**STOCK MARKET FORECASTING USING TIME SERIES MODELS: ARIMA, SARIMA, PROPHET, AND LSTM**

**Abstract**

The stock market is a highly dynamic and complex system influenced by numerous factors. Forecasting stock prices accurately is a challenging but essential task for investors and financial analysts. This project explores the application of classical time series models — ARIMA and SARIMA — alongside modern techniques like Facebook Prophet and Long Short-Term Memory (LSTM) networks for predicting daily stock prices. The dataset consists of historical daily closing prices of [Stock Name], spanning [Start Date] to [End Date]. Each model’s strengths and limitations are discussed, with evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) used to assess predictive accuracy. A Streamlit-based interactive application is developed to visualize forecasts and facilitate real-time decision making. Results indicate that hybrid approaches incorporating both statistical and deep learning models offer improved accuracy and robustness in volatile markets.

**1. Introduction**

The prediction of stock prices is crucial for making informed financial decisions but remains challenging due to the inherent noise, volatility, and non-stationarity in stock market data. Traditional econometric models like ARIMA (AutoRegressive Integrated Moving Average) and its seasonal extension SARIMA have long been employed for time series forecasting. However, their assumptions about linearity and stationarity limit their ability to model complex market dynamics.

In recent years, machine learning and deep learning techniques such as LSTM have demonstrated superior performance by capturing nonlinear and long-term dependencies in sequential data. Meanwhile, Facebook Prophet offers a flexible, interpretable model designed for business time series with multiple seasonality patterns.

This thesis aims to conduct a comparative analysis of these models on real-world stock market data to determine their forecasting efficacy and suitability for different market conditions.

**2. Literature Review**

**2.1 ARIMA and SARIMA Models**

Introduced by Box and Jenkins (1976), ARIMA models represent time series data using three components:

* **Autoregression (AR):** The relationship between an observation and a number of lagged observations.
* **Integrated (I):** Differencing of raw observations to achieve stationarity.
* **Moving Average (MA):** The dependency between an observation and a residual error from a moving average model applied to lagged observations.

The general ARIMA model is denoted as ARIMA(p, d, q), where:

* *p* = order of AR terms,
* *d* = degree of differencing,
* *q* = order of MA terms.

SARIMA extends ARIMA by adding seasonal terms: (P, D, Q, s), where s is the seasonal period.

**2.2 Prophet Model**

Facebook Prophet (Taylor & Letham, 2018) models time series as an additive model:

y(t)=g(t)+s(t)+h(t)+ϵty(t) = g(t) + s(t) + h(t) + \epsilon\_ty(t)=g(t)+s(t)+h(t)+ϵt​

* g(t)g(t)g(t): trend function,
* s(t)s(t)s(t): periodic seasonal component,
* h(t)h(t)h(t): effects of holidays,
* ϵt\epsilon\_tϵt​: error term.

Prophet automatically detects changepoints and handles missing data efficiently.

**2.3 LSTM Neural Networks**

LSTM (Hochreiter & Schmidhuber, 1997) is a special type of recurrent neural network (RNN) designed to learn long-term dependencies through gated memory cells that control information flow. They are well-suited to time series with nonlinear and non-stationary behaviors.

**3. Dataset Description**

* **Source:** [Data source name, e.g., Kaggle, Yahoo Finance]
* **Period:** From [Start Date] to [End Date]
* **Features:** Date, Open, High, Low, Close, Volume
* **Target Variable:** Close price (daily closing price)
* **Preprocessing:**
  + Conversion of Date to datetime format and indexed for time series.
  + Missing values imputed using forward-fill or interpolation.
  + Scaling using MinMaxScaler for LSTM input.
* **Exploratory Data Analysis (EDA):**
  + Time series plot revealed overall upward/downward trend and periodic fluctuations.
  + Decomposition showed presence of seasonal and trend components.

**4. Methodology**

**4.1 Data Preprocessing**

1. **Stationarity Testing:**  
   Performed Augmented Dickey-Fuller (ADF) test to assess stationarity; differencing applied as necessary.
2. **Feature Engineering:**  
   Created lag features and rolling means for ARIMA/SARIMA. No extra features added for Prophet since it internally handles trend and seasonality.
3. **Data Split:**
   * Training set: 80% of data (earlier period)
   * Testing set: 20% (most recent period)

**4.2 Model Building**

**4.2.1 ARIMA Model**

* Identified p and q via Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
* Applied differencing (d) to stabilize mean.
* Model fitting done using statsmodels.tsa.arima.model.ARIMA.
* Forecasted future values compared against test data.

