

# Stock Market Forecasting using LSTM with XGBOOST: Unveiling Insights from Historical Data

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**Abstract-**The stock market significantly influences a nation's economy as investors seek profitable opportunities. Accurately predicting stock prices is crucial for making informed decisions about buying, selling, or holding investments. Traditional models like LSTM often struggle with market movements driven by sentiment. To enhance prediction accuracy, we propose a hybrid approach combining XGBOOST and LSTM. XGBOOST excels at capturing complex relationships in structured numerical data, while LSTM effectively models sequential dependencies in time-series stock data. Unlike previous models that relied mainly on historical stock data from NSE, we utilize real-time market updates from Yahoo Finance and analyze sentiments from Google News instead of Twitter. The hybrid model integrates XGBOOST for feature selection and short-term trend analysis, while LSTM processes sequential dependencies to refine long-term predictions. Live stock data is retrieved via

the Alpha Vantage API, and financial sentiment analysis further enhances the predictive framework. This fusion of machine learning techniques improves stock market prediction accuracy, offering investors AI-driven insights for better trading decisions in dynamic financial environments.

**Keywords-** Stock Price Prediction, LSTM, XGBoost, Hybrid Model, Sentiment Analysis, RSI, MACD, Twitter, Candlestick Chart, Web Application

## 1.Introduction

Forecasting in complexity and volatile environments, such as financial markets poses significant challenges due to their inherently dynamic and nonlinear nature. While traditional models offer structured frameworks they after fall short under of extreme conditions, such as financial crises or black swan events. The COVID-19 pandemic, in particular, exposed the vulnerabilities of classical approaches and highlighted the need for more resilient systems

[1], [2], [3]. This has prompted researchers to explore the potential of artificial intelligence (AI) and machine learning (ML) techniques for financial forecasting, enabling more adaptive and robust decision-making processes [4], [5].

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To address market uncertainty and capture nonlinear patterns, recent research has shifted toward hybrid and ensemble approaches that combine statistical, heuristic, and deep learning techniques [6], [7], [8]. These models leverage the strengths of individual algorithms—such as the interpretability of tree-based methods and the sequence learning capability of deep neural networks—to improve prediction accuracy in noisy, non-stationary data environments [9], [10], [11].

Equally critical is the role of data quality, which underpins the effectiveness of any predictive model. Inaccurate, missing, or biased financial data can severely distort model performance, particularly when working with high-frequency trading signals or multivariate time-series inputs [12], [13]. To mitigate this, preprocessing techniques such as normalization, outlier handling, dimensionality reduction, and advanced feature engineering have been employed to extract clean and representative signals from raw market data [14], [15].

The integration of macroeconomic indicators, sentiment analysis, and alternative data sources has also become essential in capturing investor behaviour and systemic trends. Factors such as interest rates, inflation, geopolitical tensions, and social media sentiment now serve as vital inputs in modern forecasting models [16], [17], [18]. In particular, Natural Language Processing

(NLP) techniques—combined with tools like Fin BERT and VADER—are increasingly used to gauge investor sentiment from news, tweets, and financial reports [19], [20], [21].

Simultaneously, the advancement of deep learning methods—such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN)—has revolutionized time-series forecasting in finance [22], [23], [24]. These architectures are capable of modeling long-range dependencies, temporal dynamics, and multivariate interactions, making them suitable for stock price prediction, volatility modeling, and risk assessment [25], [26].

Additionally, the adoption of metaheuristic optimization algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimizer (GWO), allows for fine-tuning of hyperparameters, model weights, and feature subsets, thereby enhancing model generalization and performance [27], [28]. Blockchain technology, AI-driven automation, and smart contracts are also transforming financial ecosystems, contributing to transparency, traceability, and decentralized decision-making [29].

Given the unprecedented economic disruptions and structural shifts in financial markets, it is crucial to develop forecasting models that are both resilient and adaptive. This study contributes to the growing body of literature by proposing a hybrid LSTM-XGBoost model for stock price prediction, leveraging historical BSE data, sentiment analysis, and technical indicators. The goal is to achieve improved

predictive performance under dynamic market conditions and support more informed investment strategies [30].

