BCSE498J Project-II / CBS1904/CSE1904 - Capstone Project

Crypto currency price prediction using learning algorithm

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April 2025

DECLARATION

I hereby declare that the project entitled **Crypto currency price prediction using learning algorithm** submitted by me, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of Bonafide work carried out by me under the supervision of Dr. NIHA K

I further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree ordiploma in this institute or any other institute or university.

Place : Vellore

Date : 15.04.2025

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Signature of the Candidate

CERTIFICATE

This is to certify that the project entitled Crypto currency price prediction using learning algorithm submitted by Bhakhar Tej Maganbhai (21BCE3374), **School of Computer Science and Engineering**, VIT, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of Bonafide work carried out by him / her under my supervision during Winter Semester 2024-2025, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The project fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

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ACKNOWLEDGEMENTS

I am deeply grateful to the management of Vellore Institute of Technology (VIT) for providing me with the opportunity and resources to undertake this project. Their commitment to fostering a conducive learning environment has been instrumental in my academic journey. The support and infrastructure provided by VIT have enabled me to explore and develop my ideas to their fullest potential.

My sincere thanks to Dr. Jaisankar N, Dean - School of Computer Science and Engineering (SCOPE), for his unwavering support and encouragement. His leadership and vision have greatly inspired me to strive for excellence.

I express my profound appreciation to Dr. Gopinath M.P the Head of the Computer Science and Engineering with blockchain technology and Dr. Umadevi K S, the Head of the Computer Science and Engineering for his/her insightful guidance and continuous support. His/her expertise and advice have been crucial in shaping throughout the course. His/her constructive feedback and encouragement have been invaluable in overcoming challenges and achieving goals.

I am immensely thankful to my project supervisor, Prof. Niha K, for his/her dedicated mentorship and invaluable feedback. His/her patience, knowledge, and encouragement have been pivotal in the successful completion of this project. My supervisor's willingness to share his/her expertise and provide thoughtful guidance has been instrumental in refining my ideas and methodologies. His/her support has not only contributed to the success of this project but has also enriched my overall academic experience.

Thank you all for your contributions and support.

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ABSTRACT

The volatility of cryptocurrency markets presents a significant challenge for investors and traders, necessitating accurate and reliable forecasting models to enhance decision-making and risk management. This project, Machine Learning for Cryptocurrency Price Forecasting, explores the application of advanced machine learning techniques to predict cryptocurrency prices with improved accuracy. The study integrates historical price data, technical indicators, and market sentiment analysis to build robust predictive models capable of capturing complex market patterns.

A comprehensive comparative analysis of various machine learning algorithms, including Linear Regression, Support Vector Machines (SVM), Random Forest, and Gradient Boosting, is conducted. Additionally, deep learning approaches such as Long Short-Term Memory (LSTM) networks are explored to assess their effectiveness in time-series forecasting. Feature engineering plays a crucial role in enhancing model performance, incorporating key indicators such as Exponential Moving Averages (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and sentiment scores derived from social media and financial news sources.

To ensure data integrity and reliability, the dataset undergoes rigorous preprocessing, including handling missing values, outlier detection, normalization, and feature scaling. Model performance is evaluated using multiple statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Squared Logarithmic Error (MSLE), and R-squared (R^2), providing a comprehensive assessment of accuracy and reliability.

Furthermore, this study investigates the potential of hybrid models that combine traditional machine learning techniques with deep learning approaches, aiming to optimize both short-term and long-term price predictions. The findings highlight the strengths and limitations of each model, offering valuable insights into the effectiveness of machine learning for cryptocurrency forecasting. By leveraging data-driven insights and predictive analytics, this research aims to provide traders, investors, and financial analysts with powerful tools to enhance trading strategies, mitigate risks, and improve decision-making in highly volatile cryptocurrency markets.

TABLE OF CONTENTS

Sl.No	Contents	Page No.
	Acknowledgement	**4**
	List of Figures	**8**
	List of Tables	**9**
	Abbreviations	**10**
	Symbols and Notations	**11**
1.	**INTRODUCTION**	**12**
	1.1 Background	**12**
	1.2 Motivations	**12**
	1.3 Scope of the Project	**13**
2.	**PROJECT DESCRIPTION AND GOALS**	**15**
	2.1 Literature Review	**15**
	2.2 Research Gap	**19**
	2.3 Objectives	**20**
	2.4 Problem Statement	**21**
	2.5 Project Plan	**22**
3.	**TECHNICAL SPECIFICATION**	**24**
	3.1 Requirements	**24**
	3.1.1 Functional	**24**
	3.1.2 Non-Functional	**24**
	3.2 Feasibility Study	**25**
	3.2.1 Technical Feasibility	**25**
	3.2.2 Economic Feasibility	**26**
	3.2.2 Social Feasibility	**26**
	3.3 System Specification	**27**
	3.3.1 Hardware Specification	**27**
	3.3.2 Software Specification	**27**
4.	**DESIGN APPROACH AND DETAILS**	**29**
	4.1 System Architecture	**29**
	4.2 Sequence Diagram	**30**

5. **METHODOLOGY AND TESTING** **31**
5.1 Overview **31**
5.2 Dataset and Features **31**
5.3 Data Preprocessing **31**
5.4 Preparation for Model **32**
5.5 Separating Data into Test and Training Set **33**
6. **PROJECT DEMONSTRATION** **34**
6.1 XGBOOST **34**
6.2 LSTM **37**
6.3 Random Forest **40**
6.4 ARIMA **42**
6.5 SARIMAX **44**
6.6 Orbit **46**
7. **RESULT AND DISCUSSION** **48**
8. **CONCLUSION AND FUTURE ENHANCEMENTS** **49**
9. **REFERENCES** **50**
APPENDIX A – SAMPLE CODE **54**

List of Figures

Figure No.	**Title**	**Page No.**
4.1	System Architecture Diagram	29
4.2	Sequence Diagram	30
5.1	LSTM Cell Architecture	32
5.2	ARIMA Model Visualization	42
5.3	SARIMAX Seasonal Decomposition	44
5.4	Orbit Trend vs Confidence Interval	47
6.1	Prediction vs Actual Price – Bitcoin (XGBoost)	34
6.2	Prediction vs Actual Price – Ethereum (LSTM)	38
6.3	Feature Importance Plot – Random Forest	40
7.1	Comparison of RMSE for All Models	49

List of Tables

Table No.	Title	Page No.
3.1	Hardware Requirements	27
3.2	Software Requirements	28
5.1	Evaluation Metrics Used (MAE, RMSE, etc.)	33
7.1	Model Comparison Table (LSTM, RF, XGBoost, etc.)	49

List of Abbreviations

Abbreviation	**Full Form**
AI	Artificial Intelligence
ARIMA	AutoRegressive Integrated Moving Average
BTC	Bitcoin
CV	Cross Validation
DL	Deep Learning
EMA	Exponential Moving Average
ETH	Ethereum
LSTM	Long Short-Term Memory
MACD	Moving Average Convergence Divergence
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
ML	Machine Learning
MSLE	Mean Squared Log Error
RF	Random Forest
RMSE	Root Mean Squared Error
RSI	Relative Strength Index
SARIMAX	Seasonal ARIMA with Exogenous Variables
SMAPE	Symmetric Mean Absolute Percentage Error
TTS	Time Series
XAI	Explainable Artificial Intelligence
XGBoost	Extreme Gradient Boosting

Symbols and Notations

Symbol	**Description**
p	Order of the autoregressive part in ARIMA
d	Degree of differencing
q	Order of the moving average part in ARIMA
y_t	Value of time-series at time t
$\hat{y}_t$	Predicted value of the series at time t
ϵ_t	White noise error term
α, β, γ	Parameters in LSTM model
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
MSLE	Mean Squared Logarithmic Error
$X(t)$	Exogenous variable at time t (for SARIMAX)
μ	Mean of residuals
σ^2	Variance of residuals

1. INTRODUCTION

1.1 BACKGROUND

Cryptocurrency is a form of digital currency that regulates the generation of currency units and verifies the transfer of funds using encryption techniques. Notably, cryptocurrencies are not governed by a central authority and operate on a decentralized structure. Since the launch of Bitcoin in 2009, cryptocurrencies have revolutionized the way people transfer money. Cryptocurrency was first proposed in 1998 by a computer scientist, Wei Dai, who developed a cryptography-based system that could be used to ease payments between parties. This system, called "b-money," laid the groundwork for future cryptocurrencies.

