<u>Report On Stock-Market Time Series</u>

📌 Project Title

Stock Market Time Series Forecasting using ARIMA, SARIMA, Prophet, and LSTM

👤 Author

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📝 Objective

The primary aim of this project is to forecast stock market prices using a combination of statistical and deep learning models. By analyzing past stock data, we attempt to make reliable short-term and long-term forecasts, comparing the performance of each model to determine the most accurate forecasting technique.

🧠 Models Implemented

1. ARIMA (Auto-Regressive Integrated Moving Average)

Captures linear trends and moving average components.
Good for stationary time series.

2. SARIMA (Seasonal ARIMA)

Extension of ARIMA with seasonality.
Helps in capturing repetitive patterns (e.g., monthly cycles).

3. Facebook Prophet

Designed for business time series with daily, weekly, and yearly seasonality.
Robust to missing data and outliers.

4. LSTM (Long Short-Term Memory)

A type of recurrent neural network (RNN).

🧰 Tools & Libraries

- **Python**
- **NumPy, Pandas** – data manipulation

- **Matplotlib, Seaborn, Plotly** – visualizations
- **Statsmodels** – ARIMA/SARIMA
- **Facebook Prophet**
- **TensorFlow/Keras** – LSTM
- **Streamlit** – deployment interface

🧪 Workflow Overview

1. **Data Loading** – Imported historical stock data (e.g., Yahoo Finance or CSV).
2. **Preprocessing** – Handled missing values, formatting, and normalization (for LSTM).
3. **EDA (Exploratory Data Analysis)** – Trend, seasonality, and volatility analysis.
4. **Model Training & Tuning** – Each model was individually trained and validated.
5. **Forecasting & Visualization** – Displayed future stock prices with confidence intervals.
6. **Model Comparison** – Based on RMSE, MAE, and MAPE scores.
7. **Deployment (Optional)** – Integrated Streamlit dashboard for user interaction.

📌 Key Visualizations

- Time Series Decomposition (Trend, Seasonal, Residual)
- Forecast Plots for all models
- Actual vs Predicted stock price comparison
- Moving Averages and Indicators (optional)

🎯 Results & Conclusions

- **ARIMA** is simple and quick but lacks seasonal adaptation.
- **SARIMA** improves by adding seasonal components but is limited in capturing non-linear trends.
- **Prophet** handles business-like time series very well with automated seasonal decomposition.
- **LSTM**, being a neural network, learned the complex temporal dependencies and gave the best performance.

🏆 **Conclusion**: LSTM is most suitable for stock price forecasting when ample data and computational resources are available.