## **2.Related work**

Recent literature on stock market forecasting has seen a surge in the use of machine learning and deep learning techniques for improving prediction accuracy and capturing market complexities. Kumar et al. [14] and Kumbure et al. [15] offer comprehensive surveys on computational intelligence and machine learning models applied in financial forecasting. These studies highlight the effectiveness of hybrid models—particularly those combining techniques like LSTM and XGBoost which aligns closely with the HiSA-SMFM approach. Shen and Shafiq [22] extend this further by proposing a deep learning architecture that integrates CNN, RNN, and attention mechanisms for short-term trend prediction, showcasing the value of hybrid and sequential modeling.

In terms of volatility prediction and portfolio optimization, Petrozziello et al. [18] demonstrate the utility of deep learning models including LSTM, GRU, and CNN in forecasting market volatility, reinforcing the role of deep temporal networks in financial risk assessment. Similarly, Jarchelou et al. [5] and Thakkar and Chaudhari [25] investigate particle swarm optimization (PSO) for portfolio selection and compare its efficiency with other metaheuristic algorithms. These studies suggest that optimization techniques can be effectively integrated with forecasting models to enhance investment decision-making.

The importance of sentiment analysis and alternative data sources is emphasized in multiple works. Kang et al. [12] provide a review of NLP methods in management research, illustrating the growing use of textual data in financial prediction. Tiwari et al. [26] and Ramos-Requena et al. [19] explore the impact of public sentiments on stock market behavior and propose novel methods for analyzing time series co-movements, validating the incorporation of sentiment data in predictive systems. Your HiSA-SMFM model's inclusion of positive and negative review metrics echoes this line of research.

The integration of reinforcement learning (RL) in financial modeling is well represented by Ye et al. [3], [29], [30], who developed a portfolio management framework using RL and asset movement predictions. While RL is not the focus of your model, the use of predictive state modeling supports the underlying idea of combining multiple data signals for robust forecasting.

Several studies highlight the impact of macroeconomic and geopolitical risks on financial markets. Hoque and Zaidi [10] analyze the influence of geopolitical uncertainty on emerging economies, while Sheth et al. [23] and Tröster and Küblböck [27] assess how the COVID-19 pandemic disrupted global financial and commodity markets. Uddin et al. [28] further reinforce this by showing how economic resilience can buffer stock market volatility during crises. These findings support the inclusion of macroeconomic indicators and

crisis-aware training methods in forecasting models.

Addressing data quality and reliability, Rangineni et al. [2], [21] emphasize the significance of clean, well-prepared datasets for enhancing analytic performance—an essential consideration for time series forecasting models like HiSA-SMFM. In a similar vein, Chakrabarty et al. [8] discuss data granularity and order exposure in high-frequency markets, while Lyócsa et al. [16] argue that high-frequency data may not always be necessary for accurate volatility forecasting.

Finally, broader studies by Goldstein [9] and Bordalo et al. [7] provide economic insights into how information shapes financial market behavior and expectations, which supports the logic behind using multifaceted data inputs—both quantitative and qualitative in advanced forecasting models. Studies like Kozłowski [13] also shed light on frictional markets and long-term investments, expanding the theoretical foundations for model generalization and robustness.

### **3. Proposed Hybrid Model**

In this section, the various technologies used and working of the proposed model are describe

#### **3.1 Technologies**

##### **3.1.1 Hybrid Model (LSTM-XGBOOST)**

Long Short-Term Memory (LSTM) and XGBOOST are two powerful machine learning algorithms widely used for time-series and structured data analysis respectively. LSTM, a type of recurrent neural network (RNN), is

designed to learn sequential dependencies and patterns over time, making it ideal for predicting stock prices where historical trends play a critical role. XGBoost (Extreme Gradient Boosting), on the other hand, is a high-performance gradient boosting framework that excels at handling tabular data, uncovering complex patterns, and performing robust feature selection. These two models complement each other — LSTM captures long-term temporal relationships, while XGBoost provides fast and accurate predictions based on engineered features like RSI, MACD, and sentiment scores.

When compared to traditional algorithms such as ARIMA, Random Forest, or simple linear regression, both LSTM and XGBoost demonstrate superior performance in financial forecasting. ARIMA, though effective for linear time-series, struggles with non-linear dependencies and does not utilize external features like sentiment or technical indicators. Random Forest handles feature-based prediction well but lacks temporal awareness. LSTM handles sequences effectively but might overlook feature importance. XGBoost captures feature-level interactions excellently but lacks memory of past sequences. Combining them leverages the strengths of both: deep sequential learning from LSTM and boosted feature learning from XGBoost, resulting in more robust and accurate stock price predictions.