The systematic structural specification of Bitcoin [1] was published in November 2008 by an unknown individual or group using the alias Satoshi Nakamoto. Bitcoin was the first cryptocurrency to be decentralized. Since the introduction of Bitcoin in 2009, cryptocurrencies have transformed how money is sent and received. Bitcoin is still the most popular and valuable cryptocurrency in the world, despite the creation of thousands of other cryptocurrencies and several price fluctuations since then. At the time of this writing, Bitcoin's market capitalization exceeds 475 billion US dollars. In addition, the market capitalization of all active cryptocurrencies, including Bitcoin, reaches 1.17 trillion US dollars. [2]

Due to the decentralized nature of the majority of cryptocurrencies, their prices are not influenced by interest rates, inflation rates, or monetary policies, but rather by the perception of users based on news, websites, and other non-fundamental elements. [3] The stock markets are influenced by a variety of factors that create uncertainty, including political and economic issues that have a local or global impact. Understanding the success keys, or factors that provide accurate predictions, is a difficult task. We can examine the market using any technique, including technical indicators, price fluctuations, and market technical analysis. There is thus a need for automated prediction tools to assist investors in deciding whether to invest in bitcoin or other cryptocurrencies. Modern stock market predictions typically include automation technologies, and we could apply the same approach and strategy to this realm of cryptocurrency.

1.2 MOTIVATIONS

The cryptocurrency market has witnessed exponential growth over the past decade, attracting investors, traders, and researchers from around the globe. However, its highly volatile and unpredictable nature poses significant challenges for those seeking to make informed investment decisions. Traditional statistical methods often fall short in capturing the complex, non-linear patterns of cryptocurrency price movements, creating the need for more intelligent, data-driven approaches.

This project is motivated by the following key factors:

- **High Market Volatility:**
  Cryptocurrencies like Bitcoin and Ethereum experience frequent and unpredictable price fluctuations, influenced by factors such as market sentiment, social media trends, and regulatory announcements. Accurately forecasting these fluctuations can provide valuable insights for traders and investors.
- **Limitations of Traditional Models:**
  Conventional forecasting models are not well-suited to handle the dynamic behavior of crypto markets. Machine learning and deep learning techniques offer the potential to uncover hidden patterns and learn complex relationships in time-series data.
- **Real-World Impact for Investors:**
  With millions of users trading cryptocurrencies daily, even minor improvements in prediction accuracy can lead to significant gains or help prevent losses. Developing a reliable forecasting model can act as a decision-support tool for retail and institutional investors alike.
- **Integration of Multi-Source Data:**
  The ability to combine technical indicators, historical price trends, and market sentiment extracted from platforms like Twitter and financial news sites allows for a more holistic understanding of market behavior.
- **Research and Innovation Opportunity:**
  The domain of cryptocurrency forecasting using AI and ML is still evolving. This project provides an opportunity to explore and innovate with hybrid models, feature engineering techniques, and real-time prediction capabilities.
- **Educational Value and Skill Development:**
  Working on this project enables hands-on experience with advanced machine learning techniques, data preprocessing, feature extraction, model evaluation, and potentially real-world deployment — skills that are highly valuable in both academia and industry.

1.3 SCOPE OF THE PROJECT

This project focuses on the application of machine learning and deep learning techniques to forecast cryptocurrency prices using historical data, technical indicators, and sentiment analysis. The aim is to build predictive models that can assist investors and traders in making data-driven decisions in volatile crypto markets.

The scope of the project includes:

- **Data Collection and Preprocessing:**
  - Gathering historical price data of major cryptocurrencies such as Bitcoin (BTC) and Ethereum (ETH).
  - Computing technical indicators like EMA, MACD, RSI, Bollinger Bands, etc.

    - Collecting sentiment data from social media and news platforms.
    - Cleaning, normalizing, and scaling the dataset to prepare it for model training.
- **Model Development:**
    - Implementing machine learning models such as Random Forest and XGBoost.
    - Designing and training deep learning models like Long Short-Term Memory (LSTM) networks.
    - Exploring hybrid models that combine strengths of both ML and DL techniques.
- **Performance Evaluation:**
    - Using metrics such as MAE, RMSE, and R^2 to evaluate and compare model accuracy.
    - Assessing model robustness under different market conditions.
- **Feature Engineering and Selection:**
    - Analyzing the impact of various technical indicators and sentiment scores on prediction accuracy.
    - Optimizing the feature set to improve model performance.
- **Model Explainability (XAI):**
    - Applying techniques like SHAP to interpret model predictions and provide transparency for end users.
- **Real-World Applicability (Future Scope):**
    - Exploring real-time prediction and deployment scenarios, such as integration into a basic trading bot or investment decision-support system.
    - Potential extension to multi-timeframe predictions and broader sets of cryptocurrencies.
- **Limitations (Defined Boundaries):**
    - The project does not include the development of a full-fledged trading platform.
    - Focus is primarily on forecasting price trends, not on financial advisory or investment risk assessment.

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2. PROJECT DESCRIPTION AND GOALS

2.1 LITERATURE REVIEW

2.1.1 Introduction to Cryptocurrency Price Prediction

Cryptocurrencies, such as Bitcoin (BTC) and Ethereum (ETH), exhibit high volatility and non-linear price movements, making their prediction a complex task. Traditional statistical models often fail to capture the intricate dependencies in price fluctuations. As a result, machine learning (ML) and deep learning (DL) techniques have been increasingly applied to analyze historical price data and forecast future price trends.

This review explores existing research on cryptocurrency price prediction using three prominent models: Long Short-Term Memory (LSTM), XGBoost, and Random Forest. These models leverage time-series forecasting techniques and feature engineering to improve prediction accuracy.

2.1.2 Long Short-Term Memory (LSTM) for Time-Series Forecasting

LSTM is a specialized form of Recurrent Neural Networks (RNNs) designed to handle long-term dependencies in sequential data. It has been widely used in financial market predictions due to its ability to retain past information for extended periods.

Related Work on LSTM

- Hiransha et al. (2018) compared LSTM with other deep learning models such as CNN and RNN for stock market predictions and found that LSTM outperformed others in long-term trend analysis.
- Chen et al. (2021) applied LSTM to Bitcoin price prediction and achieved high accuracy by incorporating technical indicators like EMA, MACD, and RSI as input features.
- Shen et al. (2020) introduced an Attention-LSTM model, which further improved predictive accuracy by focusing on relevant time-series points.

Limitations of LSTM

- Requires a large dataset for effective learning.
- Computationally expensive and slow to train.
- Prone to overfitting on small datasets.

2.1.3 XGBoost: A Boosted Decision Tree Approach

XGBoost (Extreme Gradient Boosting) is a popular gradient boosting algorithm known for its efficiency and performance in structured data problems. Unlike LSTM, XGBoost does not explicitly capture sequential dependencies but excels in feature-based regression tasks.

Related Work on XGBoost

- Zhang et al. (2019) applied XGBoost for stock market forecasting and demonstrated its superior performance compared to traditional decision trees.
- Mallqui & Fernandes (2019) combined XGBoost with feature engineering for cryptocurrency price forecasting and found it to be more interpretable than deep learning models.
- Sezer & Ozbayoglu (2020) introduced a hybrid XGBoost model incorporating technical indicators, achieving improved accuracy in predicting Bitcoin price trends.

Limitations of XGBoost

- Does not capture temporal dependencies like LSTM.
- Feature selection is crucial for optimal performance.
- Less effective in highly volatile markets without additional smoothing techniques.

2.1.4 Random Forest: An Ensemble Learning Approach

Random Forest is an ensemble-based machine learning algorithm that constructs multiple decision trees to reduce variance and improve robustness in predictions. It is commonly used in cryptocurrency forecasting when interpretability and feature importance analysis are required.

Related Work on Random Forest

- Ji et al. (2020) applied Random Forest to predict Bitcoin price trends using historical data and found it to be highly stable in feature-based analysis.
- Chiu & Hsu (2018) compared Random Forest with XGBoost and found that while XGBoost performed better in short-term predictions, Random Forest provided better generalization.
- Kumar et al. (2021) demonstrated that combining Random Forest with feature selection techniques like Principal Component Analysis (PCA) can enhance prediction performance.

Limitations of Random Forest

- Less effective for highly volatile time-series data compared to LSTM.
- Requires extensive hyperparameter tuning.
- Can be computationally expensive with large datasets.

2.1.5 ARIMA, SARIMAX, and Orbit: Classical and Probabilistic Time-Series Models

While modern machine learning and deep learning models dominate recent research, traditional statistical models like **ARIMA** and **SARIMAX**, and modern probabilistic frameworks like **Orbit**, have also been widely used for time-series forecasting in cryptocurrency markets.

