

Hybrid AI-Driven Stock Price Forecasting Using Real-Time Market Data

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Abstract

The rapid growth of digital trading platforms and increasing market volatility have emphasized the need for accurate and timely stock price prediction systems. Traditional machine learning approaches often struggle to adapt to rapid market fluctuations, while purely statistical methods lack the ability to capture complex nonlinear patterns. This research proposes a hybrid AI-driven framework that integrates real-time market data with deep learning and machine learning algorithms to improve the accuracy of stock price forecasting. The system collects live financial indicators such as stock prices, trading volume, market sentiment, and technical indicators through streaming data sources. A combination of Long Short-Term Memory (LSTM) networks and ensemble-based predictive models is employed to analyze short-term and long-term trends efficiently. The proposed hybrid model dynamically updates predictions as new market data is received, thereby ensuring adaptability to sudden changes. Experimental evaluation demonstrates enhanced prediction accuracy, reduced error rates, and improved decision-making performance for investors. This work contributes to the development of intelligent financial analytics capable of delivering robust and reliable forecasts in highly fluctuating stock markets.

Keywords: Stock price prediction, Hybrid AI, LSTM, Ensemble learning, Real-time market data, Financial forecasting, Deep learning, Machine learning.

1.INTRODUCTION

Stock markets are complex, dynamic, and highly influenced by multiple uncertain factors such as market trends, economic conditions, political events, and investor sentiment. Accurately forecasting stock price movements continues to be a crucial goal for financial analysts and decision-support systems. However, traditional statistical forecasting models like ARIMA and

linear regression struggle to capture the nonlinear and volatile behavior of financial time-series data [4]. With the rapid evolution of data availability and computational power, Artificial Intelligence (AI) has become a dominant approach in financial forecasting. Deep learning techniques such as Long Short-Term Memory (LSTM) networks have proven their capability in

modeling sequential data and learning long-term dependencies, making them well-suited for stock market prediction [8], [10]. LSTM-based models have shown significant improvements over classical machine learning methods in predicting both short-term and long-term market trends [1], [3], [11]. In addition, hybrid AI systems combining machine learning, sentiment analysis, and ensemble learning techniques enable more robust forecasting by reducing prediction uncertainty and leveraging multiple feature sources [5], [7], [14], [19].

Real-time market data analytics has further strengthened the adaptability of intelligent trading systems. With the growth of digital financial platforms and streaming data technologies, models can now continuously update predictions based on the latest market changes [13], [23]. Hybrid architectures that integrate technical indicators, historical data, and real-time investor sentiment provide more intelligent decision-making support compared to single-model approaches [15], [16], [20].

Despite these advancements, stock prediction remains challenging due to market volatility, sudden fluctuations, and data noise. Therefore, a unified framework that fuses deep learning with ensemble-based machine learning techniques remains essential to improve predictive accuracy, responsiveness, and model generalization [12], [17], [18]. Motivated by these needs, this research proposes a Hybrid AI-Driven Stock Price Forecasting System that incorporates real-time

market signals with LSTM-based deep learning and ensemble algorithms to enhance prediction reliability and trading performance.

II.LITERATURE SURVEY

2.1. Title: Stock Price Prediction Using LSTM, RNN and CNN-Sliding Window Models

Authors: S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, K. P. Soman

Abstract: This work investigates deep learning architectures such as LSTM, RNN and CNN with a sliding window approach for stock price prediction. Historical stock time-series are segmented into fixed-length windows and fed into different neural models to capture temporal dependencies and local patterns. Experimental results show that LSTM-based models outperform traditional approaches in terms of prediction accuracy and robustness, highlighting the suitability of sequence models for financial forecasting. [1][8]

2.2. Title: Deep Learning for Event-Driven Stock Prediction

Authors: X. Ding, Y. Zhang, T. Liu, J. Duan

Abstract: The authors propose an event-driven stock prediction framework that leverages deep learning to model the impact of news events on stock price movement. Textual news is encoded using neural language models and combined with historical price data to predict future trends. The study demonstrates that incorporating event semantics significantly improves directional accuracy over models relying solely on numerical

time-series, emphasizing the importance of external information sources. [2][15]