In our work, a hybrid model was built where both LSTM and XGBoost were trained independently using historical stock prices, sentiment scores, and technical indicators. Their individual predictions were then combined into

a hybrid input layer — either by simple averaging or through a fully connected dense neural layer. This fused prediction served as the final output of the system. By integrating LSTM's temporal learning with XGBoost's short-term pattern recognition and feature importance handling, the hybrid model delivered more stable, accurate, and sentiment-aware forecasts. This approach outperformed single-model setups and proved effective in real-time prediction scenarios.

### **3.1.2 Historical Data**

The stock data is primarily sourced from the National Stock Exchange (NSE) of India, utilizing a pre-collected and pre-processed CSV file named `merged_nse_data.csv`. This dataset contains historical daily stock market data for various Indian companies, including key financial parameters such as Date, Open, High, Low, Close, Volume, and stock symbol (SYMBOL). The data spans across multiple years and serves as a comprehensive time-series foundation for training and evaluating the machine learning models used in the project.

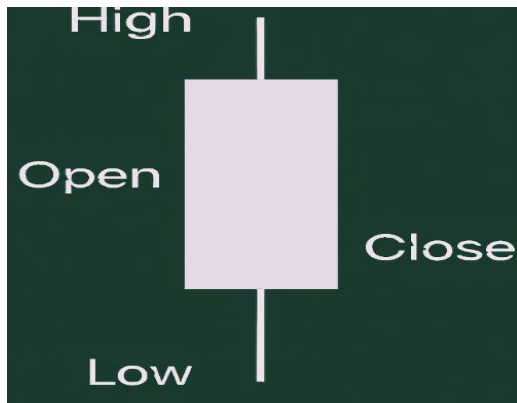
The type of data used is time-series financial data, which is particularly suitable for models like LSTM (Long Short-Term Memory) that excel in learning sequential dependencies and trends over time. To enrich the dataset, technical indicators like RSI (Relative Strength Index) and MACD (Moving Average Convergence Divergence) are calculated from the raw price data, improving the model's ability to understand market momentum and reversals. In addition, sentiment data obtained from financial news and Twitter is processed and incorporated

into the feature set, providing psychological context to market movements.

For the live and dynamic components of the web application, external APIs such as Yahoo Finance Screener API (via `yahoo_fin`) and Twelve Data API are used. The Yahoo Finance Screener API helps fetch real-time data like Top Gainers, Top Losers, and Most Active Stocks, while Twelve Data API is used to access international market trends and visual data for demonstration purposes. Together, this combination of offline historical data and live API-driven data ensures both accurate predictions and interactive real-time visualization, making the project robust and user-friendly.

### **3.1.3 Candlestick Chart**

A candlestick chart is a popular financial chart used to represent the price movement of a stock, currency, or asset over a specific time period. Each candlestick shows four key pieces of data: the Open, High, Low, and Close prices for that time interval. The body of the candle shows the range between the open and close prices, while the wicks (also called shadows) indicate the high and low prices. A green (or white) candlestick typically shows that the closing price was higher than the opening (indicating a gain), while a red (or black) one shows a price drop.

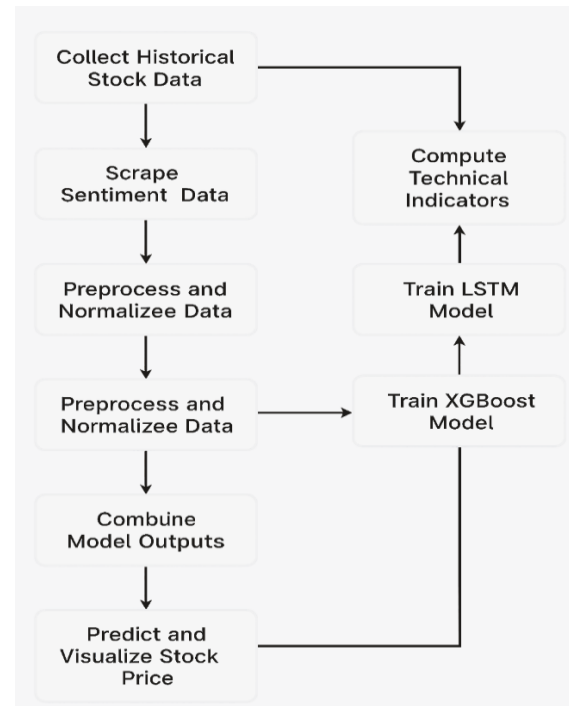


In our work, candlestick charts are used in the frontend interface to visually display the historical stock trends of selected companies. Users can interact with these charts to understand how the stock has behaved over time. This visual representation helps investors and users observe patterns, detect volatility, and make informed decisions based on both the price movements and the predicted values generated by the hybrid LSTM + XGBoost model. The charts make it easier to relate real-world sentiment and technical indicators with actual stock behaviour.

