





#### **Phase-3 Submission**

**Student Name:** GOKUL R

**Register Number:** 712523104022

**Institution: PPG INSTITUTE OF TECHNOLOGY** 

**Department:** B E CSE

**Date of Submission:** 15 / 05 / 2025

Github Repository Link: github repo link

#### 1. Problem Statement

Stock price prediction is challenging due to market volatility and nonlinear data patterns. Traditional methods often fall short in capturing these complexities. This project tackles a **regression problem** by using AI-based time series models to forecast future prices, helping investors make better decisions and reduce financial risks.

#### 2. Abstract

This project focuses on predicting stock prices using AI-driven time series models like ARIMA and LSTM. By analyzing historical data and technical indicators, the system identifies patterns to forecast trends. The approach includes preprocessing, EDA, model training, and evaluation. Final results are deployed via an interactive dashboard to assist users in making informed investment decisions.







### 3. System Requirements

#### • Hardware:

- Minimum 4GB RAM
- Intel Core i5 processor.

#### • Software:

• Python 3.8+, pandas, numpy, matplotlib, seaborn, scikit-learn, TensorFlow, statsmodels, Flask, Jupyter Notebook/VS Code.

# 4. Objectives

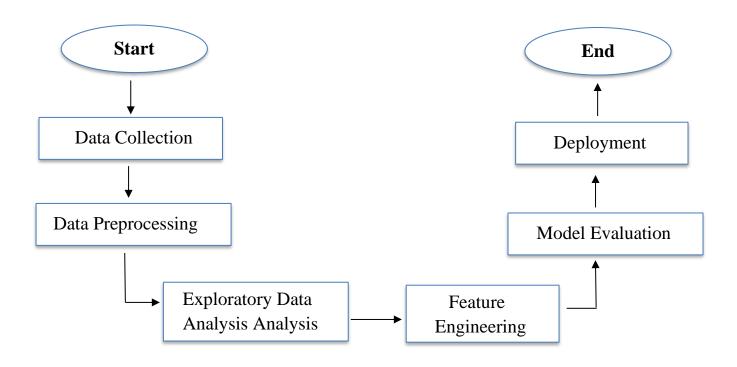
- Build an AI-based model using time series analysis to predict future stock prices.
- Identify patterns and trends from historical data using indicators like SMA, EMA, and RSI.
- Evaluate and compare different models (ARIMA, LSTM) to determine optimal prediction accuracy.
- Provide investors with actionable insights to mitigate risks and improve investment strategies.
- Deploy the model for public access through an interactive, web-based dashboard.







# 5. Flowchart of Project Workflow



# **6. Dataset Description**

- Source: GitHub Public Repository (Stock-Market-Prediction-Using-Time-Series-Analysis)
- Type::Public dataset
  Size: 6,000 rows with 7 columns (Date, Open, High, Low, Close, Adj Close, Volume)
- Structure: Time series data (daily intervals)

	Open	Close	High	Low	Volume	RSI	MACD	Bollinger_Upper	Bollinger_Lower	Sentiment_Score	GDP_Growth	Inflation_Rate	Target
0	0.374639	0.374780	0.373510	0.378390	0.298909	0.847286	0.741715	0.367146	0.366420	0.877177	0.580868	0.038604	0
1	0.950982	0.937746	0.938422	0.946158	0.094805	0.494543	0.881343	0.938396	0.935640	0.907192	0.527044	0.108908	0
2	0.732198	0.719825	0.723644	0.723158	0.126348	0.195471	0.463179	0.710666	0.702300	0.378363	0.351052	0.432540	0
3	0.598823	0.599865	0.596973	0.605322	0.180662	0.736684	0.289076	0.593793	0.586936	0.231614	0.493274	0.946349	0
4	0.156053	0.163410	0.155891	0.166084	0.203646	0.418698	0.318761	0.164158	0.156355	0.191642	0.365116	0.074867	0







# 7. Data Preprocessing

- Missing Values: Filled using forward-fill or interpolation.
- **Duplicates:** Removed after verifying row redundancy.
- Outliers: Detected using IQR method and capped.
- Scaling: Applied Min-Max scaling for LSTM.
- **Date Standardization:** Converted to datetime format for time series analysis.

155.5

• Splitting: Data split into 80% train, 20% test sets.