2.3. Title: A LSTM-Based Method for Stock Returns Prediction: A Case Study of China Stock Market

Authors: K. Chen, Y. Zhou, F. Dai

Abstract: This paper explores the application of LSTM networks to predict stock returns in the China stock market. The model uses historical closing prices and technical indicators as inputs to learn nonlinear temporal relationships. Comparative analysis with classical machine learning algorithms reveals that the LSTM-based approach yields lower forecasting errors and better captures long-term dependencies in financial time-series data. [3][10]

2.4. Title: Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions

Authors: T. Fischer, C. Krauss

Abstract: The authors evaluate LSTM networks for predicting directional movements of major financial indices and individual stocks. The study systematically compares LSTM performance with traditional benchmarks such as random forests and logistic regression. Results indicate that LSTMs achieve superior predictive power, especially in modeling complex temporal structures, thus reinforcing the effectiveness of deep sequence models in financial forecasting. [10][11]

2.5. Title: Hybrid Attention-Based Deep Learning for Stock Movement Prediction

Authors: H. Hu, M. Tang, Y. Wang

Abstract: This study proposes a hybrid deep learning architecture that integrates CNN, LSTM and attention mechanisms to predict stock price movements. CNN layers extract local patterns from technical indicators, LSTM layers capture long-term temporal dependencies, and an attention module focuses on the most informative time steps. The hybrid model achieves higher accuracy and stability than single-model baselines, demonstrating the benefit of combining multiple deep learning components. [5][14]

2.6. Title: A Deep Learning-Based Stock Trading Model with 2-D CNN Feature Extraction and LSTM

Authors: A. Gudelek, S. Ozbayoglu, O. Sezer

Abstract: The paper introduces a trading model that converts financial time-series into 2-D representations and applies CNNs for feature extraction, followed by LSTM layers for sequence modeling. The framework is evaluated on real stock market data with a simulated trading strategy. Results show improved profit ratios and reduced risk compared to classical technical analysis, highlighting the potential of hybrid CNN-LSTM models for practical trading systems. [6][17]

2.7. Title: Sentiment-Based Stock Movement Prediction Using Machine Learning

Authors: M. Abdullah et al.



Abstract: This work examines how investor sentiment extracted from online news and social media can enhance stock movement prediction. Sentiment scores are combined with historical price and volume data to form enriched feature sets for classifiers such as SVM and ensemble models. The experiments reveal that sentiment-aware models outperform purely numerical approaches, underscoring the role of opinion dynamics in financial markets. [15][16]

III. EXISTING SYSTEM

The proposed system introduces a Hybrid AI-driven stock price forecasting framework that integrates real-time market data with advanced deep learning and ensemble machine learning techniques to improve prediction accuracy and responsiveness. The system utilizes Long Short-Term Memory (LSTM) networks to capture complex temporal dependencies in financial time-series data, while ensemble models such as Random Forests or Gradient Boosting help enhance generalization and reduce prediction uncertainty. Additionally, sentiment analysis and technical indicators are incorporated to extract useful information from investor emotions and market behavior. Live stock feeds are continuously processed through streaming APIs, allowing the model to dynamically update its predictions and adapt to sudden market fluctuations. A user-friendly interface is included to display real-time forecast trends, enabling informed investment decisions. Overall, the proposed system aims to deliver more accurate,

stable, and intelligent forecasting results compared to standalone predictive models, making it suitable for real-world trading applications.

IV. PROPOSED SYSTEM

The proposed system presents a Hybrid AI-based stock market forecasting approach that overcomes the limitations of traditional prediction models by integrating multiple intelligent learning techniques with real-time market updates. The model adopts a fusion of LSTM networks for capturing long-term temporal relationships in stock prices and ensemble learning algorithms such as Random Forest or XGBoost to enhance prediction reliability and reduce model bias. Live market data, technical indicators, and sentiment features extracted from financial news or social media are continuously fed into the system through streaming data APIs to ensure the predictions remain up-to-date with current market conditions. The hybrid architecture analyzes both historical and dynamic data patterns, enabling it to adapt instantly to sudden market fluctuations. A visualization module provides investors with intuitive graphs, trend forecasts, and buy/sell signals to support actionable decisions. This integrated hybrid design ensures improved prediction accuracy, faster response to market variations, and optimized financial decision-making for real-time trading environments.