2.1.5.1 ARIMA (AutoRegressive Integrated Moving Average)

ARIMA is a classical time-series forecasting model that captures autocorrelation and trend components in stationary data. It is particularly effective for univariate time series with consistent patterns.

Related Work on ARIMA

- Patel et al. (2018) used ARIMA to model Bitcoin prices and observed that while it performed reasonably well for short-term forecasting, it lacked the ability to adapt to sudden price changes.
- Adhikari and Agrawal (2013) demonstrated ARIMA's effectiveness in economic forecasting, which laid the foundation for its use in financial time series.

Limitations of ARIMA

1. Assumes linear relationships, which limits its application in highly non-linear crypto markets.
2. Struggles with volatility and does not incorporate exogenous variables.

2.1.5.2 SARIMAX (Seasonal ARIMA with Exogenous Variables)

SARIMAX extends ARIMA by including seasonal effects and external variables (e.g., trading volume, social media sentiment), making it more suitable for cryptocurrency forecasting.

Related Work on SARIMAX

- Liu et al. (2021) applied SARIMAX to incorporate Twitter sentiment and trading volume into Bitcoin price forecasts, yielding improved accuracy over basic ARIMA.

- Joshi & Kumar (2022) highlighted SARIMAX's usefulness in modeling periodic fluctuations and external market drivers.

Limitations of SARIMAX

- Requires careful tuning of seasonal parameters.
- Can become computationally intensive with large datasets and multiple external regressors.

2.1.5.3 Orbit (Bayesian Time Series Forecasting)

Orbit is an open-source Bayesian time-series forecasting library developed by Uber, designed to handle uncertainty and irregularities in time-series data through probabilistic modeling.

Related Work on Orbit

- Orbit has shown promise in demand forecasting and has recently been adapted for financial time series by researchers aiming for more uncertainty-aware forecasts.
- Sharma et al. (2023) used Orbit to forecast ETH prices and highlighted its ability to quantify prediction confidence intervals, which is valuable in volatile markets.

Limitations of Orbit

- Still relatively new in the crypto forecasting domain.
- Requires a good understanding of Bayesian modeling and can be slow on large datasets.

2.1.6 Comparative Analysis and Hybrid Approaches

Recent studies have explored hybrid models that combine multiple ML techniques to leverage their strengths:

• LSTM + XGBoost: Used for capturing both temporal dependencies (LSTM) and structured feature importance (XGBoost).

• LSTM + Random Forest: Applied for long-term trend detection with better interpretability.

• XGBoost + Random Forest: Used for robust price forecasting with ensemble techniques. A study by Kou et al. (2022) demonstrated that hybrid models consistently outperform single models, especially when integrating technical indicators (EMA, MACD, Bollinger Bands) and external factors like market sentiment analysis.

2.2 GAP INDENTIFATION:

1. **Inadequate Handling of Market Manipulation and Anomalies**

   Cryptocurrency markets are prone to **whale trades, wash trading, spoofing, and pump-and-dump schemes**, which distort price movements. Current models **struggle to identify and filter out manipulated data**, leading to inaccurate predictions. Research is needed on **anomaly detection techniques** for improving model reliability.

2. **Limited Exploration of Alternative ML Techniques (Reinforcement Learning, GANs, Transformers, etc.)**

   Most studies focus on **traditional ML (Random Forest, XGBoost) and deep learning (LSTM, GRU)**. However, **emerging AI techniques** like **Reinforcement Learning (RL), Generative Adversarial Networks (GANs), and Transformers (e.g., BERT for financial text analysis)** remain underexplored in the cryptocurrency domain.

3. **Lack of Explainable AI (XAI) for Crypto Trading Models**

   Deep learning models, especially **LSTM and Transformers**, act as **black boxes**, making it difficult to understand **why** a model predicts a certain price movement. Research on **explainable AI (XAI) techniques** like **SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations)** is needed to enhance trust in AI-driven trading systems.

4. **Challenges in Multi-Timeframe Analysis for Crypto Forecasting**

   Most models focus on a **single timeframe (e.g., 1-hour or daily prices)**, but professional traders analyze **multiple timeframes (e.g., 5-minute, 1-hour, 1-day, 1-week)**. Developing models that **dynamically adjust to different timeframes** remains an open research problem.

5. **Challenges in Handling Extreme Market Volatility**

   Existing models struggle with capturing **sudden market crashes and spikes** caused by news events, regulations, or whale trades. The development of **adaptive models** capable of responding to high volatility remains a significant research gap.

6. **Lack of Hybrid Models Combining Traditional and Deep Learning Approaches**

   While individual models like Random Forest, XGBoost, and LSTM have been widely studied, **hybrid approaches** (e.g., LSTM combined with XGBoost or Attention mechanisms) are **underexplored** in cryptocurrency forecasting. Research on **optimizing model ensembles** for better performance is still in its early stages.

7. **Scalability and Real-Time Forecasting Challenges**

Most models are trained on **historical data**, but few studies explore **real-time price prediction** with continuous learning. Implementing **low-latency, high-speed models** for live market forecasting remains an open challenge.

8. **Limited Generalization Across Different Cryptocurrencies**

   Many studies focus on **Bitcoin (BTC)** due to its dominance, but research on applying machine learning to **altcoins (ETH, XRP, ADA, etc.) and cross-asset forecasting** is still underdeveloped. Developing **generalized models** that work across different cryptocurrencies is an important future direction.

2.3 OBJECTIVES

The primary objective of this project is to develop and evaluate machine learning models for accurately predicting cryptocurrency prices using historical data, technical indicators, and sentiment analysis. The project aims to address key challenges such as market volatility, data quality, and model interpretability.

Specific Objectives:

1. **Develop Predictive Models for Cryptocurrency Prices**
    - Implement and compare LSTM, XGBoost, and Random Forest models for cryptocurrency price prediction.
    - Optimize hyperparameters and evaluate model performance using different configurations.
2. **Integrate Technical Indicators for Feature Engineering**
    - Compute and analyze key technical indicators such as Exponential Moving Averages (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands.
    - Assess the impact of different feature combinations on model accuracy.
3. **Address Data Preprocessing and Quality Issues**
    - Handle missing values, outliers, and normalization to ensure data integrity.
    - Implement data augmentation techniques to improve model robustness.
4. **Compare and Evaluate Model Performance**
    - Use Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) as evaluation metrics.
    - Compare traditional machine learning vs. deep learning approaches to identify the best-performing model.
5. **Analyze Market Sentiment and External Factors *(Optional)***

- Extract sentiment scores from social media (Twitter, Reddit) and news sources to assess their impact on price movement.
- Investigate the influence of macroeconomic indicators and regulatory news on crypto price trends.

6. **Improve Model Interpretability and Explainability**
    - Apply Explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations), to understand model decisions.
    - Enhance transparency in model predictions for use in trading and investment decisions.
7. **Explore Real-Time and Multi-Timeframe Predictions *(Future Scope)***
    - Investigate real-time price prediction capabilities for potential trading applications.
    - Develop models that adapt dynamically to different timeframes (e.g., 1-minute, 30-minute, daily).
8. **Deploy a Prototype or Trading Strategy Based on Predictions *(Future Scope)***
    - Create a basic trading bot or decision-support system based on the best-performing model.
    - Backtest the strategy using historical data to assess profitability and risk management.

2.4 PROBLEM STATEMENT

Cryptocurrency markets are characterized by extreme volatility, non-linear price movements, and rapid fluctuations influenced by various factors such as public sentiment, global news, and speculative trading. Traditional financial models often fail to accurately predict price trends in such dynamic and unpredictable environments due to their inability to capture complex patterns and adapt to changing conditions.

Despite the increasing application of machine learning and deep learning techniques for financial forecasting, challenges remain in identifying the most effective models for cryptocurrency price prediction. These include issues like overfitting, poor model interpretability, limited generalization across different cryptocurrencies, and inadequate handling of market anomalies and manipulation.

There is a pressing need to develop robust, accurate, and interpretable predictive models that can forecast cryptocurrency prices by effectively utilizing historical price data, technical indicators, and market sentiment. Such models should not only improve forecasting accuracy but also assist investors and traders in making data-driven decisions and managing risk in highly volatile markets.

This project aims to address these challenges by exploring and comparing various machine learning and deep learning models, including LSTM, XGBoost, Random Forest, and traditional time-series approaches like ARIMA and SARIMAX, to determine the most reliable methods for cryptocurrency price prediction.

