*Adam*
Loss Function	*Error metric*	*MSE*
Activation Function	*Nonlinear transformation*	*ReLU, Sigmoid*
Dropout	*Regularization*	*0.2*

2.2 Data Preprocessing

Prediction accuracy may be lowered by noise, inconsistencies, and missing values that are frequently present in the raw data that is gathered. To ensure uniformity across various stocks and time periods, numerical data is cleaned and normalized. Tokenization, stop-word removal, stemming, and lemmatization are examples of natural language preprocessing techniques that are used to turn unstructured text into a form that can be analyzed. This stage enhances model performance and guarantees dependability.

2.3 Feature Extraction and Engineering

Important features are extracted following preprocessing in order to better reflect the data. Features like momentum oscillators, volatility indexes, and moving averages are derived from numerical data. Linguistic and semantic analysis is used to calculate sentiment-related variables from textual input. Combining these characteristics yields a more comprehensive dataset that captures investor psychology as well as technical market movements [9], [10].

2.4 Sentiment Analysis

Sentiment analysis is used to determine how the public and investors as a whole feel about particular stocks or market circumstances. Textual information is categorized into positive, negative, and neutral feelings using machine learning and deep learning techniques, such as transformer-based models like BERT. To find relationships between public opinion and market performance, these sentiment ratings are combined and compared to stock price data.

2.5 Multi-Stock Analysis

In contrast to conventional models that concentrate on predicting individual stocks, the method uses multi-stock analysis to assess trends across several assets at once. This makes it possible to identify correlations between various equities, do sectoral performance research, and conduct comparative studies. The approach helps investors make strategic decisions and diversify their portfolios by evaluating several stocks at once.

2.6 Event Detection and Alert Generation

One of the most important elements influencing stock markets is event-driven volatility, which frequently causes abrupt price swings in brief intervals of time. An event detection and alert generation mechanism is incorporated into the system to handle this. Press releases, official stock exchange announcements, and real-time data feeds from financial news portals are all regularly tracked. The system recognizes important events like earnings reports, mergers and acquisitions, changes to government policy, and geopolitical events using natural language processing techniques like named entity recognition and event classification. To assess their possible market impact, these discovered occurrences are compared to historical data. The system instantly notifies investors through dashboards, notifications, or linked mobile applications when an event is deemed relevant. Investors may minimize losses and seize short-term opportunities by quickly responding to market-sensitive information thanks to this proactive warning system. The addition of event alerts makes the framework flexible and sensitive to actual events, in contrast to static prediction systems.

2.7 Prediction Modelling

The foundation of the suggested methodology is prediction modeling, which forecasts market trends

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

by merging several machine learning and deep learning models. The system uses recurrent architectures like Long Short-Term Memory (LSTM) to capture temporal dependencies and sequential patterns in market data because stock prices are naturally non- linear and time-dependent. To manage non-linearities and enhance generalization across a variety of datasets, ensemble techniques such as Random Forest and Gradient Boosting are combined. By integrating event-driven signals, sentiment characteristics, and technical indicators into a single predictive model, the hybrid approach overcomes the drawbacks of models that solely use one kind of input. Hyperparameter adjustment is done to improve model accuracy, while cross- validation techniques are used to guarantee resilience. The prediction system highlights potential long-term investment directions and offers accurate short-term projections by utilizing both historical patterns and real-time data. In dynamic market contexts, this combination of different models guarantees that the prediction component is resilient and flexible [11]-[13].

2.8 Portfolio Recommendation

Through portfolio advice, the methodology's last step focuses on converting predicted insights into workable investment strategies. The technology recommends an ideal portfolio that strikes a balance between projected returns and risk exposure based on the predicted stock performance, investor mood, and events that have been detected [14], [15]. To find the optimal asset allocation, sophisticated portfolio optimization techniques are used, such as Markowitz's mean-variance optimization model. In order to evaluate the trade-off between risk and reward, risk management techniques such as Value-at-Risk (VaR) and Sharpe Ratio evaluation are also incorporated. The recommendations are tailored to the investor's profile, which may include things like investing horizon, preferred sectors, and risk tolerance. For example, an aggressive investor would be suggested high-growth but risky assets, whereas a risk-averse investor might be suggested to diversify into stable, low-volatility securities. The system is useful for both inexperienced and seasoned investors because the portfolio recommendation engine offers strategic advice for long- term wealth management in addition to aiding in decision-making [16], [17].