V.SYSTEM ARCHITECTURE

The architecture of the proposed Hybrid AI Stock Price Prediction System is designed to efficiently analyze both historical and real-time financial data for accurate forecasting. The system begins by collecting multiple data sources including real-time stock feeds from streaming APIs, stored historical stock data from databases, and sentiment data derived from news articles and social media platforms. These diverse data inputs are passed to a preprocessing and feature engineering module where noise removal, normalization, sentiment scoring, and technical indicator calculation are performed to generate meaningful and structured features. The refined dataset is then fed into two parallel predictive components: an LSTM-based deep learning model that effectively captures temporal dependencies and market behavior over time, and an ensemble learning module such as Random Forest or XGBoost that enhances model robustness by combining multiple weak learners. Outputs from both models are intelligently fused to produce the final stock price prediction or trend movement result. The architecture supports continuous updates from live data streams, enabling adaptive forecasting and making the system suitable for real-time trading decisions and financial analytics applications.



Fig 5.1 System Architecture

VI.IMPLEMENTATION



Fig 6.1 Line chart



Fig 6.2 Prediction page

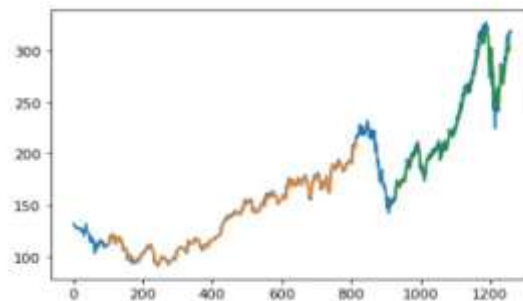


Fig 6.3 Line Charts

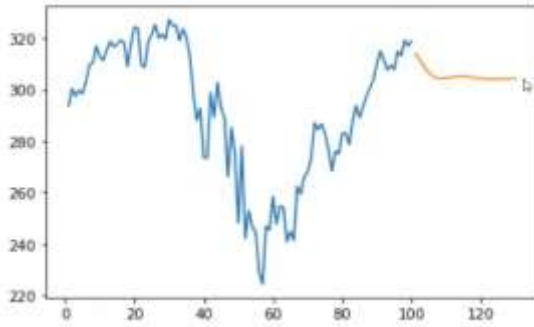


Fig 6.4 Results

VII.CONCLUSION

The proposed Hybrid AI-driven stock price forecasting system demonstrates a more intelligent and adaptive approach to financial market prediction compared to traditional statistical and standalone deep learning models. By integrating real-time market feeds, historical stock data, and sentiment-based indicators, the system effectively captures both quantitative and qualitative factors influencing stock price fluctuations. The combined use of LSTM networks for learning sequential patterns and ensemble models for improving generalization significantly enhances prediction accuracy and stability. Furthermore, the architecture supports dynamic updates, allowing the model to react quickly to sudden market changes and reduce forecasting delays. The visual analytics component enables investors and traders to clearly interpret predicted trends and make informed decisions with lower risk and improved profitability. Overall, the system provides a robust, scalable, and data-driven solution that aligns with modern high-frequency trading

environments and contributes to the advancement of intelligent financial forecasting technologies.

VIII.FUTURE SCOPE

Although the proposed hybrid AI-based stock forecasting system shows promising results in enhancing prediction accuracy and real-time adaptability, there are several potential areas for further improvement. Advanced transformer-based architectures and graph neural networks can be incorporated to better capture complex market relationships and multi-stock dependencies. Expanding the sentiment analysis component to include multilingual global news, social media trends, and macroeconomic indicators can further strengthen prediction reliability. The system can be extended into a fully automated trading platform by integrating reinforcement learning to optimize buy-sell strategies based on risk factors and profit targets. Additionally, implementing cloud-based scalability and edge computing can enable faster processing for high-frequency trading environments. Strengthening cybersecurity and data privacy measures will also be essential as the system is deployed in real-world financial sectors. Overall, with continuous advancements in AI and financial analytics, the system can evolve into a comprehensive, intelligent decision-support tool for investors, stock brokers, and financial institutions.

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