**Final Report on ARIMA Model Findings**

### Introduction

This document presents a comparative analysis of three ARIMA models developed for stock price prediction over different time horizons: one month, six months, and one year. The objective is to understand the differences in their forecasting ability, model effectiveness, and the potential implications of each timeframe.

### 1. One-Month ARIMA Model

**Inputs:** The dataset used for this model is not explicitly mentioned but is assumed to be historical stock price data.

**Objective:** The model applies an ARIMA (1,1,1) configuration to predict stock prices for a one-month period.

**Outputs:** Although exact forecast details are not explicitly documented, the model generates a time series forecast for the upcoming month.

**Process:**

1. An Augmented Dickey-Fuller (ADF) test is performed to assess stationarity and determine the necessity of differencing.
2. The ARIMA model with order (1,1,1) is fitted to the data.
3. The model then performs forecasting over the defined one-month horizon.

**Inference:** A visual comparison of actual vs predicted values is presented, showing the model’s performance in a short-term forecasting scenario.

### 2. Six-Months ARIMA Model

**Inputs:** Similar to the one-month model, the dataset is not explicitly stated but follows the same structure.

**Objective:** This model also uses ARIMA (1,1,1) but extends the forecast horizon to six months, aiming to capture medium-term trends.

**Outputs:** The model provides a time series forecast for the next six months, though exact forecast accuracy details are not included.

**Process:**

1. The ADF test is conducted to check stationarity.
2. The ARIMA model is fitted using historical data.
3. Forecasting is performed for a six-month duration.

**Inference:** The model produces a visualization comparing actual vs predicted values. Given the extended forecast horizon, greater variability is expected in predictions compared to the one-month model.

### 3. One-Year ARIMA Model

**Inputs:** The dataset remains consistent with the previous models but is used to generate a longer-term forecast.

**Objective:** This model applies ARIMA (1,1,1) to predict stock prices for the next one year, making it the longest-term forecast among the three.

**Outputs:** Forecasting is done for a full year, but quantitative performance metrics such as RMSE or MAE are not included.

**Process:**

1. ADF test is executed to confirm stationarity.
2. The ARIMA model is fitted using past stock prices.
3. Forecasting is extended to cover a 12-month period.

**Inference:** The visual comparison suggests that long-term forecasts exhibit higher uncertainty and potential divergence from actual price movements due to accumulating errors over time.

### Key Differences and Findings

1. **Forecasting Horizon Impact:**
2. The one-month model offers the most reliable short-term predictions due to minimal accumulated error.
3. The six-month model introduces a moderate level of uncertainty, as market fluctuations become harder to anticipate over a longer period.
4. The one-year model likely suffers from significant forecast deviation, as ARIMA models generally struggle with long-term trends in volatile datasets.
5. **Model Similarity:**
6. All three models use the same ARIMA order (1,1,1), which may not be optimal across all timeframes.
7. A longer forecast period generally requires additional parameter tuning to improve accuracy.
8. **Need for Performance Metrics:**
9. None of the notebooks explicitly include evaluation metrics like RMSE (Root Mean Squared Error) or MAE (Mean Absolute Error), which are crucial for assessing prediction accuracy.
10. Implementing these metrics would provide better justification for the reliability of each model.

### Conclusion

The findings indicate that while ARIMA models are effective for short-term stock price forecasting, their accuracy deteriorates as the forecast period extends. The one-month model is the most reliable, while the one-year model introduces significant uncertainty. Future improvements could include hyperparameter tuning, performance metric evaluation, and potentially integrating other forecasting techniques like LSTM or hybrid models for better long-term predictions.

1. Mean Absolute Error (MAE) Scale: Same as the original data (e.g., if stock prices are in INR, MAE is also in INR). Interpretation: Represents the average absolute error between actual and predicted values. Lower values indicate better model performance. Example: If MAE = 10, on average, the model's prediction is off by 10 INR per stock price.
2. Mean Squared Error (MSE) Scale: Squared units of the original data (e.g., if stock prices are in INR, MSE is in INR²). Interpretation: Penalizes larger errors more than MAE due to squaring, making it sensitive to outliers. Example: If MSE = 100, the squared differences between actual and predicted values average to 100 INR².
3. Root Mean Squared Error (RMSE) Scale: Same as the original data (e.g., INR). Interpretation: Similar to MAE but gives more weight to larger errors. Provides a measure of overall prediction error. Example: If RMSE = 12, on average, the model's prediction deviates from actual values by about 12 INR.
4. Mean Absolute Percentage Error (MAPE) Scale: Percentage (%). Interpretation: Measures the error as a percentage of actual values, making it scale-independent. Example: If MAPE = 5%, on average, the model's prediction is 5% off from actual values. Key Limitation: MAPE is unreliable when actual values are close to zero (division by zero issue).