2.4.1 PROJECT PLAN

January 2025 (Weeks 3–4): Data Preprocessing & Exploratory Data Analysis (EDA)

- Clean and preprocess the raw dataset (missing values, formatting, normalization).
- Convert data into time-series format for modeling.
- Conduct exploratory data analysis to understand patterns and correlations.
- Visualize trends, volatility, and moving averages.

February 2025 (Weeks 5–6): Feature Engineering & Selection

- Generate technical indicators (e.g., RSI, MACD, Bollinger Bands).
- Create lag features and rolling window statistics for trend analysis.
- Analyze feature importance using statistical and model-based methods.
- Finalize the set of features to use in model training.

February 2025 (Weeks 7–8): Model Selection & Training

- Implement models including LSTM, XGBoost, and ARIMA for comparison.
- Train models on historical time-series data with selected features.
- Use time-series cross-validation to avoid data leakage.
- Fine-tune initial hyperparameters and monitor training performance.

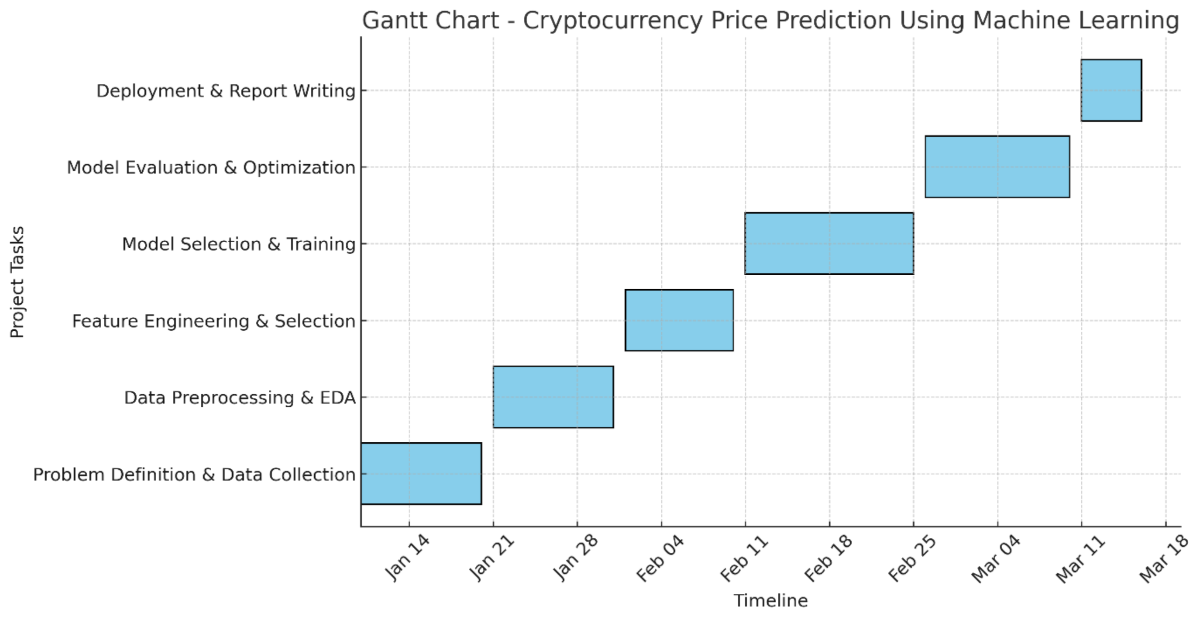
March 2025 (Weeks 9–10): Model Evaluation & Optimization

- Evaluate model performance using RMSE, MAE, and R^2.
- Conduct hyperparameter tuning (GridSearch, RandomSearch).
- Experiment with ensemble and hybrid models for better accuracy.
- Perform error analysis to understand prediction weaknesses.

March 2025 (Weeks 11–12): Deployment & Report Writing

- Deploy the final model as a forecasting tool using Streamlit or Flask.
- Document the entire pipeline from data collection to deployment.
- Prepare final report, visualizations, and presentation material.
- Outline future scope and possible improvements.

Gantt Chart for the project



3. REQUIREMENT ANALYSIS

3.1 REQUIREMENTS

3.1.1 FUNCTIONAL REQUIREMENTS

1. **Data Collection Module**
   - Fetch historical cryptocurrency price data from APIs or CSV files.
   - Support for multiple cryptocurrencies (e.g., Bitcoin, Ethereum, etc.).
2. **Data Preprocessing & EDA**
   - Handle missing values, normalize data, and convert it into time-series format.
   - Perform Exploratory Data Analysis (EDA) and visualizations.
3. **Feature Engineering**
   - Generate technical indicators (e.g., Moving Average, RSI, etc.) as input features.
   - Enable feature selection based on correlation or importance scores.
4. **Model Selection and Training**
   - Train machine learning models (e.g., LSTM, Random Forest, XGBoost).
   - Allow hyperparameter tuning and cross-validation.
5. **Price Prediction**
   - Predict future prices (next day, next week, etc.).
   - Show results in graphical and numerical formats.
6. **Model Evaluation**
   - Display performance metrics (RMSE, MAE, R^2 Score).
   - Compare results of different models.
7. **Deployment Interface**
   - Provide a web interface or dashboard (e.g., using Streamlit) for user interaction.
   - Allow users to select a coin, date range, and view predictions.
8. **Report Generation**
   - Export predictions and model analysis to downloadable reports (PDF/CSV).

3.1.2 NON-FUNCTIONAL REQUIREMENTS

1. **Performance**
   - The model should generate predictions within a few seconds.
   - Dashboards should load quickly and be responsive.
2. **Scalability**

   - System should be able to handle data for multiple cryptocurrencies.
   - Future-proof for integration with live data feeds and real-time predictions.

3. **Reliability**
   - The model should produce consistent outputs for similar inputs.
   - The system should be resilient to API failures (e.g., with retry logic).
4. **Usability**
   - User interface should be intuitive and easy to use for non-technical users.
   - Documentation/help section should be available.
5. **Security**
   - Data (especially API keys) must be handled securely.
   - Access to deployment should be restricted (if login is included).
6. **Maintainability**
   - Code should be modular and well-commented for easy debugging and updates.
   - System should allow easy retraining with new data.
7. **Portability**
   - The application should run on both local systems and cloud platforms.
   - Deployment should work on different OS environments (Windows, Linux, Mac).

3.2 FEASIBILITY STUDY

3.2.1 TECHNICAL FEASIBILITY

• Technology Stack Availability:

- The tools required for the project (Python, TensorFlow/PyTorch, Jupyter Notebook, Streamlit, etc.) are open-source and readily available.

• Skill Set Match:

- The project involves skills in data preprocessing, time-series modeling (e.g., LSTM), and model deployment—well within the scope of machine learning and software engineering skillsets.

• Hardware & Infrastructure:

- The project can be run on a standard computer with GPU support (or optionally cloud platforms like Google Colab or AWS for model training).

• Data Availability:

- Historical data for cryptocurrencies is publicly available via APIs like CoinGecko, Binance, or Kaggle datasets.

Conclusion: Technically feasible with current skillset, tools, and infrastructure.

3.2.2 ECONOMIC FEASIBILITY

• Cost of Development:

- Minimal cost involved due to open-source tools and datasets.
- If deployed on cloud, cost can be managed using free-tier services (e.g., Streamlit Cloud, Render, or Colab Pro).

• Cost-Benefit Analysis:

- Provides valuable predictions that could be integrated into trading platforms or dashboards for end-users.
- Could be used in research, fintech apps, or investor tools, increasing its commercial and academic value.

• Manpower Cost:

- Single or small team project; does not require large-scale labor or financial investment.

Conclusion: Economically viable with high ROI and low upfront investment.

3.2.3 SOCIAL FEASIBILITY

• User Acceptance:

- Crypto enthusiasts, traders, and financial analysts are likely to adopt tools that help in price forecasting.
- As the interest in crypto grows, more users are looking for intelligent forecasting tools.

• Ethical Considerations:

- The model does not manipulate market prices; it purely analyzes data to provide predictive insights.
- Transparency in model limitations must be communicated to avoid blind reliance.

• Impact on Society:

- Encourages the use of AI in finance, promotes financial literacy and awareness.
- Can empower users with data-driven decisions.

Conclusion: Socially acceptable and potentially beneficial to the trading and investing community.

