GitHub Link : https://github.com/manikandan3456/Phase--2

Project Title

Cracking the Market Code with AI-Driven Stock Price Prediction Using Time Series Analysis

- ## Problem Statement

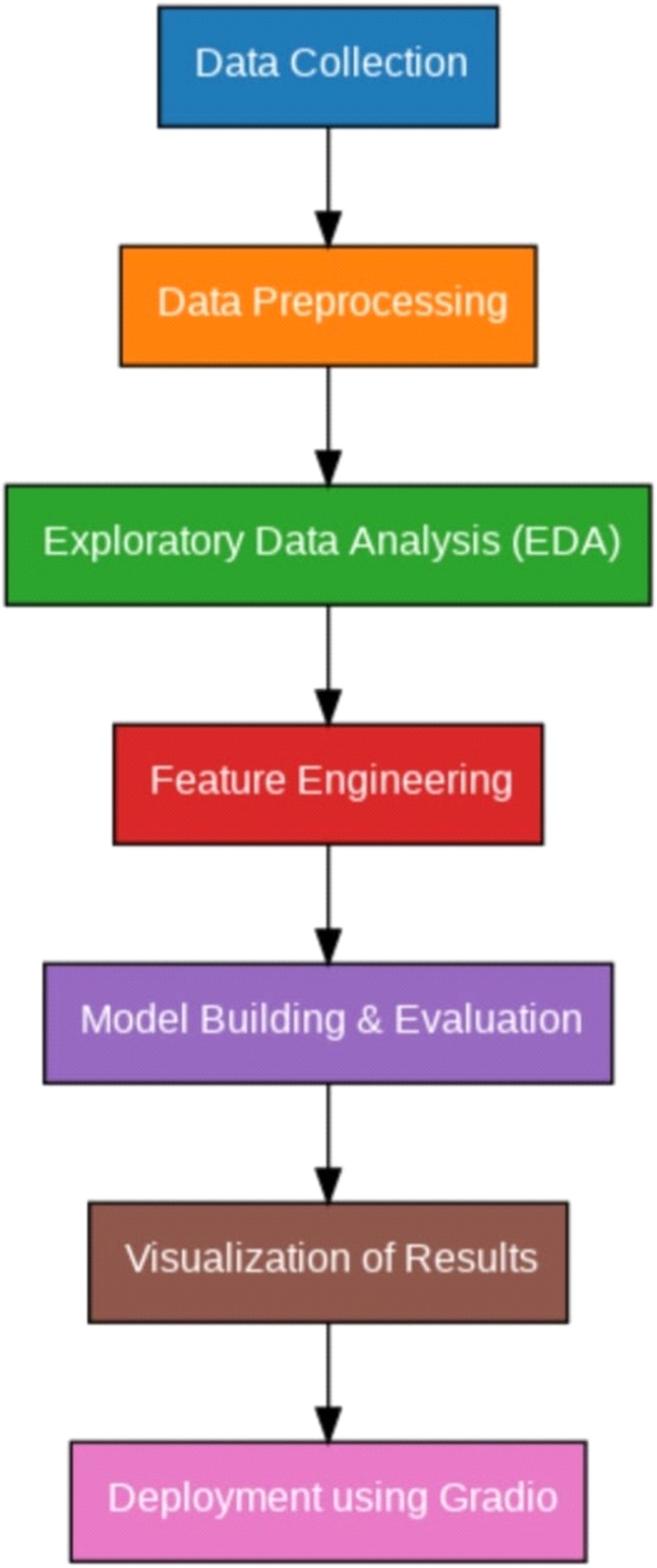
Forecasting stock prices is a complex and highly valuable challenge in financial markets due to their volatile, nonlinear, and dynamic nature. The aim of this project is to use historical time series data and AI-based models to predict future stock prices. Accurate forecasting models can support informed investment decisions, reduce risks, and potentially increase profitability for traders and analysts.

- ## Project Objectives

- Develop a machine learning model to accurately predict stock prices using time series data.
- Analyze historical price patterns and identify influential indicators.
- Compare different algorithms (ARIMA, LSTM, Prophet) for forecasting effectiveness.
- Visualize trends and predictions to enhance interpretability.
- Build an interactive interface (optional: Streamlit or Gradio) for real-time prediction demonstration.

- ## Flowchart of the Project Workflow

3. Flowchart of the Project Workflow



- **Data Description**

• Dataset Name: Stock Price Dataset

• Source: Kaggle

• Type of Data: Time Series

• Attributes: Date, Open, High, Low, Close, Volume

• Target Variable: Closing Price

• Nature of Dataset: Dynamic, real-world financial data

• Dataset Name: https://www.kaggle.com/

• dataset link : https://github.com/manikandan3456/Phase--2.git

- **Data Preprocessing**

• Handled missing values in price columns.

• Converted date into datetime format and set as index.

• Performed log-scaling or differencing for stationarity (if using ARIMA).

• Normalized data (for LSTM model).

• Engineered features like moving averages and RSI.

- **Exploratory Data Analysis (EDA)**

• Line plots for price trends over time.

• Rolling mean and standard deviation for trend detection.

• Autocorrelation and Partial Autocorrelation plots.

• Volatility analysis using standard deviation and price range.

- **Feature Engineering**

• Created lag-based features (e.g., Close_t-1, Close_t-2).

• Derived technical indicators like:

  • 7-day and 21-day Moving Averages

  • Relative Strength Index (RSI)

  • MACD

• Differencing for stationarity in ARIMA.

- **Model Building**

• ARIMA Model for linear trends in stationary series.

• LSTM Model for capturing long-term dependencies and patterns.

• Facebook Prophet for trend + seasonality modeling.

- **Evaluation Metrics**

• RMSE (Root Mean Squared Error)

• MAE (Mean Absolute Error)

• MAPE (Mean Absolute Percentage Error)

• R^2 Score (for LSTM models)

- **Visualization of Results & Model Insights**

• Actual vs Predicted closing prices for test data.

• Residual plots for error analysis.

• Feature importance (if using models like XGBoost).

• Comparison plots of model performance.

- **Tools and Technologies Used**

• Language: Python

• IDE: Jupyter Notebook / Google Colab

• Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, keras, statsmodels, fbprophet

• Optional Interface: Streamlit or Gradio for user interaction

- **Team Members and Contributions**

- S. Kalaiyarasan

  • Data Collection and Preprocessing

  • EDA and Feature Engineering

- N. Manikandan

  • LSTM Model Development

  • ARIMA Implementation

  • Visualization

- S. Gokul

- Evaluation and Model Comparison
- Documentation and Report Preparation