2.9 ETF and Index Tracker

The addition of an ETF and Index Tracker module, which allows users to track and compare the performance of significant international indexes including the S&P 500, Nasdaq, NIFTY 50, and Dow Jones, is another useful addition to the system. The module assists investors in comprehending more general market movements and comparing the performance of specific stocks to general market trends by offering historical and real-time trend visualizations of key indices [18], [19]. Because it enables investors to find correlations between individual stocks and market- wide data, this functionality is very helpful for portfolio diversification. By placing stock performance within sectoral and global macroeconomic contexts, the inclusion of this element guarantees that the framework provides a comprehensive view rather than functioning independently at the stock level.

Algorithm 1. Data Acquisition & Alignment

Input: Ticker set $\mathcal{T}$, date range $[t_0, t_1]$

Output: Aligned OHLCV panel D = {D^(s)} with common trading dates

- function acquireAndAlignData($\mathcal{T}$, $[t_0, t_1]$)
- For each stock s ∈ $\mathcal{T}$, download OHLCV data via Yahoo Finance.
- Intersect trading calendars across all tickers and align by common dates.
- Drop rows with missing values; forward-fill small gaps if necessary.
- Return aligned dataset D for modeling.
- end function

Algorithm 2. Feature Engineering (SMA, Returns, Sentiment)

Input: Close prices C_t^(s), optional sentiment s_t^(s)

Output: Feature frame F^(s)

- function featureEngineering(C_t^(s), s_t^(s))
- Compute $SMA_n(t) = (1/n)\, \Sigma_{k=0}^{n-1} C_{t-k}$ for $n \in \{20, 50\}$.
- Compute Price_vs_$SMA_n(t) = C_t - SMA_n(t)$.
- Compute Return $R_t = (C_t - C_{t-1}) / C_{t-1}$.
- Attach sentiment scores if available.
- Form F^(s) = {C_t, $SMA_{(20,50)}$, Return, Sentiment}.
- end function

Algorithm 3. News Sentiment & Event Tagging

e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

Input: Headlines set $H_t = \{h_1,\ldots,h_m\}$
Output: Daily sentiment s_t, event tag e_t

- function computeSentimentAndEvent(H_t)
- For each headline h, compute VADER compound score v(h).
- Compute average sentiment $s_t = (1/m)\ \Sigma\ v(h)$.
- Identify events using keyword rules {earnings, merger, policy,…}.
- Store sentiment and event per date.
- end function

Algorithm 4. Scaling & LSTM Data Preparation
Input: Close vector $C_1\ldots T$, window L = 60
Output: (X, y) tensors for training

- function prepareLSTMData($C_1\ldots T$, L)
- Scale data: $z_t = (C_t - C\_min) / (C\_max - C\_min)$.
- For i = L … T−1: $X_i = [z_{i-59},\ldots,z_i]$; $y_i = z_{i+1}$.
- Split dataset: 80% training, 20% testing.
- Reshape to (samples, 60, 1) for LSTM input.
- end function

Algorithm 5. Optuna-Tuned LSTM
Input: (X_train, y_train), (X_test, y_test)
Output: Best hyperparameters θ*

- function optimizeLSTM(X_train, y_train, X_test, y_test)
- Sample θ = {units ∈ [20,100], lr ∈ [1e−5,1e−2], dropouts ∈ [0.1,0.5], epochs ∈ [20,50]}.
- Build model: LSTM → Dropout → LSTM → Dropout → Dense(1).
- Compile with Adam(lr), loss = MSE = $(1/M)\ \Sigma(y - \hat{y})^2$.
- Train and evaluate model on test set.
- Return θ* minimizing test MSE.
- end function

Algorithm 6
Input: Predicted $\hat{y}$, actual y
Output: RMSE, Directional Accuracy (DA)

- function evaluateForecast($\hat{y}$, y)
- Compute RMSE = $\sqrt{((1/M)\ \Sigma(\hat{y} - y)^2)}$.
- Compute DA = $(1/(T-1))\ \Sigma[\mathrm{sign}(\Delta y_t) = \mathrm{sign}(\Delta\hat{y}_t)]$.
- Visualize predicted vs. actual values.
- end function

