Explainable AI for Stock Market Prediction Using LSTM and SHAP

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***Abstract*—This paper presents a machine learning-based approach for predicting stock prices using Long Short-Term Memory (LSTM) models integrated with Explainable Artificial Intelligence (XAI) techniques. The project aims not only to achieve accurate stock price predictions but also to provide interpretability to the model using SHAP (SHapley Additive exPlanations). The entire process, from data collection to explainability, ensures transparency and trust in financial forecasting.**

***Index Terms*—Stock Market Prediction, LSTM, SHAP, Explainable AI, Machine Learning, Yahoo Finance API.**

I. I. INTRODUCTION

Stock price prediction is a complex problem influenced by multiple market factors. Traditional statistical methods often fail to capture non-linear patterns in stock data. Deep learning models, particularly LSTM networks, can effectively learn temporal dependencies in time-series data. However, their black-box nature raises concerns regarding interpretability. This project bridges that gap by using SHAP to explain LSTM model predictions, providing actionable insights into feature importance.

II. II. DATA COLLECTION

Stock market data was collected using the **Yahoo Finance API**. The dataset includes key indicators such as Open, High, Low, Close prices, and Volume for a selected company (Apple Inc.) from 2020 to 2025. The raw data serves as the foundation for preprocessing and model training.

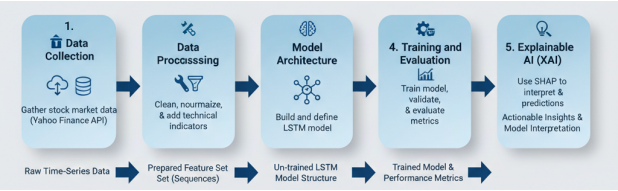

Fig. 1: Workflow of Explainable AI for Stock Market Prediction.

III. III. DATA PREPROCESSING

Data preprocessing involves cleaning, normalizing, and engineering technical indicators from raw stock data. Normalization ensures that all features are scaled within a uniform range. Technical indicators such as Moving Average (MA), Relative Strength Index (RSI), and Exponential Moving Average (EMA) are computed to enhance model learning and performance.

IV. IV. MODEL ARCHITECTURE

The model is based on a **Long Short-Term Memory (LSTM)** neural network, which is well-suited for time-series prediction. The LSTM layers capture sequential dependencies in stock price movements. The model outputs future price values based on input sequences, using past values and technical indicators as input features.

V. V. TRAINING AND EVALUATION

The dataset was divided into training and testing sets. The model was trained using Mean Squared Error (MSE) as the loss function and the Adam optimizer for gradient updates. Performance was evaluated using Root Mean Squared Error (RMSE) and R^2 score.

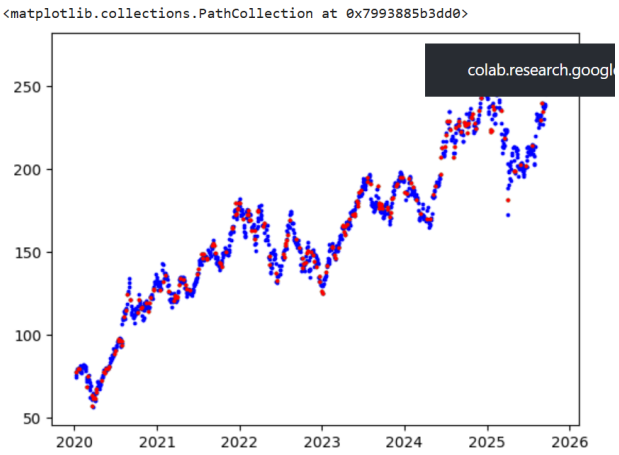

Fig. 2: Predicted vs Actual Stock Prices.

VI. VI. EXPLAINABLE AI (XAI) WITH SHAP

To interpret model predictions, the **SHAP** library was used. SHAP assigns each feature an importance value for individual predictions, helping to understand how each input contributes to the output. This interpretability layer enhances model transparency and decision-making.

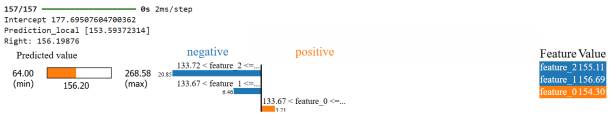

Fig. 3: SHAP Summary Plot Showing Feature Impact.

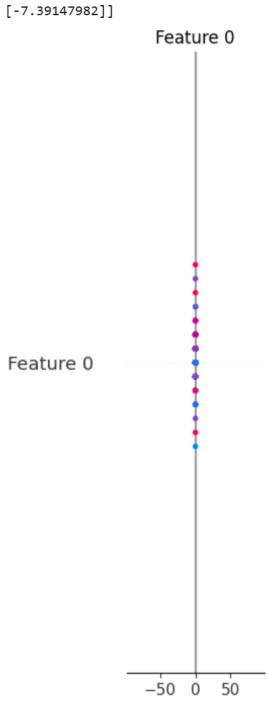

Fig. 4: SHAP Force Plot Explaining a Single Prediction.

VII. VII. RESULTS AND DISCUSSION

The LSTM model successfully predicted stock price trends with high accuracy. SHAP analysis revealed that recent closing prices and moving averages significantly influence predictions. The explainability feature provided clear insights into how different indicators affected the model's decisions, making the system more interpretable and trustworthy.

VIII. VIII. CONCLUSION

This study demonstrates an integrated framework of deep learning and explainable AI for stock market prediction. The combination of LSTM and SHAP provides both predictive power and interpretability, essential for practical financial decision-making. Future work can extend this approach to multi-stock and cross-market analysis for broader applications.

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