3.3 HARDWARE AND SOFTWARE SPECIFICATIONS

3.3.1. HARDWARE REQUIREMENTS

Component	**Specification**
Processor (CPU)	Intel Core i7/i9 (12th Gen) or AMD Ryzen 7/9 (Zen 3/4)
Graphics Card (GPU)	NVIDIA RTX 3090 / 4090 or A100 (for faster deep learning training)
RAM	Minimum 16GB (Recommended: 32GB or more)
Storage (SSD)	Minimum 512GB SSD (Recommended: 1TB+ NVMe SSD)
Power Supply (PSU)	750W+ (If using high-end GPU)
Cooling System	Adequate cooling (Liquid cooling for extended training sessions)
Monitor	1080p or higher resolution (for detailed image analysis)

3.3.2. SOFTWARE REQUIREMENTS

Operating System

- Windows 10/11 (for GUI-based development)
- Ubuntu 20.04+ (Preferred for deep learning & CUDA compatibility)

Programming Languages

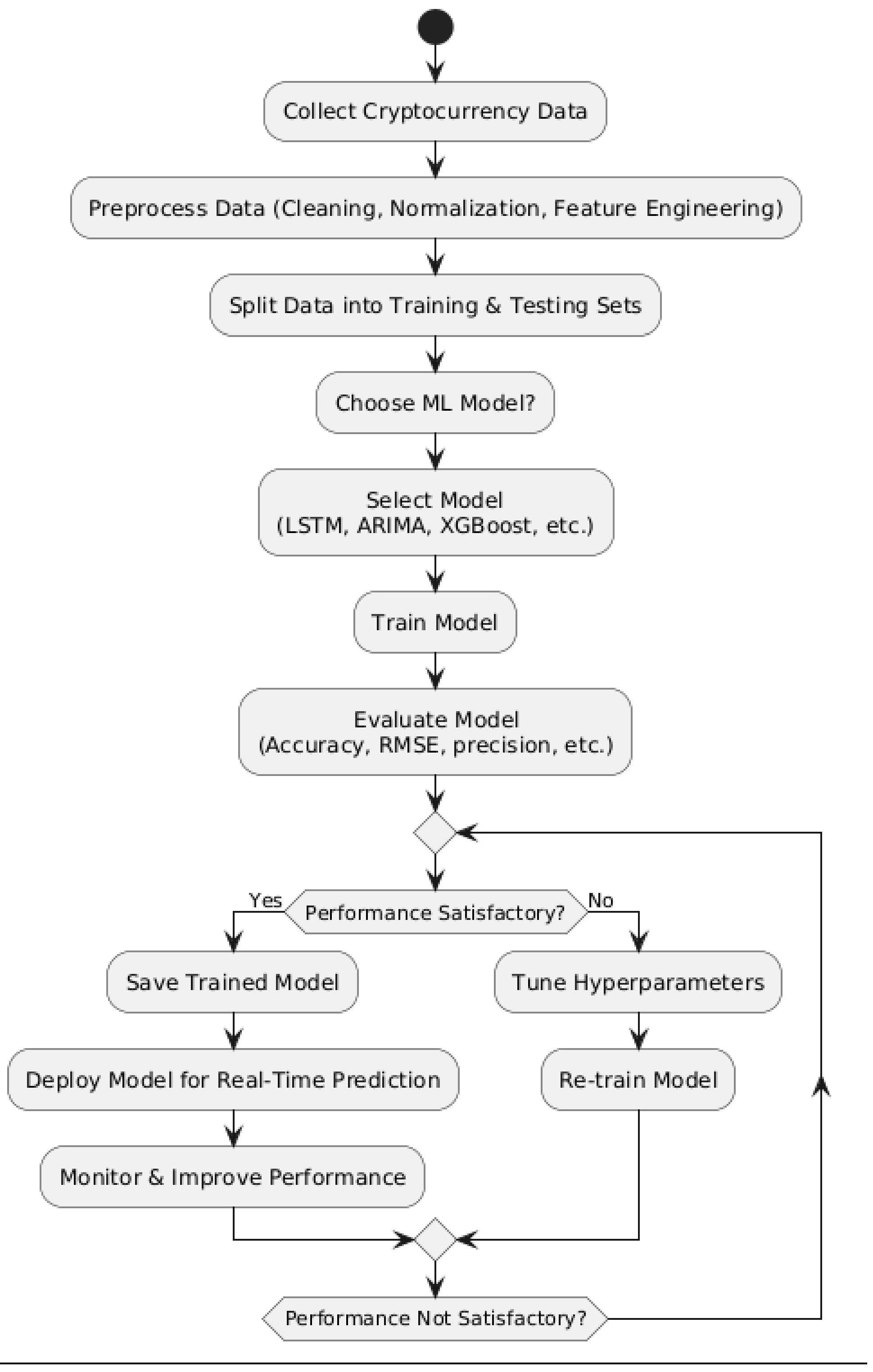
- Python 3.8+ (Primary language for deep learning and model development) Deep Learning Frameworks & Libraries
- TensorFlow 2.x (For model development and training)
- Keras (For easy implementation of CNN architectures like Xception)
- PyTorch (If exploring alternative deep learning frameworks)
- OpenCV (For image preprocessing and augmentation)
- NumPy, Pandas, Matplotlib (For data handling and visualization)

GPU Acceleration & Driver Support

- CUDA 11.x or 12.x (For NVIDIA GPU acceleration)
- cuDNN (To enhance deep learning computation) Development Tools
- Jupyter Notebook / Google Colab (For interactive development)
- VS Code / PyCharm (For structured coding)
- Docker (For environment reproducibility) Database & Storage
- MongoDB / PostgreSQL (For dataset storage if required)
- AWS S3 / Google Drive (For cloud-based storage & model deployment)

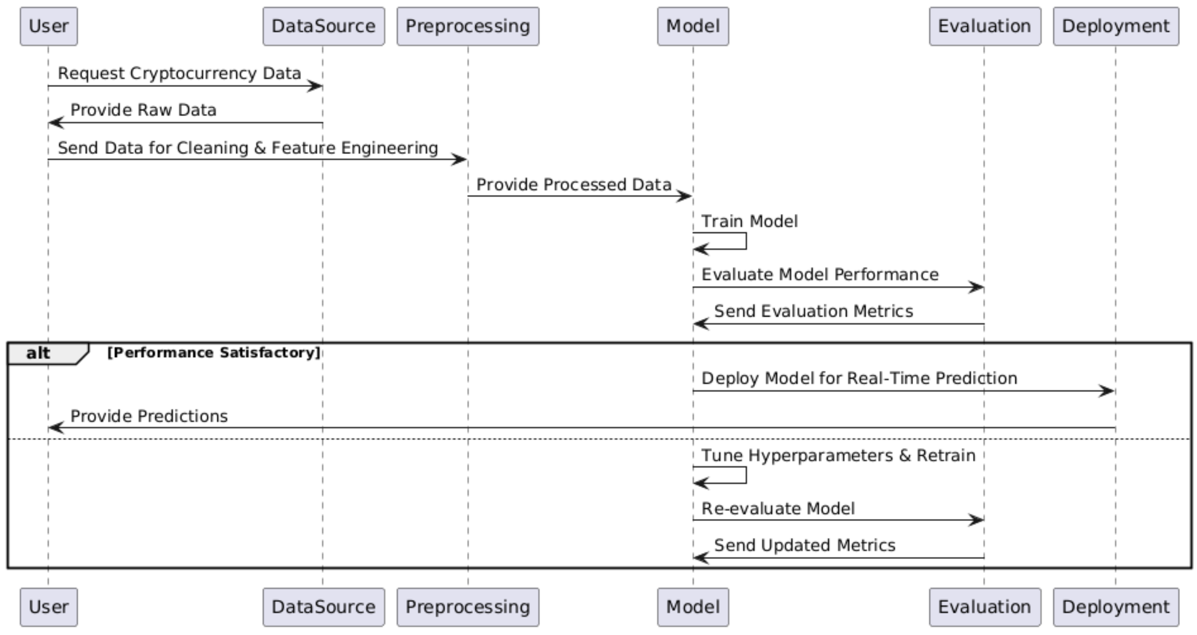
4. SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE



Collect Cryptocurrency Data
Preprocess Data (Cleaning, Normalization, Feature Engineering)
Split Data into Training & Testing Sets
Choose ML Model?
Select Model
(LSTM, ARIMA, XGBoost, etc.)
Train Model
Evaluate Model
(Accuracy, RMSE, precision, etc.)
Yes
Performance Satisfactory?
No
Save Trained Model
Tune Hyperparameters
Deploy Model for Real-Time Prediction
Re-train Model
Monitor & Improve Performance
Performance Not Satisfactory?