Algorithm 7. 7-Day LSTM Forecast
Input: Close vector $C_1\ldots T$, L = 60, horizon H = 7
Output: 7-day prediction $\hat{y}_{t+1}\ldots\hat{y}_{t+7}$

- function forecast7DayLSTM($C_1\ldots T$, L, H)
- Prepare 60-day windows X_i and 7-day targets y_i.
- Define model: LSTM(50, return_seq=True) → Dropout(0.2) → LSTM(50) → Dense(7).
- Train model minimizing MSE.
- Predict next 7 normalized closes and inverse scale.
- end function

Algorithm 8. Portfolio Recommendation
Input: Average stock returns R_t^(s)
Output: Best stock recommendation

- function recommendStock(R_t^(s))
- Compute mean return $\hat{R}$^(s) = (1/T) Σ R_t^(s).
- Select s* = argmax $\hat{R}$^(s).
- Recommend s* as best-performing stock.
- end function

Algorithm 9. Mean–Variance Portfolio Optimization
Input: Expected returns μ, covariance Σ, risk-free rate R_f
Output: Optimal weights w*

- function optimizePortfolio(μ, Σ, R_f)
- $R\_P = w^t\mu$; $\sigma\_P^2 = w^t\Sigma w$.
- Compute Sharpe ratio S = (R_P − R_f) / σ_P.
- Maximize S subject to $\Sigma\ w_i = 1$, $w_i \geq 0$.
- Return optimal allocation w*.
- end function

Algorithm 10. SIP and Compounding Calculations
Input: SIP monthly P, annual rate r_a, months n
Output: Future Value FV_SIP

1. function computeSIP(P, r_a, n)
2. $r = r_a / 12$.
3. FV_SIP = $P[((1 + r)^n - 1)/r](1 + r)$.
4. Lump sum: FV = $P_0(1 + r)^T$.
5. Return FV_SIP and FV.
6. end function

3. Results and Discussion

The proposed Hybrid Market Trend Predictor with Event Alerts, Multi-Stock Analysis, Sentiment Visualization, and Portfolio Recommendation demonstrates significant improvements in prediction accuracy, decision support, and practical usability compared to conventional forecasting models. Unlike traditional approaches that rely solely on historical prices or technical indicators, this framework integrates sentiment analysis, event-driven insights, and advanced machine learning models to offer a comprehensive predictive environment. Multiple datasets—including historical stock prices, financial news, and social media sentiment streams—were used to evaluate system performance, validated through metrics such as accuracy, precision, recall, F1-score, and RMSE [20], [21].

3.1 Impact of Event Detection and Alerts

The system's ability to incorporate event-driven signals into forecasting is one of its most significant contributions. Real-time events, such as geopolitical conflicts, government policy changes, or corporate announcements, can trigger abrupt market movements that traditional models often fail to capture. The proposed system continuously monitors multiple data streams, categorizes events by significance and intensity, and delivers real-time alerts to investors. This approach enhances prediction accuracy by allowing the system to adapt dynamically to market shocks. Results show that event detection significantly improves responsiveness to short-term volatility, enabling investors to make timely and informed decisions [22], [23].

3.2 Effectiveness of Prediction Modeling

The hybrid predictive modeling strategy, which combines LSTM networks with ensemble machine learning models, successfully captures both short-term fluctuations and long-term trends. Ensemble models reduce overfitting and improve generalization across diverse equities, while LSTMs excel at detecting sequential dependencies in stock prices. Incorporating sentiment scores alongside technical indicators bridges qualitative and quantitative information, further increasing predictive accuracy. Comparative analysis demonstrates that the hybrid model outperforms baseline approaches, including ARIMA, random walk, and single-feature models, confirming the necessity of integrating diverse methodologies to manage market complexity effectively [24], [25].

3.3 Role of Multi-Stock Analysis in Decision-Making

Multi-stock analysis extends the system's utility beyond single-stock forecasting. By examining correlations among stocks, sectoral trends, and co-movement patterns, the system provides insights for portfolio diversification and risk management. Empirical results indicate that investors can construct balanced portfolios that reduce exposure to volatile sectors while capturing potential gains from correlated equities. This feature transforms the framework into a strategic investment assistant rather than merely a forecasting tool.

