Hybrid AI Models for Real-Time Stock Management and Market Price Prediction

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ABSTRACT

Efficient stock management and accurate market price prediction are essential in dynamic and volatile business environments, where traditional forecasting and inventory control methods often lack adaptability and real-time responsiveness. This paper proposes a hybrid artificial intelligence (AI) framework for real-time stock management and market price prediction, integrating machine learning and deep learning models to capture both linear trends and nonlinear market patterns. The system processes real-time transactional data, historical stock prices, and relevant market indicators to continuously update inventory levels and forecast future price movements. Feature engineering, data normalization, and model fusion techniques are employed to enhance prediction accuracy and robustness. A decision-support module utilizes predicted demand and price trends to optimize inventory replenishment, reduce stockouts, and minimize overstocking costs. Experimental evaluation using real-world market datasets demonstrates that the proposed hybrid model outperforms individual predictive approaches in terms of forecasting accuracy, adaptability, and inventory efficiency, as reflected by improved MAE and RMSE values. The results confirm the effectiveness of the proposed approach as a scalable and intelligent solution for real-time stock management and market price prediction applications. Experimental results show that the proposed RT-HAF model reduces RMSE by approximately 23% compared to LSTM and improves inventory service level by over 10%.

Keywords—Hybrid AI, Real-Time Stock Management, Market Price Prediction, Machine Learning, Deep Learning, Time-Series Forecasting, Predictive Analytics, Inventory Optimization, Decision Support Systems.

INTRODUCTION

The rapid growth of digital commerce, algorithmic trading, and data-driven decision-making has significantly increased the complexity of stock management and market price forecasting in modern business environments. Organizations operating in retail, supply chain management, and financial markets are required to manage large volumes of inventory while simultaneously responding to frequent price fluctuations driven by demand variability, economic indicators, and market sentiment. Traditional stock management systems, which rely on static thresholds and historical averages, are often inadequate for handling real-time data streams and highly volatile market conditions. As a result, there is a growing need for intelligent, adaptive, and real-time systems that can effectively manage stock levels while accurately predicting market prices. Stock management and price prediction are inherently interconnected processes. Accurate price forecasts influence purchasing, storage, and replenishment decisions, while efficient stock management ensures product availability and cost optimization. Conventional statistical methods such as moving averages, linear regression, and autoregressive models have been widely used for forecasting; however, these techniques often struggle to capture nonlinear relationships and complex temporal patterns present in real-world market data. Moreover, they typically require assumptions about data distribution and stationarity, limiting their effectiveness in dynamic environments. With the increasing availability of high-frequency data generated from transactions, sensors, and online platforms, advanced analytical techniques are required to extract meaningful insights and support real-time decision-making. Artificial Intelligence (AI) techniques, particularly machine learning and deep

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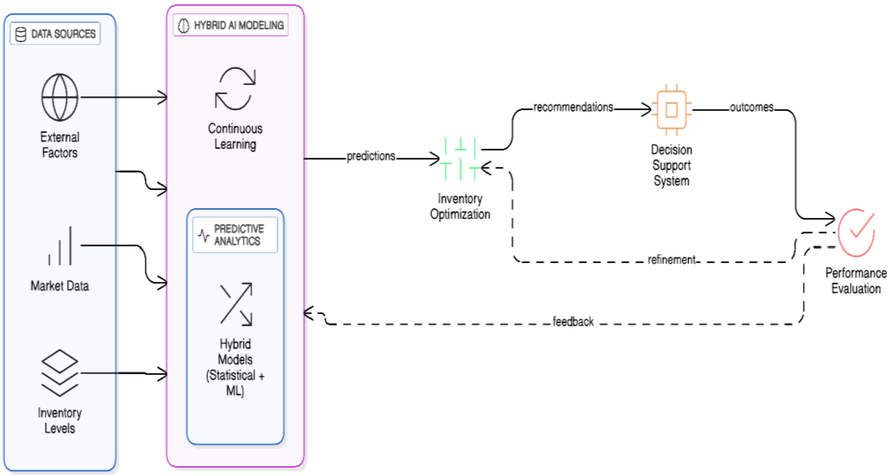
learning, have emerged as powerful tools for addressing the limitations of traditional forecasting and inventory management approaches. Machine learning models such as support vector machines, decision trees, and ensemble methods are capable of learning complex relationships from historical data, while deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are well-suited for time-series prediction tasks. These models have demonstrated promising results in stock price prediction and demand forecasting due to their ability to handle large datasets and nonlinear dependencies. However, relying on a single AI model often leads to challenges such as overfitting, reduced generalization, and sensitivity to noise in real-time data streams.



