Stock Market Prediction Using LSTM & Prophet

1 Data Preprocessing

1.1 Data Collection

- Source: Yahoo Finance (yfinance library).
- Timeframe: Extracted historical stock data.
- Columns Used: Date, Open, High, Low, Close, Volume.

1.2 Handling Outliers Using IQR

- Method: Interquartile Range (IQR) method was applied to detect and remove outliers.
- Formula Used:

$$Q1 = 25 \text{th percentile}$$

$$Q3 = 75 \text{th percentile}$$

$$IQR = Q3 - Q1$$

$$Lower \ Bound = Q1 - (1.5 \times IQR)$$

$$Upper \ Bound = Q3 + (1.5 \times IQR)$$

• Action: Values outside these bounds were removed to prevent extreme fluctuations.

1.3 Filling Missing Values

• **Method:** Median imputation was used to fill missing values for numerical columns.

1.4 Feature Selection Using Correlation Matrix

- Threshold Applied: Features with an absolute correlation greater than 0.6 with the target (Close Price) were selected.
- Process:

- 1. Compute the correlation matrix.
- 2. Extract features with |correlation| > 0.6.
- 3. Generate a heatmap for visualization.

• Selected Features:

- SMA_20 (Simple Moving Average)
- MACD_Signal
- Bollinger_High & Bollinger_Low
- ATR_14 (Average True Range)
- Cumulative Returns

1.5 Normalization

- Scaler Used: MinMaxScaler() from sklearn.preprocessing.
- Reason: LSTMs perform better with scaled inputs between 0 and 1.

2 Feature Engineering & Technical Indicators

- SMA_20 (Simple Moving Average, 20-day): Identifies short-term trends.
- MACD & MACD Signal: Measures momentum changes and trend strength.
- Bollinger Bands (Upper & Lower): Indicates volatility by plotting bands around moving averages.
- RSI_14 (Relative Strength Index, 14-day): Identifies overbought or oversold conditions.
- ATR_14 (Average True Range, 14-day): Measures market volatility.
- Cumulative Returns: Tracks total percentage change in stock price over time.
- Rolling Volatility (20-day): Identifies fluctuations in price movements.
- Bollinger %B: Normalizes stock price position relative to Bollinger Bands.

3 Model Selection & Hyperparameter Tuning

3.1 LSTM (Long Short-Term Memory) Model

- Architecture:
 - Input Layer: Sequences of selected stock features.
 - Two LSTM Layers: Each with 30 units.
 - **Dropout Layers:** Dropout rate of 0.2 to prevent overfitting.
 - **Dense Layer:** Fully connected output layer.
- Loss Function: Mean Squared Error (MSE).
- Optimizer: Adam optimizer.
- Hyperparameters:
 - **Epochs:** 50
 - Batch Size: 32
 - Validation Split: 20% of training data.

3.2 Facebook Prophet

- Why Used? Handles time-series decomposition and seasonality trends.
- Forecasting Process:
 - Inputs: ds (date) and y (closing price).
 - Trends: Prophet automatically detects trends and seasonal patterns.
 - Holidays: No custom holiday effects were added in this case.

4 Model Evaluation & Insights

4.1 Evaluation Metrics

Metric	Value
Mean Absolute Error (MAE)	4.0004
Mean Squared Error (MSE)	23.5446
Root Mean Squared Error (RMSE)	4.8523
R ² Score	0.9508
Akaike Information Criterion (AIC)	617.9845
Bayesian Information Criterion (BIC)	621.2575

Table 1: LSTM Model Evaluation Metrics

4.2 Key Insights

- \bullet LSTM performed well in capturing stock price trends with a high $\mathbf{R^2}$ score.
- Prophet was better suited for long-term forecasting but was less accurate for short-term movements.
- A hybrid approach (combining LSTM & Prophet) might improve accuracy by leveraging both short-term and long-term trend detection.