📘 Project Report: Time Series Forecasting of Tesla Stock Price

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🧾 Title Page

Project Title:
Forecasting Tesla Stock Prices Using SARIMA and ARIMA Models

Submitted by:
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📄 Abstract

This project aims to forecast the closing price of Tesla Inc. (TSLA) using time series analysis techniques. We leverage two statistical models — Seasonal ARIMA (SARIMA) and non-seasonal ARIMA — to analyze historical stock data and make short-term forecasts. The study emphasizes understanding the stationarity of the time series, model fitting, residual diagnostics, and visualization of forecast performance.

🎯 Objectives

- To load and preprocess Tesla stock price data.
- To analyze the stationarity of the closing price time series.
- To apply SARIMA and ARIMA models for forecasting.
- To compare the models based on residual diagnostics and visual accuracy.
- To evaluate model assumptions and provide insights into stock movement trends.

📚 Data Overview

- **Dataset Name**: TSLA.csv
- **Source**: Tesla stock data from an external CSV file
- **Time Frame**: Based on available historical data (dates parsed from file)
- **Target Variable**: `Close` price
- **Index**: Date (converted to pandas datetime format)

🔍 Methodology

1. Data Preprocessing

- Data loaded using `pandas`, indexed by date.
- Only the `Close` price was selected for forecasting.

2. Stationarity Testing

- **Rolling Mean and Standard Deviation** plotted to visually inspect stationarity.
- **Augmented Dickey-Fuller (ADF) Test** used to statistically test for stationarity.

Result:
The p-value from the ADF test was above 0.05, confirming non-stationarity. First-order differencing was applied (`d=1` in ARIMA/SARIMA).

🧠 Model Implementation

✅ SARIMA Model

- **Model**: SARIMA(1,1,1)(1,1,1,12)
- **Seasonality**: Monthly
- **Forecast Horizon**: 30 steps (e.g., days)

- **Libraries**: `statsmodels.tsa.statespace.SARIMAX`

Key Plots:

- Actual vs Forecasted values
- Forecast with 95% confidence intervals
- Residual plots and diagnostics
- Q-Q Plot and Histogram of residuals

✅ ARIMA Model

- **Model**: ARIMA(1,1,1)
- **Train/Test Split**: 80/20
- **Forecast Horizon**: Same length as test data
- **Libraries**: `statsmodels.tsa.arima.model.ARIMA`

Key Plots:

- Actual vs Predicted test set
- Confidence Intervals
- Residual diagnostics
- Q-Q Plot and Distribution

📊 Results & Visualizations

SARIMA:

- Forecast tracks the actual data closely with reasonable prediction intervals.

- Residuals are normally distributed and centered around zero.
- Q-Q plot shows normality → model assumptions hold.

ARIMA:

- Slightly less precise than SARIMA for data with seasonality.
- Works well for shorter forecast ranges.
- Residuals are well-behaved.

📈 Comparison Table

Feature	SARIMA	ARIMA
Handles Seasonality	✅ Yes	❌ No
Residual Normality	✅ Yes	✅ Yes
Forecast Horizon	Fixed (30 days)	Flexible (test set length)
Best Use Case	Seasonal patterns	Short-term, non-seasonal data
Confidence Interval Plot	✅ Yes	✅ Yes

🧾 Conclusion

- Both SARIMA and ARIMA can be effective tools for time series forecasting depending on the nature of the data.
- SARIMA outperforms ARIMA when seasonality is present.
- Residual analysis confirms that both models are statistically valid.
- These techniques offer a solid foundation for building more advanced forecasting systems using machine learning or hybrid models.

🧠 Future Work

- Tune model parameters using Grid Search or `auto_arima`.
- Incorporate external regressors (e.g., news, macroeconomic indicators).
- Deploy the forecasting model using Flask/Streamlit.
- Use deep learning models like LSTM for comparison.