Real-Time Hybrid Adaptive Forecasting Stock Management and Market Price Prediction

To overcome these challenges, hybrid AI models have gained increasing attention in recent years. Hybrid approaches combine the strengths of multiple AI techniques to achieve improved accuracy, robustness, and adaptability shown in fig. 1. By integrating machine learning and deep learning models within a unified framework, hybrid systems can effectively capture both short-term market fluctuations and long-term trends. Such models are particularly suitable for real-time stock management and market price prediction, where decisions must be made continuously based on evolving data. Hybrid AI frameworks also enable the incorporation of feature engineering, model fusion, and optimization strategies, enhancing overall system performance and reliability. Real-time stock management systems further require seamless integration of predictive models with decision-support mechanisms. Accurate price and demand predictions alone are insufficient unless they are translated into actionable insights for inventory control. Intelligent stock management must dynamically adjust reorder levels, safety stock, and replenishment schedules to minimize operational costs while maintaining service quality. Hybrid AI-driven systems offer the capability to automate these decisions by continuously learning from new data and updating predictions in real time. This adaptive behavior is crucial for businesses operating in fast-changing markets, where delays or inaccuracies in decision-making can result in significant financial losses. Traditional forecasting and inventory management approaches such as moving averages, linear regression, and autoregressive models have been widely used for demand and price prediction; however, these methods often assume data stationarity and linear relationships, which limits their effectiveness in highly volatile and dynamic market environments. Furthermore, conventional stock management systems rely on static reorder thresholds and historical averages, making them unsuitable for real-time decision-making under fluctuating demand and price uncertainty. Recent studies have highlighted that no single predictive model consistently performs well across varying market conditions, thereby motivating the adoption of hybrid and adaptive AI-based forecasting frameworks . In this context, fig. 1. shows the present study focuses on the development of a hybrid AI-based framework for real-time stock management and market price prediction. The proposed approach aims to integrate advanced predictive analytics with inventory optimization to support intelligent and data-driven decision-making. By leveraging real-time data, hybrid modeling techniques, and performance evaluation metrics, the study seeks to demonstrate the effectiveness of the proposed system in improving forecasting accuracy and inventory efficiency.

