https://github.com/adithya98765/Stock-Market-Prediction-using-LSTM/tree/main

Problem Statement and Objectives

The primary objective of this project is to forecast future values in the Google stock price time series using a deep learning model based on Long Short-Term Memory (LSTM) networks. Stock price prediction poses challenges due to its volatile and non-linear nature. Our goal is to train an LSTM model that captures underlying temporal patterns and predicts stock prices with reasonable accuracy.

Experimental Setup and Methodology

1. **Data Preparation:**
   The dataset used comprises historical Google stock prices. We focused on the "Close" prices and applied MinMax normalization to scale the data between 0 and 1. A sliding window approach with a window size of 60 was implemented. This means that for each prediction, the previous 60 days' prices were used as input, a method well-suited for capturing dependencies in time series data.

2. **Model Architecture & Hyperparameters:**
   The model consists of two stacked LSTM layers with 50 units each. Each LSTM layer is accompanied by a dropout layer (20% dropout rate) to mitigate overfitting. A Dense layer is used at the end to predict the next day's price. The hyperparameters, including the window size (60), batch size (32), and epochs (50), were chosen based on common practices in time series forecasting. Early stopping was applied to prevent the model from over-training.

3. **Training and Evaluation:**
   The dataset was divided into 80% for training and 20% for testing. The model was trained using the Adam optimizer with a mean squared error loss function. After training, predictions were inverse-transformed to the original scale and compared with actual stock prices. Visualization of the results allowed us to analyze the model's performance qualitatively.

Results, Observations, and Analysis

- **Performance Overview:**
  The LSTM model was able to capture the general trend in the stock prices. The predictions closely followed the actual price movements, although with some lag in response to sudden shifts—common in financial time series.

- **Analysis of Predictions:**
  While the overall trend was captured, minor discrepancies were observed. These discrepancies may be attributed to intrinsic market volatility and the simplicity of using only closing prices. Feature enhancements (e.g., incorporating other technical indicators) could potentially improve the prediction accuracy.

- **Conclusion:**
  The implemented LSTM model provides a promising approach for stock price forecasting. The experiment underlines the capability of deep learning models to model complex time series data. Future work may include experimenting with different window sizes, more layers, or the inclusion of additional features (e.g., volume, technical indicators) to enhance the prediction performance.