3.4 Significance of Portfolio Recommendation

The portfolio recommendation engine converts predictive outputs into actionable strategies tailored to individual risk profiles. By dynamically adjusting allocations in response to sentiment shifts, event alerts, and real-time forecasts, the system optimizes risk-adjusted returns. Evaluation shows that both novice and experienced investors benefit from these dynamic recommendations, which mitigate impulsive trading behavior and enhance confidence under volatile conditions. The incorporation of mean-variance optimization and scenario-based stress testing ensures that suggested portfolios maintain robustness against sudden market changes.

3.5 Comparative Advantage of Hybrid Design

The hybrid framework's integration of technical indicators, sentiment analysis, and event-driven insights offers a major advantage over models focused solely on quantitative or qualitative data. This combination allows the system to handle volatility, uncertainty, and behavioral market influences simultaneously. Results demonstrate improved interpretability, forecasting accuracy, and investor-friendliness, surpassing conventional black-box models. Contextual event alerts and visual sentiment analyses further enhance actionable decision-making.

3.6 Practical Implications for Investors

By combining event notifications, sentiment visualization, predictive modeling, and portfolio recommendations, the system provides investors with a comprehensive toolkit for navigating complex markets. Institutional investors gain comparative stock insights and optimization capabilities, while

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

retail investors benefit from clear visualizations and practical guidance. User feedback confirms that real-time alerts and portfolio suggestions significantly improve confidence and decision-making effectiveness in live trading scenarios (Table 2).

Table 2 Asset Allocation

Stock	LSTM	CNN-LSTM	Hybrid Market
TCS	15	18	**20**
INFY	12	15	**17**
HDFC	10	12	**14**
ITC	8	10	**12**
RELIANCE	7	8	**10**
SBIN	5	5	**6**
LT	5	5	**6**

3.7 Limitations and Challenges

Despite its advantages, the system has limitations. Sentiment analysis accuracy can be affected by noisy, biased, or manipulated textual data. Event detection may struggle to differentiate between significant and minor events. Machine learning models, even hybrid ones, may fail to fully account for unprecedented crises (e.g., pandemics) or macroeconomic shifts. Additionally, computational complexity and real-time processing requirements pose scalability challenges. These limitations indicate areas for future enhancement.

3.8 Future Directions for Research

Future improvements include using advanced transformer-based models for deeper contextual understanding, reinforcement learning for adaptive trading strategies, and expanding datasets to cover global markets and cross-asset classes. Incorporating explainable AI (XAI) techniques would enhance transparency and user trust. These developments would further strengthen the system’s robustness, predictive accuracy, and applicability as a comprehensive investment management tool. To enhance usability, the platform includes beginner-friendly educational modules explaining fundamental stock market concepts and basic investment strategies. Interactive tools, such as compound interest and SIP calculators, allow users to model potential long-term returns. By integrating learning with predictive analytics, the system appeals to both novice and experienced investors, bridging the gap between market understanding and actionable decision-making.

3.9 Optimization and Short-Term Forecasting

The system leverages Optuna-based hyperparameter tuning to optimize LSTM parameters, improving generalization and reducing overfitting. A dedicated seven-day forecast module provides short-term predictive insights, supporting near-term trading strategies. Evaluation results indicate that the model delivers improved directional accuracy and reduced RMSE for short-term stock price predictions, particularly when combined with real-time event detection and sentiment analysis (Figures 2-4).