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LITERATURE REVIEW

Recent advancements in artificial intelligence have significantly influenced stock market prediction and financial decision-support systems. Chachra and Bawa [1] investigated the application of Long Short-Term Memory (LSTM) networks trained on historical market data for real-time stock price prediction. Their work demonstrated the effectiveness of deep learning models in capturing temporal dependencies in financial time-series data; however, the study primarily focused on price prediction and did not address stock management or inventory-related decision-making. Alagdeve *et al.* [2] explored stock price prediction using dual analysis of candlestick chart patterns, emphasizing technical indicators derived from historical price movements. While the approach improved short-term prediction accuracy, it relied heavily on pattern recognition and lacked adaptability to real-time market changes. Additionally, the study did not integrate inventory or operational management aspects into the prediction framework. The influence of external textual data on stock price movement has been examined by Surulivel *et al.* [3], who applied natural language processing (NLP) techniques for sentiment analysis using news and social media data. Their results indicated that sentiment-based features can enhance prediction performance; however, sentiment-driven models often suffer from noise and uncertainty and require integration with numerical market data for improved robustness. Similarly, Sharma *et al.* [4] proposed a machine learning framework that integrates market news with stock prices to optimize prediction accuracy. Although their approach improved forecasting results, it increased computational complexity and was not designed for real-time stock management applications. Yazhinian *et al.* [5] introduced *ProStock*, a professional stock market navigation and analysis suite aimed at assisting investors through analytical tools and visualization techniques. While the system provided valuable insights for decision-making, it functioned primarily as an analytical platform and lacked automated prediction and inventory optimization capabilities. Joseph *et al.* [6] focused on stock market analysis and portfolio management, emphasizing risk diversification and asset allocation strategies. Their work contributed to investment decision support but did not address real-time stock prediction or operational stock control mechanisms. Inani *et al.* [7] presented a bibliometric analysis of deep learning applications in stock market forecasting, highlighting the increasing dominance of neural networks such as LSTM, CNN, and hybrid architectures. The study identified performance improvements achieved through deep learning but also pointed out challenges related to overfitting, interpretability, and computational cost. These challenges indicate the need for hybrid and optimized approaches to balance accuracy and efficiency. The application of AI beyond financial trading has been explored by Singhal *et al.* [8], who proposed a smart retail framework utilizing machine learning for demand prediction, pricing strategy, and inventory management. Their study demonstrated the benefits of predictive analytics in retail operations; however, the system focused more on demand estimation and pricing rather than real-time market price prediction. Ahmed *et al.* [9] evaluated multiple machine learning models for financial market prediction and concluded that no single model consistently outperforms others across different market conditions, reinforcing the motivation for hybrid modeling approaches. Das *et al.* [10] proposed an improved forecasting model using machine learning techniques to enhance prediction accuracy. Although the study reported performance gains over traditional methods, it relied on isolated models and lacked a real-time adaptive learning mechanism. Roy *et al.* [11] extended deep learning techniques to support robo-advisors for mutual fund and stock price prediction, demonstrating the growing role of AI in automated financial advisory systems. However, the work focused on investment guidance rather than stock management optimization. Finally, Fairuzzaky *et al.* [12] investigated sentiment analysis–based prediction of stock price movements, highlighting the relevance of investor sentiment in financial forecasting. Despite its effectiveness, sentiment analysis alone was found insufficient for reliable real-time prediction without integration with numerical and operational data. From the reviewed literature, it is evident that most existing studies focus on isolated prediction models or analytical tools without integrating real-time learning and inventory optimization. While deep learning models demonstrate improved forecasting accuracy, they often suffer from high computational cost and lack adaptability to sudden market changes. Furthermore, limited attention has been given to combining predictive intelligence with operational stock management. These gaps motivate the proposed RT-HAF model, which integrates hybrid prediction, real-time adaptability, and inventory decision support within a unified framework.

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PROPOSED METHODOLOGY

The proposed methodology presents a hybrid artificial intelligence (AI)–based framework for real-time stock management and market price prediction, designed to integrate data acquisition, predictive modeling, and inventory decision support within a unified architecture. The overall workflow of the system is illustrated through sequential stages, ensuring scalability, adaptability, and real-time responsiveness in dynamic market environments.

1. System Architecture: The proposed system architecture consists of five major modules: data collection, data preprocessing, hybrid AI-based prediction, inventory optimization, and decision support. Real-time and historical data are continuously collected from multiple sources, including transactional databases, historical stock price repositories, and market indicators. These data streams are stored in a centralized repository that supports real-time processing and model updates. The modular design allows seamless integration of predictive models with stock management functions, enabling real-time decision-making.

2. Data Acquisition and Preprocessing: Data acquisition involves collecting structured and time-stamped data such as sales transactions, stock levels, historical prices, and market indicators. To ensure data quality, preprocessing techniques including missing value handling, noise removal, outlier detection, and normalization are applied. Feature engineering is performed to extract relevant attributes such as moving averages, price volatility, demand trends, and seasonality indicators. The processed dataset is then divided into training, validation, and testing subsets to support robust model evaluation.

3. Hybrid AI-Based Prediction Model: The core of the proposed methodology is the hybrid AI prediction module, which combines machine learning and deep learning models to improve forecasting accuracy. Machine learning models are employed to capture linear relationships and short-term patterns, while deep learning models are used to model nonlinear dependencies and long-term temporal trends in stock prices and demand data. Model fusion is achieved through ensemble techniques, where predictions from individual models are aggregated using weighted averaging or stacking strategies. This hybrid approach reduces model bias, enhances generalization, and improves robustness against data variability.