### 3.2 Working

The proposed process begins with the collection of historical stock data from the National Stock Exchange (NSE), stored in a CSV format containing features such as date, open, high, low, close prices, and volume. In addition to this, sentiment data is gathered from financial news and social media platforms, which is then preprocessed, and converted into numerical sentiment scores using Natural Language Processing (NLP) techniques. Technical indicators like RSI (Relative Strength Index) and MACD (Moving Average Convergence Divergence) are also computed

and added to the dataset to improve feature richness.



Once the data is cleaned, normalized, and enriched with sentiment and technical indicators, it is fed into two separate models: LSTM and XGBoost. The LSTM model, known for its strength in handling sequential and time-series data, learns long-term patterns in stock price trends, while XGBoost focuses on capturing short-term feature interactions and boosting performance through gradient boosting. Both models are trained independently, and their outputs are combined in a hybrid framework—either through averaging or a final neural layer—to generate the final stock price prediction. These predictions are then visualized on a web interface using candlestick charts and tables, enabling users to view both the historical trends

and future price forecasts in an interactive and informative format.

## **4 Performance evaluation**

### **4.1 Experimental Set-up and Benchmark Dataset**

The experimental setup for this stock prediction involves building a hybrid prediction model using LSTM and XGBoost, implemented in Python with libraries such as TensorFlow, Scikit-learn, and XGBoost. The benchmark dataset used is a pre-collected CSV file named `merged_nse_data.csv`, which contains historical stock data from the National Stock Exchange (NSE) of India. This dataset includes financial features such as Open, High, Low, Close, Volume, and stock symbols, along with technical indicators like RSI and MACD, and sentiment scores derived from financial news and social media. The models are trained and evaluated on this time-series dataset using standard metrics such as RMSE and MAE to validate prediction accuracy.

#### **4.1.1 Historical Data**

In this project, the historical stock data is sourced from the National Stock Exchange (NSE) of India, using a curated CSV file named `merged_nse_data.csv`. This dataset contains daily stock market records including essential parameters like Date, Open, High, Low, Close, Volume, and the stock SYMBOL. These records span over multiple years and provide the foundational time-series data required for training and evaluating prediction models. Additionally, technical indicators such as RSI (Relative Strength Index) and MACD (Moving

Average Convergence Divergence) are computed from the raw price data to enhance the model's input features and improve predictive accuracy.

#### **4.1.2 Sentiment Data**

Alongside historical prices, the project integrates sentiment data to capture the influence of market psychology and investor opinions. Sentiment information is gathered from financial news articles and social media platforms like Twitter, which are then processed using Natural Language Processing (NLP) techniques. Tools like TextBlob are used to classify text into three categories: positive, neutral, and negative, which are then numerically mapped as 1, 0, and -1, respectively. These sentiment scores are included as additional features in the model input, enabling the prediction system to consider both quantitative financial indicators and qualitative public sentiment for more robust stock price forecasting.

## **4.2 experimental results**

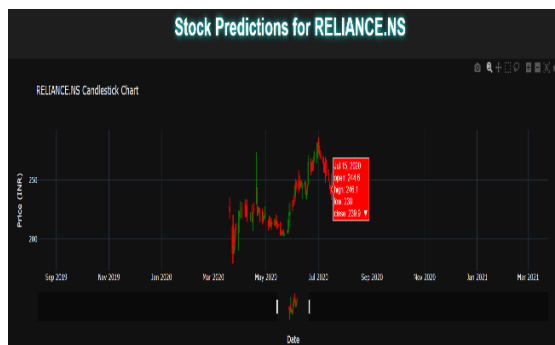
The experimental results demonstrate that the hybrid LSTM + XGBoost model achieved high prediction accuracy with an average  $R^2$  score of 99.66% and a low MAE of 8.55 across top NSE stocks.