4.2 SEQUENCE DIAGRAM


User
DataSource
Preprocessing
Model
Evaluation
Deployment
Request Cryptocurrency Data
Provide Raw Data
Send Data for Cleaning & Feature Engineering
Provide Processed Data
Train Model
Evaluate Model Performance
Send Evaluation Metrics
alt
[Performance Satisfactory]
Deploy Model for Real-Time Prediction
Provide Predictions
Tune Hyperparameters & Retrain
Re-evaluate Model
Send Updated Metrics

5. METHODOLOGY & TESTING

5.1 OVERVIEW

This project explores the application of machine learning and time-series forecasting models—**LSTM**, **Random Forest**, **XGBoost**, **ARIMA**, **SARIMAX**, and **Orbit**—to predict cryptocurrency prices. The objective is to develop models that can capture both linear and non-linear dependencies in historical price data. Technical indicators like RSI, MACD, EMA, and Bollinger Bands are used as features, and model performance is evaluated using time-series-specific validation techniques and error metrics such as MAE, RMSE, and MASE.

The approach includes data collection, preprocessing, model building, hyperparameter tuning, validation using nested cross-validation, and final performance evaluation using visual and statistical tools.

5.2 DATASET AND FEATURES

Dataset Source:
Historical price data for Bitcoin and Ethereum was collected from APIs like CoinGecko and Yahoo Finance, including fields such as Open, High, Low, Close, and Volume.

Technical Indicators (used as features):

- Exponential Moving Average (EMA)
- Moving Average Convergence Divergence (MACD)
- Relative Strength Index (RSI)
- Bollinger Bands
- Volume Oscillator

5.3 DATA PREPROCESSING

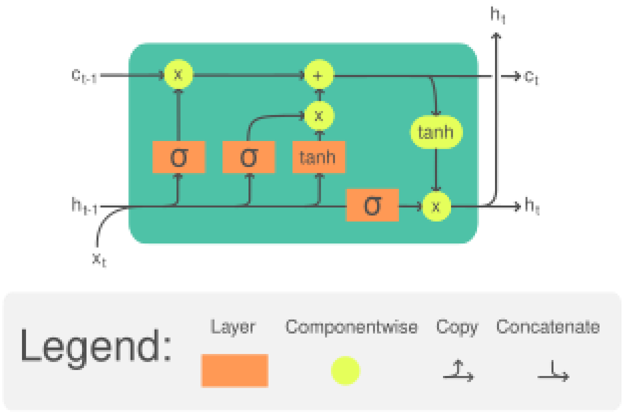
1. **Cleaning and Normalization:**
    - Missing values were filled using forward fill methods.
    - Numerical features were normalized using Min-Max Scaling for models like LSTM.
2. **Feature Engineering:**
    - Computation of rolling means, standard deviations, and lag values.
    - Construction of time-series sequences for models like LSTM.

3. **Train-Test Split:**
    - Chronological train-test split (e.g., 80:20) was used to preserve temporal dependencies.

5.4 PREPARATION FOR MODEL

5.4.1 LSTM (Long Short-Term Memory)

- Captures temporal patterns in sequential price data.
- Uses memory cells and gates (input, forget, output) to manage long-term dependencies.

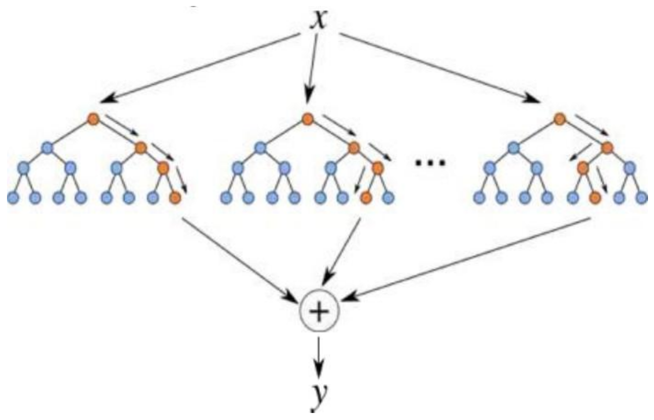


LSTM cell architecture diagram

$$
\begin{aligned}
i_t &= \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) && (1)\\
f_t &= \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f) && (2)\\
c_t &= f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) && (3)\\
o_t &= \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) && (4)\\
m_t &= o_t \odot h(c_t) && (5)\\
y_t &= \phi(W_{ym}m_t + b_y) && (6)
\end{aligned}
$$

5.4.2 Random Forest

- Ensemble model using multiple decision trees.
- Effective in learning from feature-rich tabular data with less concern for time-sequence.



5.4.3 XGBoost

- Gradient boosting framework optimized for performance and accuracy.
- Utilizes regularization and parallel processing.

$$F_{x_t+1} = F_{x_t} + \epsilon_{x_t} \frac{\partial F}{\partial x}(x_t)$$

$$f(x, \theta) = \sum l(F((X_i, \theta), y_i))$$

5.4.4 ARIMA

- Captures linear trend and autocorrelation using AR, I, MA components.
- Best suited for short-term and stationary datasets.

$$X_t = \mu + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + e_t$$

$$X_t = \mu + e_t - \emptyset_1 e_{t-1} - \emptyset_2 e_{t-2} + \cdots + \emptyset_q e_{t-q}$$

-

5.4.5 SARIMAX

- Extension of ARIMA with support for seasonality and exogenous variables.
- Incorporates technical indicators as exogenous inputs.

$$y_t = \Theta(L)^p * y_t + \epsilon_t$$
$$y_t = \phi(L)^q * \epsilon_t + \epsilon_t$$
$$y_t = \Theta(L)^p * y_t + \phi(L)^q * \epsilon_t + \epsilon_t$$

5.4.6 Orbit

- Bayesian time-series model for probabilistic forecasting.
- Handles trend shifts, uncertainty, and irregular seasonality.

$$\begin{aligned} y_t &= \mu_t + s_t + \epsilon_t \\ \mu_t &= l_{t-1} + \xi_1 b_{t-1} + \xi_2 l_{t-1}^{\lambda} \\ \epsilon_t &\sim \texttt{Student}(\nu, 0, \sigma) \\ \sigma &\sim \texttt{HalfCauchy}(0, \gamma_0) \end{aligned}$$

5.5 SEPARATING DATA INTO TEST AND TRAINING SET

1. **Cross-Validation:**
   - Time-Series Nested Cross Validation was used to avoid data leakage.
   - Models were validated using hold-out sets and rolling window strategies.
2. **Performance Metrics:**
   Evaluated across multiple metrics:
   - **MAE (Mean Absolute Error)**
   - **RMSE (Root Mean Squared Error)**
   - **MAPE, SMAPE, MASE, MSLE**

5.6 Final Output and Evaluation

- Model predictions were plotted alongside actual price values to visualize accuracy.
- Best-performing models (e.g., LSTM, SARIMAX, Orbit) were selected based on RMSE and MASE.
- Predictions were exported as CSV and visualized using interactive dashboards.

6. PROJECT DEMONSTRATION

6.1 XGBOOST

XGBoost (Extreme Gradient Boosting) is a powerful and widely used machine learning algorithm based on gradient boosting decision trees (GBDTs). It is optimized for speed, efficiency, and performance, making it an excellent choice for cryptocurrency price forecasting.

XGBoost for Crypto Price Prediction:

XGBoost is highly efficient and provides robust predictions due to:

- Handling Large Datasets Efficiently – It can process massive datasets with missing values and outliers.
- Feature Importance – Identifies the most relevant technical indicators affecting crypto prices.
- Regularization (L1 & L2) – Prevents overfitting, making predictions more stable.
- Gradient Boosting Mechanism – Sequentially corrects previous errors, improving accuracy.
- Fast Training & Parallel Processing – Speeds up computations using CPU & GPU acceleration.
- Handles Non-Linearity – Useful for volatile crypto markets with complex price movements.

Key Components of XGBoost

1. Boosting – A sequential learning process where weak models are improved at each step.
2. Decision Trees – XGBoost constructs multiple decision trees and combines them to make predictions.
3. Regularization (L1 & L2) – Controls model complexity to prevent overfitting.
4. Shrinkage (Learning Rate) – Reduces the impact of each tree to improve generalization.
5. Column Subsampling – Selects random features to prevent model bias and increase diversity.