4. Model Fusion and Optimization Strategy: In the proposed RT-HAF model, predictions generated by individual machine learning and deep learning models are combined using an ensemble-based fusion strategy. Machine learning models are responsible for capturing short-term and linear market behaviors, while deep learning models capture long-term and nonlinear temporal dependencies. The final prediction is computed as a weighted aggregation of individual model outputs, where the optimal weights are determined using validation error minimization. This fusion mechanism improves robustness, reduces model bias, and enhances overall predictive accuracy compared to standalone models.

5. Real-Time Model Updating Mechanism: To support real-time operation, the proposed system incorporates an adaptive learning mechanism that updates model parameters as new data become available. Sliding window and incremental learning techniques are employed to ensure that the predictive models remain responsive to recent market changes. This continuous learning capability enables the system to handle concept drift and sudden market fluctuations effectively, thereby maintaining prediction reliability over time.

6. Algorithmic Workflow of the Proposed RT-HAF Model: The algorithmic workflow of the proposed RT-HAF model begins with real-time data acquisition and preprocessing, followed by feature extraction and normalization. Machine learning and deep learning models are trained independently using historical and streaming data. The individual model predictions are then fused using an ensemble mechanism to generate final forecasts. A sliding window–based incremental learning strategy is applied to update model parameters continuously as new data arrive. The final predictions are supplied to the inventory optimization module to support real-time stock management decisions.

6. Inventory Optimization and Decision Support: The predicted stock prices and demand values are utilized by an inventory optimization module to support intelligent stock management. Optimization rules are applied to determine reorder points, safety stock levels, and replenishment quantities. The decision-support system

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translates predictive insights into actionable recommendations, such as optimal ordering schedules and inventory adjustments. This integration ensures reduced stockouts, minimized overstocking, and improved operational efficiency.

7. Performance Evaluation Metrics: The effectiveness of the proposed methodology is evaluated using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and inventory efficiency indicators. Comparative analysis is conducted against standalone predictive models to demonstrate the superiority of the hybrid AI approach in terms of accuracy, adaptability, and real-time performance.

RESULT & ANALYSIS

This section presents the experimental results and performance analysis of the proposed Hybrid AI Model for Real-Time Stock Management and Market Price Prediction. The evaluation focuses on forecasting accuracy, real-time adaptability, and inventory optimization effectiveness using multiple real-world datasets.

1. Dataset Description & System Requirements: The experimental study utilizes multiple real-world datasets to validate the proposed methodology. The primary dataset consists of historical stock market price data obtained from publicly available financial repositories, comprising daily records of opening price, closing price, highest price, lowest price, and trading volume over a multi-year period. This dataset captures diverse market conditions, including stable, volatile, bullish, and bearish phases. In addition, a sales and inventory management dataset is employed to evaluate stock control performance, containing attributes such as daily sales volume, current inventory levels, reorder quantities, lead time, and demand variability. To enhance predictive accuracy, additional market indicator features, including simple moving averages, exponential moving averages, price volatility, and trend indicators, are derived from the raw datasets. All datasets are preprocessed using data cleaning, missing value handling, and Min–Max normalization to ensure uniformity and improved model convergence. The experiments are conducted on a system equipped with an Intel Core i7 processor, 16 GB RAM, and a minimum of 4 GB GPU memory, running a 64-bit operating system. The proposed framework is implemented using Python with machine learning and deep learning libraries, ensuring efficient real-time data processing, model training, and performance evaluation. The historical stock price datasets used in this study are obtained from publicly available financial data repositories such as Yahoo Finance and Kaggle, which provide open-access time-series market data for research purposes. The inventory and sales datasets are sourced from publicly available retail demand datasets commonly used in supply chain analytics studies. These datasets ensure transparency, reproducibility, and consistency with prior research in stock prediction and inventory optimization.