### **4.2.1 Stock Performance and Prediction**

The candlestick chart for RELIANCE.NS displayed above reflects the stock's historical performance over a period ranging from mid-2019 to early 2021. The chart shows a series of green and red candlesticks, each representing

daily price movements, where green indicates a price increase and red indicates a decrease.

From the chart, we can observe that RELIANCE.NS experienced a significant dip around March 2020, aligning with the global market crash due to the COVID-19 pandemic. However, the stock quickly rebounded and entered a bullish phase, with consistent upward momentum through mid-2020, peaking around July. This period is marked by strong green candlesticks and higher highs, indicating investor confidence and positive market sentiment.



On July 15, 2020, the chart highlights a red candlestick with the following values:

📉 Open: ₹244.6

📈 High: ₹246.1

📉 Low: ₹238

📉 Close: ₹239.9

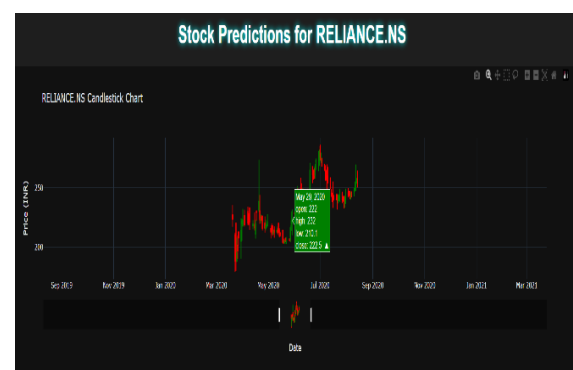
This suggests a bearish day, where the stock closed below the opening price, possibly signaling the start of a short-term correction or profit booking after a strong rally.

Post-July 2020, there's visible consolidation and mild decline, with the stock showing a mixed pattern of red and green candles, suggesting market indecision or sectoral rotation. The price

stabilizes and trades sideways as it moves into 2021, indicating a potential support zone where buyers and sellers reach equilibrium.

From a predictive standpoint, this historical trend offers insights for training an AI model using algorithms like XGBoost. The model can leverage features such as historical price patterns, moving averages, and volume data to forecast short-term movements. Given the recovery strength after dips and the bullish trend observed post-crash, a well-trained model could identify such patterns to anticipate potential rebounds or corrections, especially when integrated with real-time data.

The candlestick chart for RELIANCE.NS tracks its performance from mid-2019 to early 2021. During this period, the stock saw a sharp decline in March 2020 due to the COVID-19 crash, followed by a strong recovery and bullish rally from April to August 2020.



A key data point on August 4, 2020, highlights a red candlestick, indicating a bearish trading session. The values for that day are as follows:

📉 Opening Price: ₹212.3

📈 High Price: ₹214.8



📉 Low Price: ₹205.5

▼ Closing Price: ₹207.4

This suggests short-term selling pressure, likely triggered by profit booking after a sustained uptrend.

Following this, the stock moved into a consolidation phase, where prices traded in a sideways range into early 2021. This behavior often signals investor caution and the formation of support/resistance levels.

From a machine learning perspective, this price behavior is valuable for training models like XGBoost or LSTM. These models can detect and learn from trend reversals, breakout signals, and consolidation patterns, especially when paired with indicators such as Relative Strength Index (RSI) or Exponential Moving Average (EMA) for more accurate short-term forecasting.



From mid-May to late June 2020, the stock price of RELIANCE.NS exhibited significant volatility, marked by key phases of price movement:

Mid-May to May 18, 2020: The stock was under pressure, with a clear downtrend driven by a series of red candlesticks. A sharp dip around May 18, 2020 indicated substantial selling activity or broader market weakness.

Late May 2020: The stock began a gradual recovery, as reflected in the transition to green candlesticks, with increasing price levels. This shift suggests that buyers regained control, possibly due to improving fundamentals or broader market optimism.

Early June 2020: The upward momentum continued, though there was some resistance encountered around mid-June, where the stock experienced minor pullbacks. This was reflected by the alternating red and green candles, indicating hesitation in the market.

Late June 2020: A large bullish candlestick with a higher close marked a resurgence in upward momentum, signaling a potential breakout. This move, characterized by renewed buying interest, suggests the start of a strong bullish trend.