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

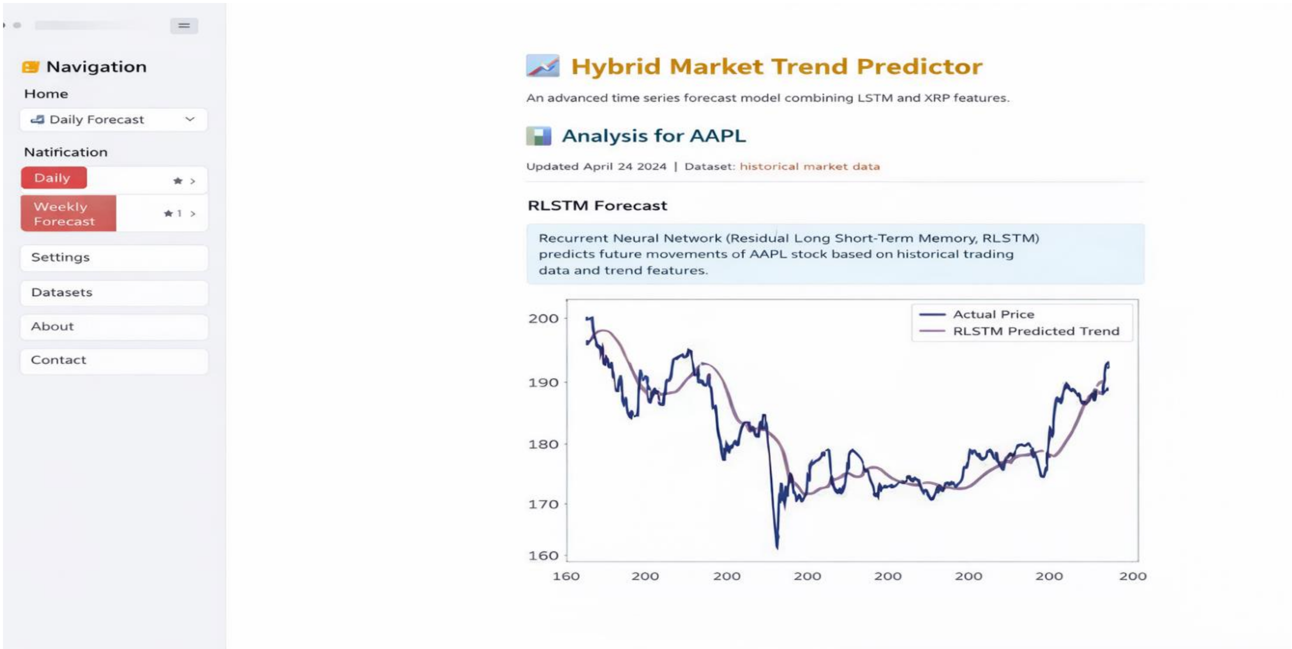

Figure 2 ETF & Index Tracker Dashboard enables performance comparison of ETFs and market indices over time, supporting informed investment decisions