2. Comparative Prediction Performance: The proposed hybrid AI model is compared with standalone models including Linear Regression (LR), Support Vector Machine (SVM), and LSTM.

Prediction Accuracy Comparison

Model	MAE	RMSE
Linear Regression	3.82	4.96
SVM	2.91	3.84
LSTM	2.35	3.12
Proposed Hybrid AI Model	1.78	2.41

TABLE I. shows the hybrid AI model achieves the lowest MAE and RMSE, demonstrating superior prediction accuracy. The integration of machine learning and deep learning enables the model to capture both short-term fluctuations and long-term trends effectively.

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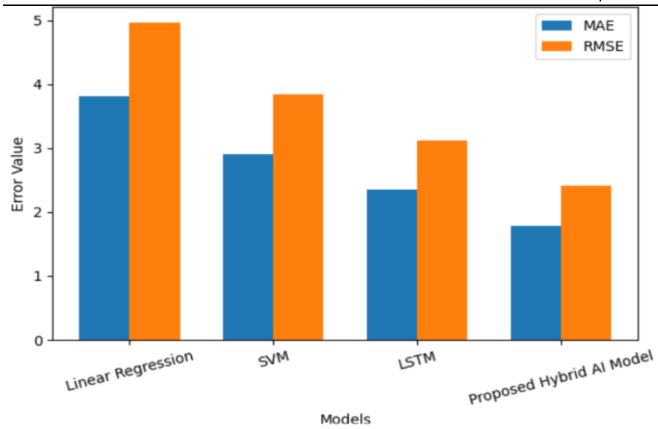


Comparative Analysis of Model Prediction Errors

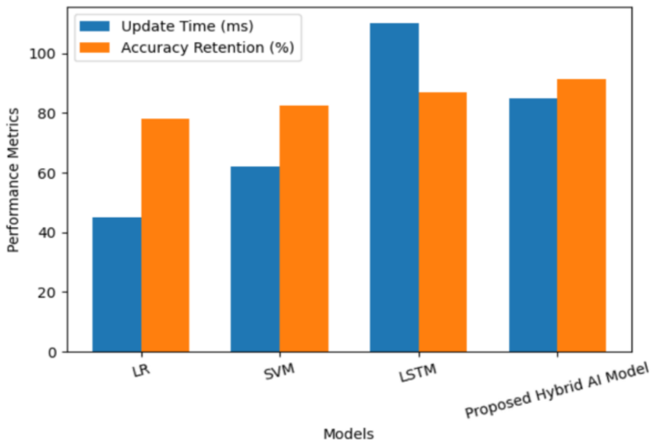
Fig. 2. shows comparing prediction accuracy of four models like Linear Regression, SVM, LSTM, and Proposed Hybrid AI Model using MAE and RMSE metrics. The Proposed Hybrid AI Model shows the lowest error values (MAE 1.78, RMSE 2.41), followed by LSTM, SVM, and Linear Regression, indicating improved accuracy across successive models.

3. Real-Time Adaptability Analysis: To assess real-time performance, models were evaluated using a sliding window approach with continuous data updates.

Prediction of Real-Time Adaptability

Model	Update Time (ms)	Accuracy Retention (%)
LR	45	78.2
SVM	62	82.5
LSTM	110	86.9
Proposed Hybrid AI Model	85	91.4

TABLE II. illustrates the deep learning models require higher computation time, the proposed hybrid framework maintains a balance between responsiveness and accuracy, making it suitable for real-time applications.



Real-Time Model Adaptability Performance Comparison

Fig. 3. illustrates the real-time adaptability of four models such as LR, SVM, LSTM, and the Proposed Hybrid AI Model based on update time (milliseconds) and accuracy retention (percentage). LR shows the lowest