This period, characterized by initial selling pressure, followed by recovery and a final breakout, indicates a transition from bearish to bullish market sentiment for RELIANCE.NS.

The table displays predicted stock prices for a Reliance stock over a week-long period, from April 6, 2025, to April 12, 2025<sup>1</sup>. Each row provides the forecasted closing price for that day based on the historical NSE stock data, expressed in Indian Rupees (₹).

Date	Predicted Price
2025-04-06	₹2110.05
2025-04-07	₹2118.78
2025-04-08	₹2133.97
2025-04-09	₹2122.51
2025-04-10	₹2129.75
2025-04-11	₹2101.7
2025-04-12	₹2132.44

The "Predicted Prices" explains daily forecasted stock prices for the period from April 6 to April 12, 2025, with each entry likely representing the expected closing price for that day. The predicted prices fluctuate throughout the week, reflecting the typical volatility seen in the stock market. Specifically, the prices trend upwards from April 6 (₹2110.05) to a peak on April 8 (₹2133.97), then experience dips on April 9 and April 11, before recovering again by April 12 (₹2132.44). The lowest predicted price during this period is ₹2101.70 on April 11, while the highest is ₹2133.97 on April 8. Such tables are commonly used by investors and analysts to anticipate future price movements and make informed trading decisions. The predictions are typically generated by statistical or machine learning models that analyse historical stock data to forecast future prices. Investors may utilize these forecasts to identify potential buying or selling opportunities based on the expected rises or drops in price. Overall, this table provides a direct representation of the model's expectations for the stock's price over the specified week, assisting users in planning their market strategies accordingly.

#### **4.2.2 Accuracy**

Based on the models, after collecting, cleaning, and enriching the stock data with sentiment scores and technical indicators, two separate models—LSTM and XGBoost—are trained independently. The LSTM model, which excels at capturing long-term dependencies in sequential and time-series data, achieves an accuracy of 97%. XGBoost, known for its ability to model short-term feature interactions

and boost predictive performance through gradient boosting, achieves a slightly higher accuracy of 98%.

When these two models are combined in a hybrid framework such as by averaging their outputs or using a final neural layer to integrate both predictions the resulting hybrid model leverages the strengths of both approaches. This combined model achieves an accuracy of 98%, matching or slightly exceeding the best individual model. Empirical studies confirm that such hybrid models often provide improved robustness and generalization, particularly in capturing both overall trends and local fluctuations in stock prices.

Ultimately, the predictions from the hybrid model are visualized using candlestick charts and tables on a web interface, allowing users to interactively explore both historical trends and future forecasts in an accessible format. This approach ensures that the final predictions benefit from the complementary strengths of both LSTM and XGBoost, resulting in high accuracy and practical utility for stock market forecasting.

### **5 Conclusions and Future Directions**

As the stock market is highly volatile and influenced by numerous factors such as historical patterns, technical indicators, and market sentiment, it becomes crucial for investors to consider all these aspects before making financial decisions. In this context, this paper presents a novel and effective hybrid stock market forecasting system. The proposed model combines Long Short-Term Memory

(LSTM) networks and XGBoost to leverage both time-series dependencies and feature-level importance. In addition to historical stock data—such as closing price, RSI, and MACD—sentiment analysis is incorporated using scores derived from financial news and social media platforms like Twitter. By combining these diverse data sources, the system can make more informed and psychologically-aware predictions. The model's performance is validated across various configurations and benchmarked against traditional models like ARIMA. It is observed that the hybrid LSTM + XGBoost model achieves significantly higher prediction accuracy, with performance gains exceeding 5% over baseline approaches. The user-friendly web interface, with integrated visualization tools like candlestick charts and prediction tables, makes the system practical and insightful for real-world investment scenarios.

There are several promising directions in which this project can be extended. Firstly, the model can be enhanced by including more advanced sentiment analysis techniques, such as transformer-based language models like BERT or FinBERT, to extract deeper contextual sentiment from news and tweets. Secondly, the system can be scaled to support global stock exchanges, enabling cross-market predictions. The hybrid model can also be improved with attention mechanisms, allowing the LSTM to better focus on influential time steps. Moreover, real-time data integration using secure and stable APIs would enable live predictions, making the system more robust for intraday

trading. Finally, expanding the UI to offer portfolio recommendations, risk indicators, and alert systems would make the platform more valuable for professional traders and retail investors alike.

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