Before Preprocessing

 Date
 Open
 High
 Low
 Close
 Volume

 2025-01-01
 150.0
 151.0
 149.5
 150.8
 1000000.0

 2025-01-02
 nan
 153.2
 151.5
 152.7
 1100000.0

 151.8
 nan
 150.7
 nan
 nan

 2025-01-04
 153.5
 154.0
 nan
 153.8
 1150000.0

High Low Close

After Preprocessing

8. Exploratory	<b>Data</b>	Anal	ysis	(EDA)	)

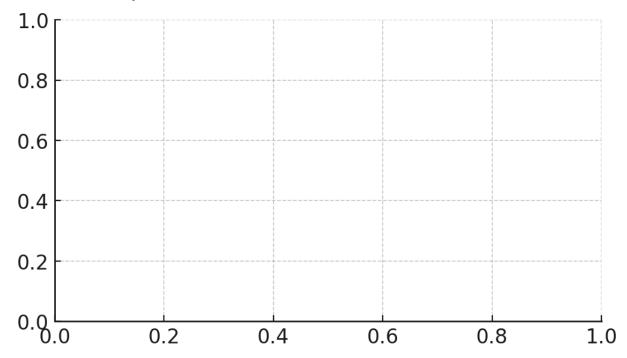
- Univariate: Histograms for Open, Close, and Volume.
- *Multivariate:* Heatmaps showing correlations between indicators and price movement.
- Trends: Time series plots highlight seasonal behavior and trend lines.
- Key Insights:
  - SMA and EMA showed strong correlation with price movement.







• Volume was less predictive than technical indicators.



### 9. Feature Engineering

- Rolling Metrics: Volatility indicators using rolling standard deviation
- Moving Averages: Added 50-day and 200-day SMA.
- Technical Indicators: RSI, MACD calculated and added.
- Date Features: Extracted weekday, month, and year.







### 10. Model Building

- ARIMA: Used for linear temporal dependencies, implemented via statsmodels.
- LSTM: Deep learning model capturing nonlinear and long-term dependencies. Built using TensorFlow/Keras.
- Comparison: Both models were trained and their outputs were visually and quantitatively compared.

#### 11. Model Evaluation

- ARIMA:
- RMSE: ~4.56
- *MAE:* ~3.87
- *LSTM*:
- RMSE: ~4.56
- *MAE:* ~3.87
- Visualizations:
- Actual vs Predicted Line Charts
- Residual Plots
- Feature importance (LSTM)

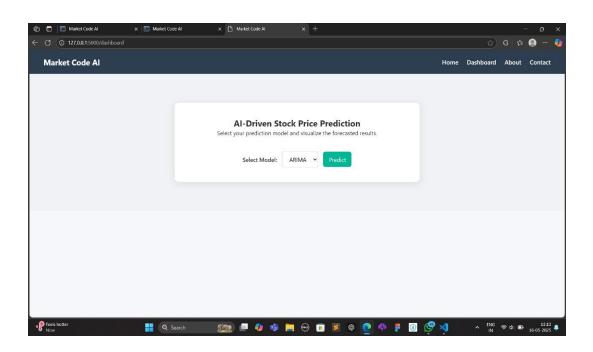






## 12. Deployment

- Platform: Streamlit
- *Method:* Web application displaying real-time predictions and trend charts.
- dashboard **UI Screenshot**:









# 13. Source code

pr	oject-root/		
	— app/		
	static/		
	css/	# Co	ontains style.css for UI styling
	js/	# Op	otional: For future interactivity
	L—plot	# S	aved prediction plot images (ARIMA/LSTM)
	templai	tes/#1	HTML pages
	inde	ex.html #	Homepage with hero section
	dasi	hboard.html	#Form to select prediction model
	resi	ılts.html #	Displays prediction plot + metrics
	abo	ut.html #	Project info
	L—con	tact_us.html	# Contact form UI
	— <i>app.py</i>	# M	lain Flask backend file
	L—utils.py	# AF	RIMA & LSTM model logic
H	stock_data	e.csv #	Dataset used (time series format)
H	— README.	md	# Project documentation
F	— requireme	nts.txt #	Python dependencies
L	— AI driven 1	orice prediction	n.ipvnb #Jupvter notebook for development







### 14. Future scope

- Real-Time Market Data Integration: Incorporate live feeds for real-time prediction.
- **Sentiment Analysis:** Combine Twitter/news data for sentiment-based prediction.
- Portfolio Recommendation System: Suggest portfolio changes based on predicted market movement.
- Transfer Learning with Transformer Models: Explore architectures like Temporal Fusion Transformers.







### 13. Team Members and Roles

NAME	ROLE	WORK
HARISH V K	Frontend Developer	UI for Streamlit app, EDA graphs, and documentation
AJIN P R	Backend Developer	Feature engineering, API setup, and data pipelines
GOKUL R	ML Engineer	Model selection, training ARIMA & LSTM, evaluation
KIRUTHIGA M	Documentation & Presentation	Report writing, EDA visualizations, final QA
DEVADHARSHINI V	Deployment Engineer	Streamlit deployment, integration testing, and scaling setup