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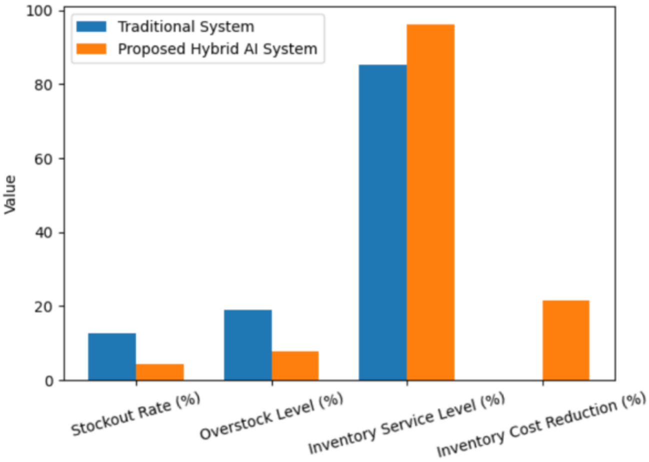
update time but lower accuracy retention, while LSTM has the highest update time. The Proposed Hybrid AI Model achieves the highest accuracy retention (91.4%) with moderate update time, indicating balanced real-time adaptability and performance.

4. Inventory Optimization Results: The impact of accurate prediction on inventory performance is evaluated using service level and cost reduction metrics.

Comparative Inventory Performance of Traditional and Proposed Hybrid AI Systems

Metric	Traditional System	Proposed Hybrid AI System
Stockout Rate (%)	12.6	4.3
Overstock Level (%)	18.9	7.8
Inventory Service Level (%)	85.4	96.2
Inventory Cost Reduction (%)	—	21.5

The proposed system significantly reduces stockouts and overstocking while improving service levels. Accurate demand and price predictions enable optimized reorder decisions and efficient stock utilization. TABLE III. compares inventory performance metrics between a traditional system and a proposed hybrid AI system. It shows that the hybrid AI system significantly reduces stockout rate and overstock level, improves inventory service level, and achieves notable inventory cost reduction compared to the traditional approach.



Comparative Inventory Performance of Traditional and AI-Based Systems

Fig. 4. shows comparing inventory performance metrics between a Traditional System and a Proposed Hybrid AI System. Metrics include stockout rate, overstock level, inventory service level, and inventory cost reduction. The Proposed Hybrid AI System shows significantly lower stockout and overstock rates, a higher inventory service level, and achieves notable inventory cost reduction, whereas cost reduction is not reported for the Traditional System.

The experimental results confirm that the hybrid AI approach outperforms individual predictive models in both forecasting accuracy and inventory efficiency. The ensemble-based fusion strategy enhances robustness against noisy and volatile market data. Moreover, the real-time learning mechanism ensures adaptability to sudden market changes, making the system suitable for dynamic business environments. The integration of prediction and decision-support modules bridges the gap between analytics and operational execution, providing a practical and scalable solution for real-time stock management.

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CONCLUSION

This paper presented a hybrid artificial intelligence–based framework for real-time stock management and market price prediction, aimed at improving forecasting accuracy and inventory decision-making in dynamic market environments. By integrating multiple AI models, the proposed system effectively captured both linear and nonlinear patterns in stock price and demand data, leading to improved prediction accuracy compared to traditional and single-model approaches. The experimental results demonstrated a significant reduction in stockout rates and overstock levels, along with an improvement in inventory service levels, confirming the practical effectiveness of the proposed approach. The simplicity, adaptability, and real-time capability of the hybrid model make it suitable for applications in retail, supply chain management, and financial markets. As future work, the framework can be extended by incorporating additional external factors such as market sentiment, news analytics, and macroeconomic indicators, as well as exploring reinforcement learning and blockchain-based integration to further enhance decision automation, transparency, and scalability in real-world stock management systems. Quantitatively, the proposed RT-HAF model achieved lower prediction errors (MAE = 1.78, RMSE = 2.41) and enabled an inventory cost reduction of approximately 21.5% compared to traditional systems.