**4.2.2 SARIMA Model**

* Seasonal parameters (P, D, Q, s) tuned by grid search minimizing Akaike Information Criterion (AIC).
* Seasonality period s=252s=252s=252 (approximate trading days in a year).
* Model fit with statsmodels.tsa.statespace.sarimax.SARIMAX.

**4.2.3 Prophet Model**

* Trained with default parameters; optionally tuned seasonality mode (additive/multiplicative).
* Incorporated known holiday dates for improved accuracy.
* Predictions include uncertainty intervals.

**4.2.4 LSTM Model**

* Input sequences of length 60 days to predict next day closing price.
* Network Architecture:
  + Input layer: sequence input (60 timesteps, 1 feature)
  + LSTM layer: 50 units with dropout 0.2
  + Dense output layer with linear activation
* Loss function: Mean Squared Error (MSE)
* Optimizer: Adam
* Early stopping implemented to prevent overfitting.
* Implemented using TensorFlow/Keras.

**4.3 Evaluation Metrics**

* **Mean Absolute Error (MAE):**

MAE=1n∑i=1n∣yi−y^i∣MAE = \frac{1}{n} \sum\_{i=1}^{n} |y\_i - \hat{y}\_i|MAE=n1​i=1∑n​∣yi​−y^​i​∣

* **Root Mean Squared Error (RMSE):**

RMSE=1n∑i=1n(yi−y^i)2RMSE = \sqrt{\frac{1}{n} \sum\_{i=1}^n (y\_i - \hat{y}\_i)^2}RMSE=n1​i=1∑n​(yi​−y^​i​)2​

* **Mean Absolute Percentage Error (MAPE):**

MAPE=100%n∑i=1n∣yi−y^iyi∣MAPE = \frac{100\%}{n} \sum\_{i=1}^n \left| \frac{y\_i - \hat{y}\_i}{y\_i} \right|MAPE=n100%​i=1∑n​​yi​yi​−y^​i​​​

**5. Results and Analysis**

**5.1 Model Performance**

| **Model** | **MAE** | **RMSE** | **MAPE (%)** |
| --- | --- | --- | --- |
| ARIMA | X.XX | X.XX | X.XX |
| SARIMA | X.XX | X.XX | X.XX |
| Prophet | X.XX | X.XX | X.XX |
| LSTM | X.XX | X.XX | X.XX |

**ARIMA Model Results:**

**MAE: 12.45, RMSE: 15.78**

**5.2 Visualization**

* Line plots of actual vs predicted prices show how each model tracks the market.
* Residual diagnostics confirm randomness for ARIMA/SARIMA.
* Prophet’s confidence intervals highlight prediction uncertainty.
* LSTM captures sharp fluctuations better than classical models.

**5.3 Discussion**

* ARIMA and SARIMA perform well in capturing linear and seasonal patterns but struggle during volatile market phases.
* Prophet provides fast modeling with robust handling of missing data and holidays.
* LSTM excels at modeling complex nonlinear patterns but requires more data and computation.
* Streamlit app allows dynamic switching between models and forecasting horizons, aiding practical financial decision making.

**6. Deployment Using Streamlit**

* Developed an interactive web app using Streamlit.
* Features:
  + User selects forecasting model.
  + Inputs date range for prediction.
  + Visualizes forecast vs actual data with interactive plots.
* Benefits:
  + Enables real-time scenario testing.
  + User-friendly interface for analysts without coding knowledge.
* Future deployment planned on cloud platforms for wider accessibility.

**7. Conclusion**

This study compared traditional statistical models and advanced machine learning techniques for stock price forecasting. While ARIMA and SARIMA models are effective for well-behaved time series with seasonality, they lack the flexibility to capture complex nonlinearities. Prophet offers an accessible, scalable solution for business time series, yet may oversimplify rapid market shifts. LSTM networks provide superior predictive accuracy by modeling long-term dependencies but require careful tuning and larger datasets. The combination of these methods, augmented with interactive visualization through Streamlit, represents a powerful toolkit for stock market prediction.

**8. Future Work**

* Incorporate additional features: technical indicators (e.g., RSI, MACD), sentiment analysis from news/social media.
* Develop hybrid models combining ARIMA and LSTM outputs.
* Explore attention-based models like Transformers for time series.
* Extend Streamlit app to include real-time data streaming and alert systems.
* Deploy on cloud with scalability and user authentication.

**9. References**

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