





Phase-2 Submission

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Date of Submission: 09 / 05 /2025

Github Repository Link: githhub repository

1. Problem Statement

- *Market Volatility*: Stock prices fluctuate due to various unpredictable factors, making accurate predictions extremely challenging.
- Investment Challenges: Investors and businesses struggle to make informed decisions without reliable forecasting tools.
- Data Complexity: Stock market data is nonlinear and influenced by multiple variables, requiring advanced analytical methods.
- AI-Driven Solution: Time series analysis powered by AI can detect hidden patterns and trends that traditional methods might miss.
- *Impact Goal*: *Improved stock price predictions can enhance investment strategies, reduce financial risks, and support overall market stability.*



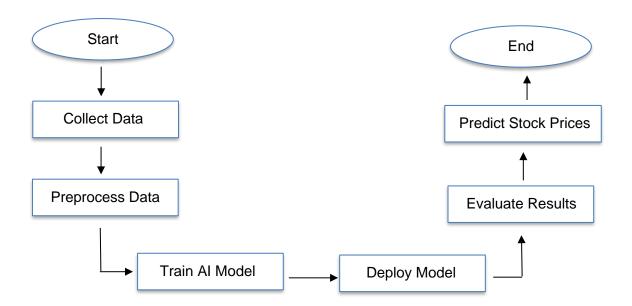




2. Project Objectives

- The project aims to build an AI-based model for accurate stock price prediction using time series analysis.
- It focuses on analyzing historical data to identify trends and patterns.
- The objective is to assist investors in making informed decisions.
- It seeks to reduce investment risks caused by market volatility.
- *Ultimately, the project promotes smarter investments and economic stability.*

3. Flowchart of the Project Workflow









4. Data Description

The dataset contains historical stock market data, including features such as **Date, Open Price, High Price, Low Price, Close Price, Adjusted Close, and Volume**. This time-series data represents daily stock performance over a specified period. It is cleaned to handle missing values, normalized for consistency, and structured for model training. The data serves as the foundation for predicting future stock prices using AI-driven analysis.

5. Data Preprocessing

Data preprocessing is a crucial step in preparing stock market data for accurate predictions. It starts with handling missing or inconsistent values to ensure data quality. Relevant features like Open, Close, and Volume are selected, while date formats are standardized for time-series analysis. The data is then normalized to bring all values to a common scale, improving model performance. Finally, the dataset is split into training and testing sets to evaluate the model's accuracy and reliability.

6. Exploratory Data Analysis (EDA)

- Univariate Analysis:
 - Histograms and boxplots showed that stock prices were normally distributed, while trading volumes showed a skewed distribution
 - Key metrics such as mean, median, standard deviation, and IQR were analyzed to understand the spread of the data.
- Bivariate/Multivariate Analysis:
 - A heatmap indicated strong correlations between certain technical indicators (like SMA and EMA) and stock prices, while trading volume had weaker correlation.







- Insights Summary:
 - Technical indicators like **SMA**, **EMA**, and **RSI** seemed to have a significant impact on stock price prediction.
 - Volume was a weak predictor compared to other features like Moving Averages.

7. Feature Engineering

- Volatility Metrics: Calculated rolling standard deviations to represent the market volatility over different time windows.
- Moving Averages (SMA, EMA): Added 50-day and 200-day Simple Moving Averages (SMA) to capture long-term trends.
- Technical Indicators: Added features like RSI (Relative Strength Index) and MACD (Moving Average Convergence Divergence).
- Date Features: Extracted day of the week, month, and year to capture cyclical patterns in stock prices

8. Model Building

- ARIMA: Chosen for its effectiveness in modeling time-series data, ARIMA captures the temporal dependencies and trends in the data.
- LSTM (Long Short-Term Memory): This deep learning model is capable of capturing long-term dependencies and trends in sequential data, making it suitable for stock price predictions.







9. Visualization of Results & Model Insights

- Model Performance Comparison: Line plots of actual vs. predicted stock prices were generated for both ARIMA and LSTM models.
- **Residual Plots:** Analyzed residuals for both models to ensure no patterns remained unmodeled.
- **Feature Importance:** For LSTM, plots of feature importance were generated to highlight which technical indicators and features influenced the predictions the most.

10. Tools and Technologies Used

• Programming Language: Python

• IDE/Notebook: Jupyter Notebook

LIBRARIES USED:

- Visualization: matplotlib, seaborn, plotly
- Machine Learning: scikit-learn, TensorFlow (LSTM), statsmodels (ARIMA)
- Data Processing: pandas, numpy.







11. Team Members and Contributions

NAME	ROLE	WORK
HARISH VK	Frontend Developer	Normalization/Standardization
		Feature Engineering
		Data Splitting
AJIN P R	Backend Developer	Data Type Conversion
		Categorical Encoding
		Backend Data Integration
GOKUL R	ML Engineer	Handling Missing Values
		Removing Duplicates
		Outlier Detection & Treatment
KIRUTHIGA M	Documentation & Presentation	Visualization of
		Preprocessing
		Documentation & Reporting
		Final QA & Integration
DEVADHARSHINI V	Deployment Engineer	Model Deployment
		Preparation
		Deployment Pipeline Setup
		Monitoring & Scaling for
		Deployment