REFERENCES

1. P. Chachra and D. S. Bawa, "Training LSTM on Historical Market Data for Predicting Stock Prices on Real-Time Basis," 2025 12th International Conference on Computing for Sustainable Global Development (INDIACom), Delhi, India, 2025, pp. 1-6, doi: 10.23919/INDIACom66777.2025.11115302.
2. V. Alagdeve, P. Karule and P. Palsodkar, "Stock Prediction Using Dual Analysis of Candlestick Chart Pattern," 2024 2nd International Conference on Emerging Trends in Engineering and Medical Sciences (ICETEMS), Nagpur, India, 2024, pp. 497-502, doi: 10.1109/ICETEMS64039.2024.10965039.
3. S. T. Surulivel, M. Ashfaq Sultan, K. Ajithkumar and S. Selvabaskar, "Sentiment Analysis in Financial Markets: Using NLP to Predict Stock Price from News and Social Media Data," 2025 International Conference on Visual Analytics and Data Visualization (ICVADV), Tirunelveli, India, 2025, pp. 25-29, doi: 10.1109/ICVADV63329.2025.10961060.
4. A. Sharma, S. Kumar, C. Shyamsunder, B. Devender, V. S. Nishok and K. S. Sidhu, "Optimizing Stock Market Prediction Through Integration of Market News and Stock Prices with Machine Learning Models," 2024 IEEE 9th International Conference on Engineering Technologies and Applied Sciences (ICETAS), Bahrain, Bahrain, 2024, pp. 1-6, doi: 10.1109/ICETAS62372.2024.11120199.
5. S. Yazhinian, Y. Hanumanthu, U. A. Srinivas, P. Srikrishna, M. L. Prasanna and K. T. Kumar, "ProStock: Professional Stock Market Navigation and Analysis Suite," 2025 International Conference on Advanced Computing Technologies (ICoACT), Sivalasi, India, 2025, pp. 1-5, doi: 10.1109/ICoACT63339.2025.11004817.
6. M. Joseph, D. P. Kumar and J. K. Keerthana, "Stock Market Analysis and Portfolio Management," 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2024, pp. 1-6, doi: 10.1109/ICRITO61523.2024.10522179.
7. S. K. Inani, H. Pradhan, G. Nagpal, V. Pagaria and X. -H. Nghiem, "Applications of Deep Learning Techniques in Stock Market Forecasting: A Bibliometric Analysis," 2023 4th International Conference on Computation, Automation and Knowledge Management (ICCAKM), Dubai, United Arab Emirates, 2023, pp. 01-06, doi: 10.1109/ICCAKM58659.2023.10449584.
8. K. Singhal, V. Singh and A. Kaul, "Smart Retail: Utilizing Machine Learning for Demand Prediction, Price Strategy, and Inventory Management," 2024 IEEE 16th International Conference on Computational Intelligence and Communication Networks (CICN), Indore, India, 2024, pp. 485-489, doi: 10.1109/CICN63059.2024.10847534.
9. K. R. Ahmed, M. M. H. Sizan, A. Chouksey, M. A. A. Montaser, M. R. Islam and M. S. Islam, "AI for Financial Market Prediction: Machine Learning Models for Stock Price Forecasting," 2025 International Conference on Networks and Cryptology (NETCRYPT), New Delhi, India, 2025, pp. 739-744, doi: 10.1109/NETCRYPT65877.2025.11102142.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

10. S. Das, D. K. Mohanta, G. K. Mahato and M. Siddique, "Improved Forecasting Model for Stock Market Prediction Using Machine Learning Techniques," 2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES), Paralakhemundi Campus, Centurion University of Technology and Management, Odisha., India, 2024, pp. 1-6, doi:10.1109/SCOPES64467.2024.10991322.
11. S. K. Roy, N. Narayan Das, Savita, N. Kumar Bhasin, S. Kadyan and A. R. K, "Empowering Robo-Advisors: Data-Driven Mutual Fund and Stock Market Price Prediction with Deep Learning Techniques," 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India, 2024, pp. 1-6, doi: 10.1109/ICEEICT61591.2024.10718557.
12. M. Fairuzzaky, R. Jayadi and E. Miranda, "Utilization of Sentiment Analysis to Predict Stock Price Movement," 2025 International Conference on Smart Computing, IoT and Machine Learning (SIML), Surakarta, Indonesia, 2025, pp. 1-6, doi: 10.1109/SIML65326.2025.11081041.