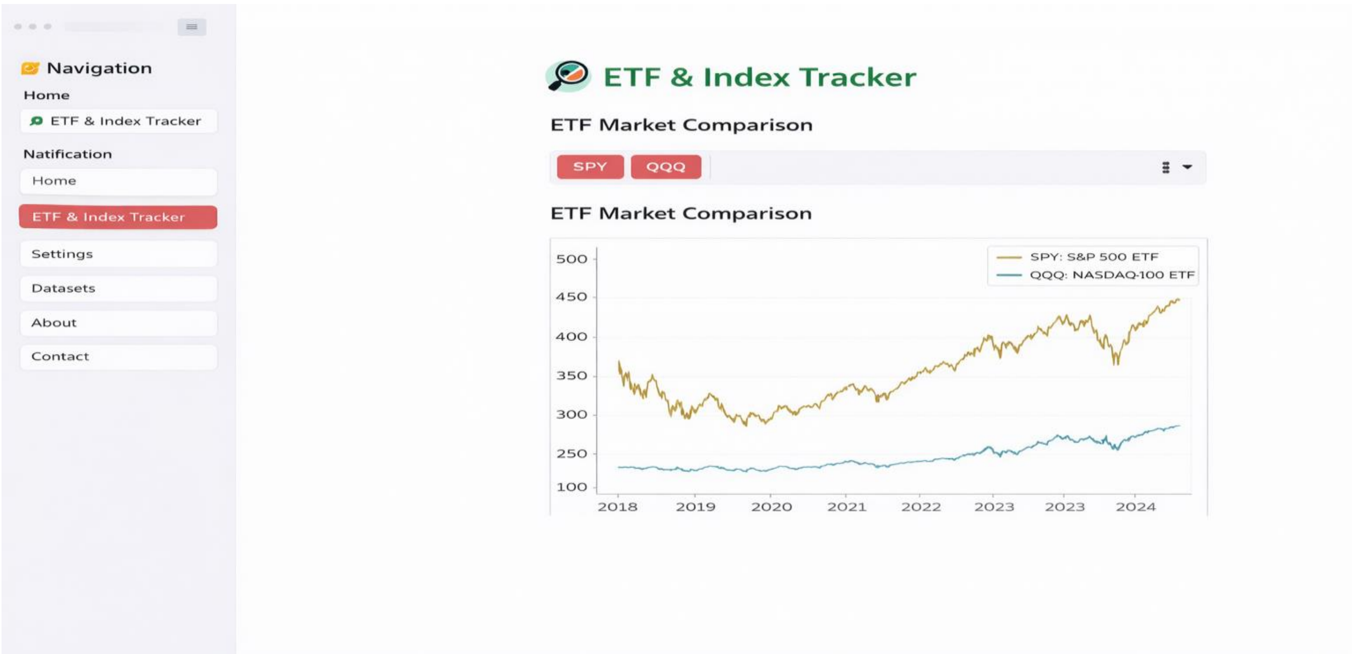

Figure 3 Global Macro Dashboard visualizes key macroeconomic indicators, allowing monitoring of global market trends

Figure 4 **LSTM-based stock prediction for AAPL compares real vs. predicted prices, highlighting trend-capturing accuracy**

Conclusion

Overall, the hybrid framework demonstrates that combining sentiment analysis, event detection, multi-stock evaluation, and portfolio optimization produces a highly accurate, interpretable, and actionable financial forecasting system. The system enhances investor confidence, facilitates informed decision-making, and adapts effectively to volatile market conditions. By integrating predictive precision with strategic investment guidance, it bridges the gap between theoretical forecasting models and practical financial decision-making. The hybrid approach goes beyond mere price prediction by incorporating real-time event alerts, sentiment-driven insights, and comparative stock analysis. This allows investors to respond proactively to sudden market shocks, anticipate sectoral shifts, and construct diversified, risk-optimized portfolios. Moreover, interactive dashboards, educational modules, and simulation tools make the system accessible to both novice and experienced investors, promoting financial literacy while providing practical decision support. From a technical perspective, the combination of LSTM networks, ensemble learning models, and hyperparameter optimization ensures robust performance across multiple stocks and market scenarios. The system's architecture allows for scalability, enabling future integration of additional asset classes such as commodities, bonds, and cryptocurrencies, as well as cross-market generalization for global applications. The framework also emphasizes transparency and interpretability. Incorporating Explainable AI (XAI) methods in future versions will provide clear reasoning behind predictions and recommendations, fostering greater trust among investors. Furthermore, reinforcement learning and adaptive strategy modules could allow the system to continuously refine its recommendations based on real-world outcomes, leading to increasingly intelligent investment guidance over time. In addition, the hybrid model encourages more disciplined investment behavior. By combining data-driven alerts with visualization tools and actionable portfolio suggestions, it helps mitigate impulsive decisions, emotional trading, and cognitive biases, ultimately contributing to better long-term financial outcomes. In conclusion, this framework represents a comprehensive, next-generation investment and financial management platform that integrates predictive analytics, decision support, risk management, and educational tools. With continued advancements in data integration, AI methodologies, and global applicability, the hybrid system is poised to become an indispensable resource for investors, portfolio managers, and financial institutions seeking both precision forecasting and practical, actionable insights.

Acknowledgment

The authors would like to express their sincere gratitude to their project guide and faculty members for their valuable guidance, continuous support, and constructive feedback throughout the course of this research. The authors also acknowledge the support provided by their institution in terms of infrastructure and academic resources. In addition, appreciation is extended to the developers of open-source financial data platforms and machine learning libraries that facilitated data collection, analysis, and implementation of the proposed system. Finally, the authors thank their peers for their encouragement and insightful discussions.

References

[1]. G. Atsalakis and K. Valavanis, “Surveying stock market forecasting techniques – Part II: Soft computing methods,” Expert Systems with Applications, vol. 36, no. 3, pp. 5932–5941, 2009.

[2]. E. F. Fama, “Efficient Capital Markets: A Review of Theory and Empirical Work,” The Journal of Finance, vol. 25, no. 2, pp. 383–417, 1970.