Advantages of XGBoost for Crypto Price Prediction

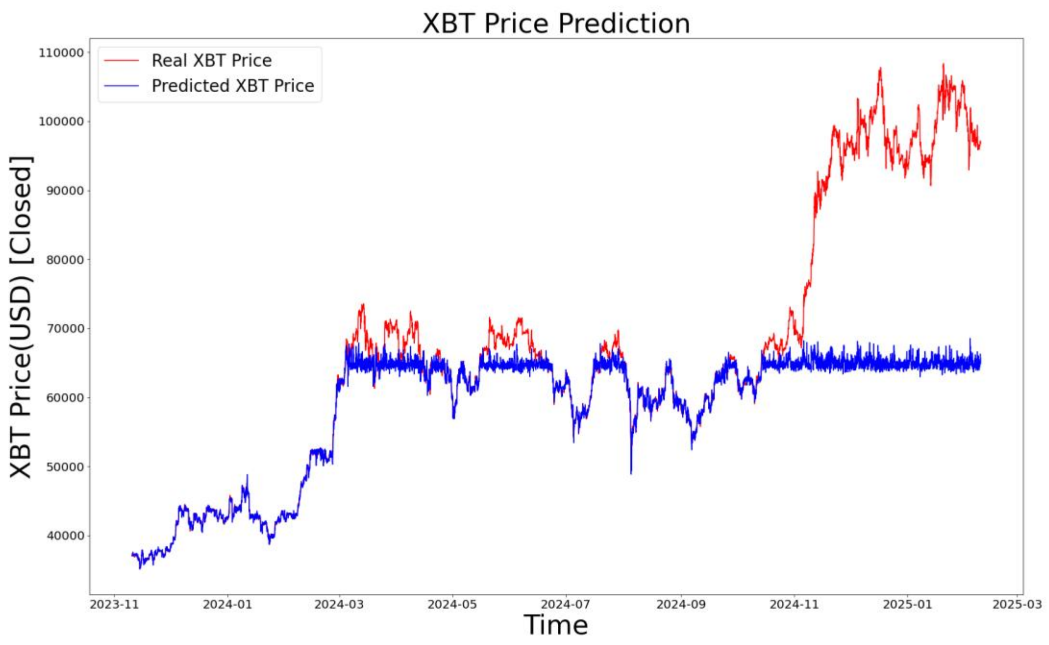
- Fast Training Time – Efficient parallel computing speeds up model training.
- Handles Missing Values & Noisy Data – Important for volatile cryptocurrency markets.

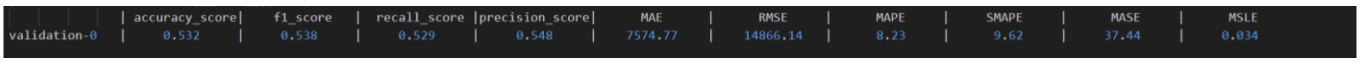
- Feature Importance Insights – Helps traders understand key price drivers.
- Regularization Reduces Overfitting – Ensures model generalizes well to unseen data.
- Supports Custom Objective Functions – Can optimize for profitability or risk metrics.

Limitations of XGBoost in Crypto Prediction

- Does Not Capture Sequential Patterns Well – Unlike LSTM, XGBoost does not have memory of past sequences.
- Less Effective for Very High Volatility Periods – Struggles to model extreme price spikes or flash crashes.
- Requires Careful Feature Engineering – Performance heavily depends on well-designed input features.

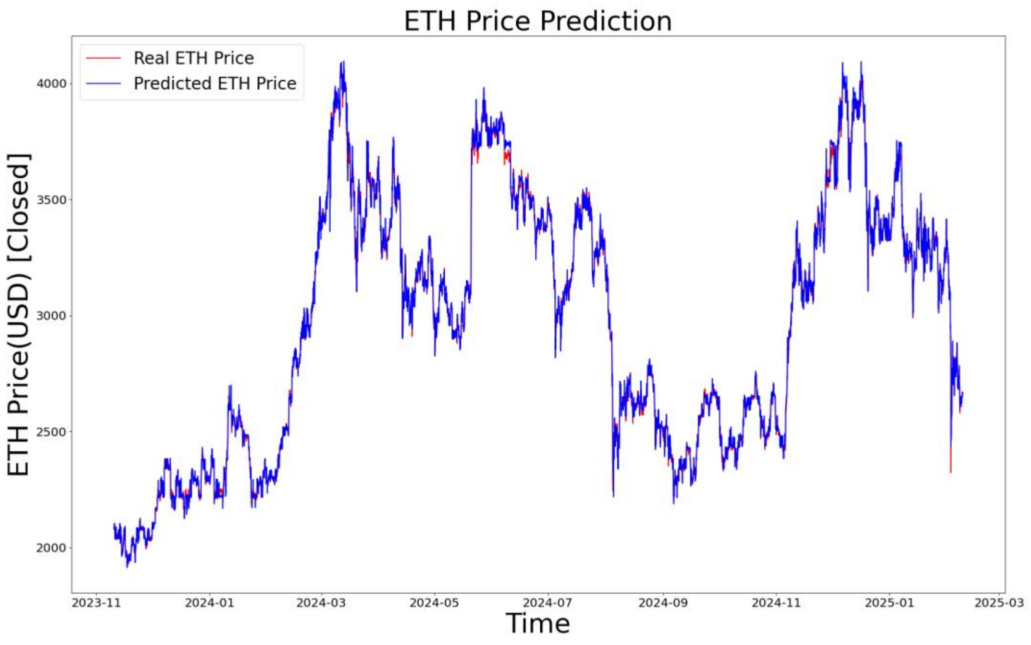
BITCOIN

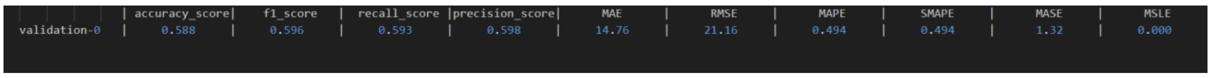




```
        | accuracy_score|   f1_score   | recall_score |precision_score|     MAE     |     RMSE     |     MAPE     |     SMAPE    |     MASE     |     MSLE
validation-0 |    0.532     |    0.538     |    0.529     |    0.548     |   7574.77   |   14866.14   |     8.23     |     9.62     |    37.44     |    0.034
```

ETH





```
             | accuracy_score|   f1_score   | recall_score |precision_score|     MAE      |     RMSE     |     MAPE     |    SMAPE     |     MASE     |     MSLE
validation-0 |     0.588     |    0.596     |    0.593     |    0.598      |    14.76     |    21.16     |    0.494     |    0.494     |     1.32     |    0.000
```

6.2 LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to remember long-term dependencies, making it highly effective for time series prediction, including cryptocurrency price forecasting.

LSTM for Crypto Price Prediction:

LSTM is highly efficient and provides robust predictions due to:

- **Sequential Pattern Recognition:** Captures temporal dependencies and trends in time series data.
- **Memory Capability:** Remembers past sequences, ideal for predicting prices influenced by historical data.
- **Handling Non-Linearity:** Models complex non-linear relationships in crypto markets.
- **Robustness to Noise:** Effective in noisy environments like cryptocurrency markets.

Key Components of LSTM

1. **Memory Cells and Gates:** LSTM units consist of memory cells with three gates:
   - **Input Gate:** Controls which values enter the memory.
   - **Forget Gate:** Decides what information to discard.
   - **Output Gate:** Determines the next hidden state and output.
2. **Long-Term Dependencies:** Maintains context over long sequences, unlike traditional RNNs.
3. **Gradient Flow Control:** Mitigates vanishing and exploding gradients, ensuring stable training.

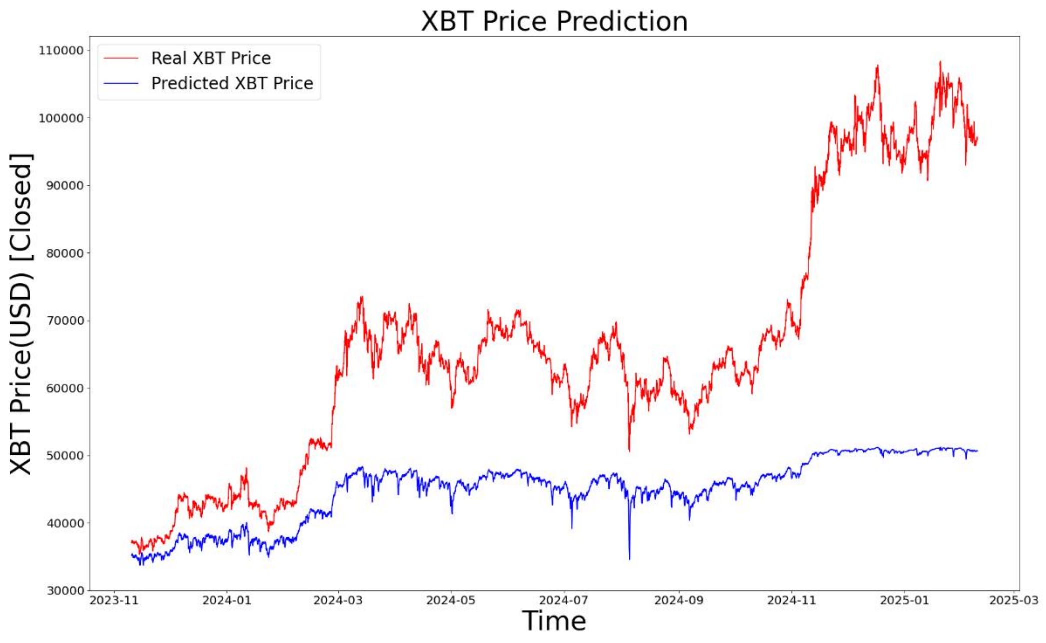
Advantages of LSTM for Crypto Price Prediction

