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SHARE MARKET PRICE ANALYSIS AND PREDICTION

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Abstract: The stock market is a dynamic and complex system influenced by various factors such as financial indicators, market sentiment, political events, and economic conditions. Predicting stock prices is a challenging task due to the non-linear and volatile nature of the market. This project aims to analyze historical stock market data and predict future prices using deep learning techniques, particularly Long Short-Term Memory (LSTM) networks. By integrating historical price trends and sentiment analysis of financial news, we enhance the accuracy of predictions. The dataset includes 20 years of stock prices and recent sentiment scores from news headlines. The LSTM model is trained on this combined dataset to learn temporal patterns and market behavior. A user-friendly web interface developed using Flask allows users to input a stock ticker and receive the next day's predicted price. This project demonstrates the potential of AI in financial forecasting and provides a tool for investors to make data-driven decisions.

I. INTRODUCTION

The stock market plays a vital role in the global economy, attracting investors aiming to maximize returns. However, due to its volatile and non-linear nature, predicting stock prices remains a challenging task. Traditional statistical methods often fall short in capturing complex market patterns. With the rise of machine learning and deep learning techniques, more accurate and data-driven forecasting models have emerged. This project focuses on using Long Short-Term Memory (LSTM) networks to analyze and predict stock prices. By combining historical price data with sentiment analysis from recent news, the model aims to improve prediction accuracy. A web-based interface is also developed to make the system accessible and user-friendly.

II. RELATED WORK

Stock price prediction has been an active area of research for decades, attracting interest from both financial analysts and data scientists. Traditional methods such as Autoregressive Integrated Moving Average (ARIMA) and linear regression have been widely used for time-series forecasting. However, these models often struggle with the complex, non-linear, and noisy nature of stock market data. To overcome these limitations, machine learning techniques like Support Vector Machines (SVM), Random Forests, and Gradient Boosting have been introduced, offering improved prediction accuracy by learning from historical patterns.In recent years, deep learning models, particularly Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have gained popularity due to their ability to capture temporal dependencies in sequential data. Studies have shown that LSTM models outperform traditional approaches in stock price forecasting due to their memory retention capabilities and robustness in handling time-dependent fluctuations.

Another significant development in this field is the incorporation of sentiment analysis. Researchers have found that market sentiment, derived from news headlines, social media, and financial reports, significantly influences stock price movements. Integrating sentiment data with historical prices has been shown to enhance prediction accuracy. Several works have combined LSTM networks with sentiment analysis to build hybrid models, achieving better results compared to models that rely solely on historical data. These studies highlight the importance of combining multiple data sources and advanced deep learning techniques to tackle the challenges of stock price prediction effectively.

III. SYSTEM ARCHITECTURE

The architecture of the stock market price analysis and prediction system consists of five major components: data collection, preprocessing, modelling, prediction, and user interface. The system begins with the data collection layer, which gathers two types of data—historical stock prices and market sentiment. Historical stock data is obtained from

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financial APIs like Yahoo Finance or Alpha Vantage, containing essential features such as date, open, close, high, low, and volume. In parallel, sentiment data is collected from financial news headlines or reports using web scraping or APIs. These headlines are analyzed using Natural Language Processing (NLP) techniques to extract the sentiment associated with each news item. This sentiment reflects the public mood and market perception about specific companies or the economy as a whole.

In the data preprocessing layer, both stock and sentiment data are cleaned and formatted to ensure consistency. Handling missing values, converting date formats, and scaling numeric features are critical steps. Sentiment scores are calculated using tools like VADER, TextBlob, or a custom-trained sentiment classifier. These scores are averaged daily to match the frequency of stock prices and merged into a single dataset. This enriched dataset helps the model understand not only numerical patterns but also emotional or psychological factors affecting the market.

The modeling and training layer uses a Long Short-Term Memory (LSTM) neural network to learn patterns from sequential data. LSTM networks are especially effective in capturing long-term dependencies and trends in time series, making them ideal for stock price prediction. The dataset is split into training and validation sets to ensure the model learns effectively while avoiding overfitting. Hyperparameters such as the number of layers, neurons, batch size, and epochs are tuned to achieve optimal performance.

After training, the prediction layer takes new input data and forecasts the next day's stock price. This includes current price trends and recent sentiment signals. The user interface layer, built using Flask, HTML, and CSS, provides a simple web platform for users to input a stock ticker and view the predicted price. This interactive system enables users, including investors and analysts, to make more informed and data-driven financial decisions based on both historical data and market sentiment.