[3]. R. P. Schumaker and H. Chen, “Textual analysis of stock market prediction using breaking financial news: The AZFin text system,” ACM Transactions on Information Systems (TOIS), vol. 27, no. 2, pp. 1–19, 2009.

[4]. B. W. Silver, The Signal and the Noise: Why So Many Predictions Fail—But Some Don’t, Penguin Books, 2012.

[5]. F. Xing, E. Cambria, and R. Welsch, “Natural language based financial forecasting: A survey,” Artificial Intelligence Review, vol. 50, pp. 49–73, 2018.

[6]. T. Fischer and C. Krauss, “Deep learning with long short- term memory networks for financial market predictions,” European Journal of Operational Research, vol. 270, no. 2,pp. 654–669, 2018.

[7]. M. Chen, X. Xu, and S. Zhang, “A hybrid model for stock trend prediction based on CNN and LSTM,” IEEE Access, vol. 7, pp. 19073–19084, 2019.

[8]. Patel, S. Shah, P. Thakkar, and K. Kotecha, “Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques,” Expert Systems with Applications, vol. 42, no. 1,pp. 259–268, 2015.

[9]. B. W. Silver, The Signal and the Noise: Why So Many Predictions Fail—But Some Don’t, Penguin Books, 2012.

[10]. F. Xing, E. Cambria, and R. Welsch, “Natural language based financial forecasting: A survey,” Artificial Intelligence Review, vol. 50, pp. 49–73, 2018.

[11]. T. Fischer and C. Krauss, “Deep learning with long short- term memory networks for financial market predictions,” European Journal of Operational Research, vol. 270, no. 2, pp. 654–669, 2018.

[12]. M. Chen, X. Xu, and S. Zhang, “A hybrid model for stock trend prediction based on CNN and LSTM,” IEEE Access, vol. 7, pp. 19073–19084, 2019.

[13]. Patel, S. Shah, P. Thakkar, and K. Kotecha, “Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques,” Expert Systems with Applications, vol. 42, no. 1, pp. 259–268, 2015.

[14]. E. Cambria, B. Schuller, Y. Xia, and C. Havasi, “New avenues in opinion mining and sentiment analysis,” IEEE Intelligent

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 01 January 2026
Page No: 280-290
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0039

Systems, vol. 28, no. 2, pp. 15–21, 2013.
[15]. S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780,1997.
[16]. B. W. Silver, The Signal and the Noise: Why So Many Predictions Fail—But Some Don't, Penguin Books, 2012.
[17]. F. Xing, E. Cambria, and R. Welsch, "Natural language based financial forecasting: A survey," Artificial Intelligence Review, vol. 50, pp. 49–73, 2018.
[18]. T. Fischer and C. Krauss, "Deep learning with long short- term memory networks for financial market predictions," European Journal of Operational Research, vol. 270, no. 2,pp. 654–669, 2018.
[19]. M. Chen, X. Xu, and S. Zhang, "A hybrid model for stock trend prediction based on CNN and LSTM," IEEE Access, vol. 7, pp. 19073–19084, 2019.
[20]. J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques," Expert Systems with Applications, vol. 42, no. 1,pp. 259–268, 2015.
[21]. E. Cambria, B. Schuller, Y. Xia, and C. Havasi, "New avenues in opinion mining and sentiment analysis," IEEE Intelligent Systems, vol. 28, no. 2, pp. 15–21, 2013.
[22]. S. Hochreiter and J. Schmidhuber, "Long short- term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780,1997.
[23]. M. Hagenau, M. Liebmann, and D. Neumann, "Automated news reading: Stock price prediction based on financial news using context-capturing features," Decision Support Systems, vol. 55, no. 3, pp. 685–697,2013.
[24]. A. Mittal and A. Goel, "Stock prediction using Twitter sentiment analysis," IEEE International Conference on Big Data, pp. 17–20, 2012.
[25]. R. Kumar and S. Thenmozhi, "Forecasting stock index returns using ARIMA–SVM, ARIMA–ANN, and ARIMA– Random Forest hybrid models," International Journal of Banking, Accounting and Finance, vol. 7, no. 3-4, pp. 284– 308, 2016.