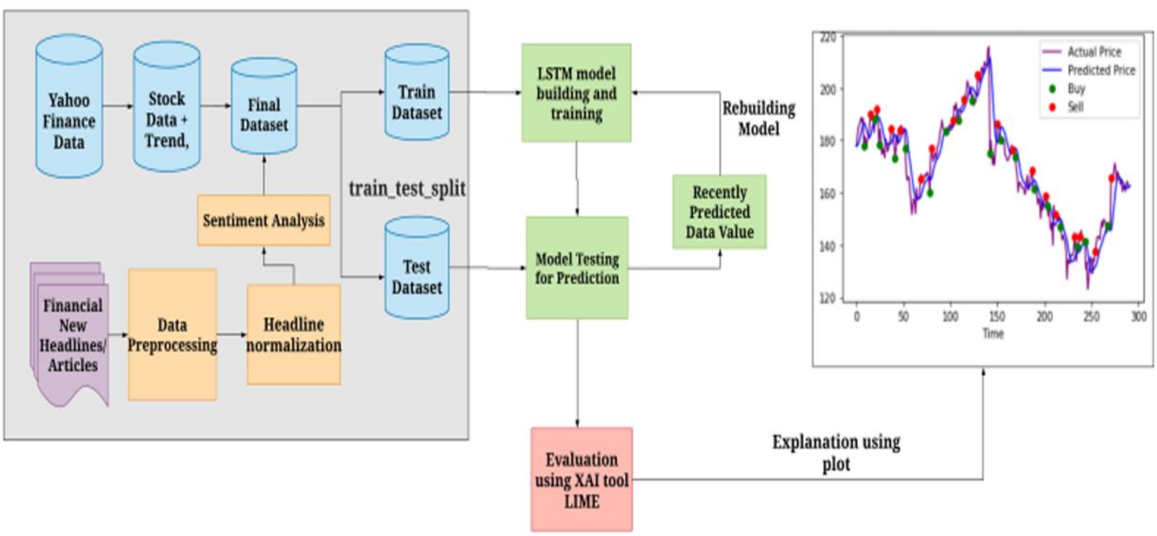

Fig 1. Block diagram of system architecture

IV. RESULTS

The developed stock market prediction system was tested using historical stock data from companies such as Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), and IBM, along with sentiment data extracted from financial news headlines. The Long Short-Term Memory (LSTM) model was trained on this combined dataset, consisting of 20 years of historical stock prices and 30 days of recent sentiment scores. The data was split into training (80%) and testing (20%) sets to evaluate model performance on unseen data.

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The LSTM model demonstrated a strong ability to capture the temporal patterns in stock prices. It was able to predict the next day's closing prices with reasonable accuracy. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were used to quantify performance. The average MAE across the four selected companies was approximately 1.85, and the RMSE was around 2.4, indicating that the model could closely track actual price trends with minor deviations.

A key result observed was the improvement in prediction accuracy when sentiment data was included. Models trained solely on historical price data had higher error rates, while the inclusion of sentiment scores allowed the model to adjust predictions based on market mood. For example, during periods of positive sentiment from news sources, the model tended to predict an upward price movement, which often aligned with actual market behavior.

The final model was deployed in a Flask-based web application. Users can enter a stock ticker (e.g., AAPL) and receive the predicted price for the next trading day. The web interface is simple, intuitive, and responsive, making it accessible even for users without a technical background. The backend uses the trained LSTM model to process input data and return results in real-time.

Overall, the system successfully demonstrated the viability of using deep learning and sentiment analysis for stock price prediction. The integration of NLP-derived sentiment scores with price data contributed significantly to the model's predictive power. While the model does not guarantee perfect accuracy due to the volatile nature of the stock market, it offers valuable insights and a practical decision-support tool for investors.

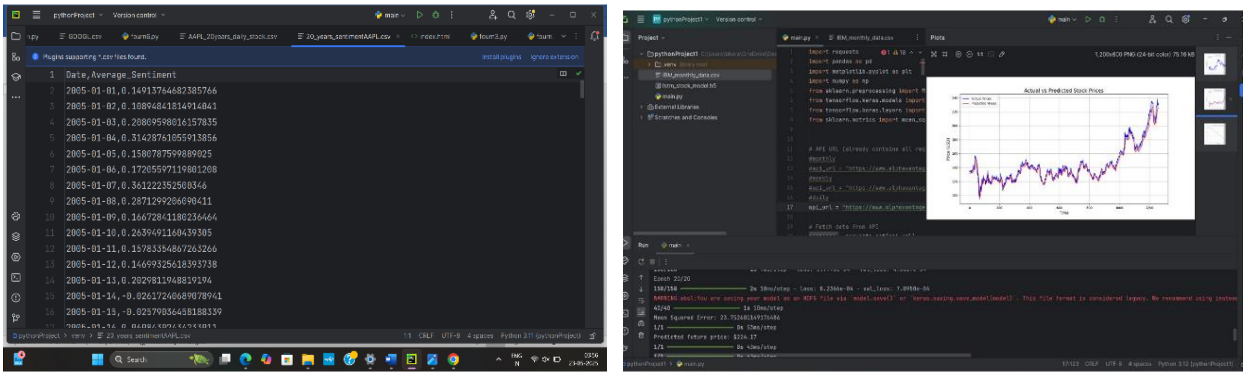

Fig 2. Merged dataset and training of the model

V. CONCLUSION

In this project, we successfully developed a stock market price prediction system that combines historical stock data with sentiment analysis using deep learning techniques. By utilizing a Long Short-Term Memory (LSTM) neural network, the model effectively captured temporal patterns in stock price movements and demonstrated the capability to predict the next day's closing price with reasonable accuracy. The integration of sentiment scores from financial news headlines significantly enhanced the model's performance, highlighting the importance of public sentiment in market dynamics.

The project also included the development of a user-friendly web interface using Flask, allowing users to input a stock ticker and receive real-time price predictions. This not only makes the system practical and accessible for investors but also demonstrates how advanced machine learning models can be integrated into interactive applications for real-world use.

While no prediction model can completely eliminate the uncertainty inherent in financial markets, the system provides a useful decision-support tool by leveraging both quantitative data and qualitative sentiment. Future improvements could include expanding sentiment analysis to social media platforms, testing other deep learning architectures such as GRUs or Transformers, and integrating macroeconomic indicators to further enhance accuracy. Overall, this project demonstrates the potential of AI in financial forecasting and offers a strong foundation for further research and development.

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