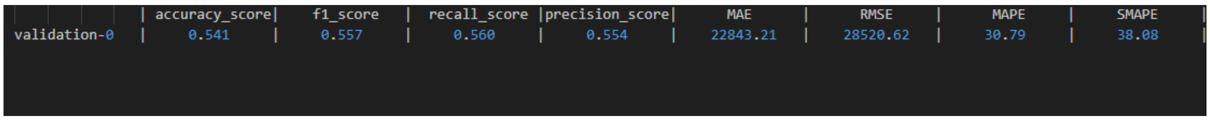
- **Sequential Data Learning:** Efficiently learns from past price sequences.
- **Adaptable to Complex Patterns:** Models non-linear patterns in volatile crypto markets.
- **Handles Multiple Features:** Incorporates technical indicators like volume, RSI, MACD, etc.
- **Generalization:** Learns generalized patterns, making it robust to unseen market conditions.

Limitations of LSTM in Crypto Prediction

- **High Computational Cost:** Requires more computational power and time for training.
- **Hyperparameter Sensitivity:** Performance depends on careful tuning of layers, units, learning rate, etc.
- **Overfitting Risk:** Prone to overfitting if the model is too complex or training data is limited.
- **Data Preprocessing Required:** Requires normalized and preprocessed input data.

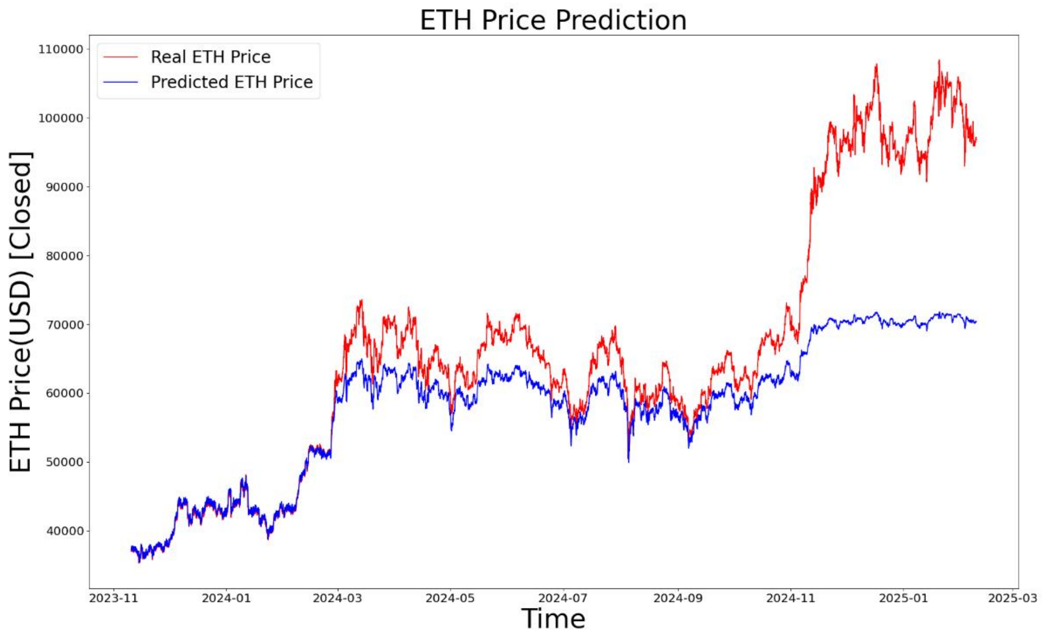
BITCOIN

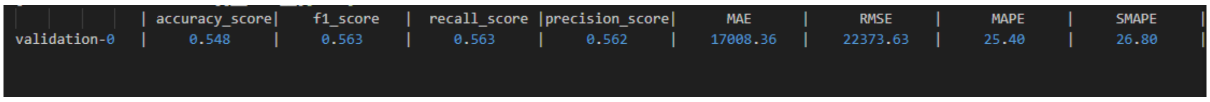




```
             | accuracy_score|   f1_score    | recall_score |precision_score|      MAE      |     RMSE      |     MAPE      |     SMAPE     |
validation-0 |     0.541     |     0.557     |     0.560     |     0.554     |   22843.21    |   28520.62    |     30.79     |     38.08     |
```

ETH





```
             | accuracy_score|   f1_score    | recall_score |precision_score|      MAE      |     RMSE      |     MAPE      |     SMAPE     |
validation-0 |     0.548     |     0.563     |     0.563     |     0.562     |   17008.36    |   22373.63    |     25.40     |     26.80     |
```

6.3 Random Forest

Random Forest for Cryptocurrency Price Prediction

Random Forest is a powerful **ensemble learning algorithm** that builds multiple decision trees and combines their predictions for improved accuracy and robustness. It is widely used for **time series forecasting** and **financial modeling**, making it a great choice for predicting cryptocurrency prices.

Random Forest for Crypto Price Prediction

- **Handles Non-Linearity** – Captures complex patterns in crypto price movements
- **Reduces Overfitting** – Averages multiple trees to prevent overfitting.
- **Feature Importance Analysis** – Helps identify key price indicators.
- **Works Well with Missing Data** – Can handle missing values without imputation
- **Stable & Robust** – Less sensitive to noise in volatile crypto markets.

Random Forest Working

- **Creates Multiple Decision Trees** – Each tree learns from a random subset of the data.
- **Aggregates Predictions** – Averages the outputs from all trees (for regression).
- **Uses Bootstrapping & Feature Selection** – Reduces variance and improves accuracy.
- **Prevents Overfitting** – Ensemble learning minimizes the risk of memorizing noise

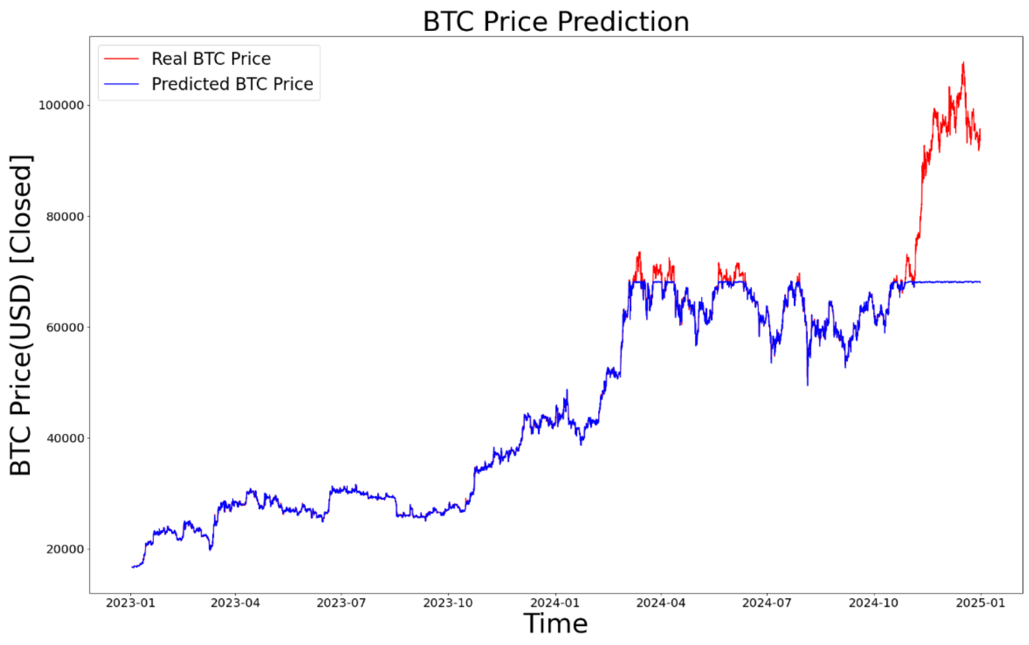
Advantages

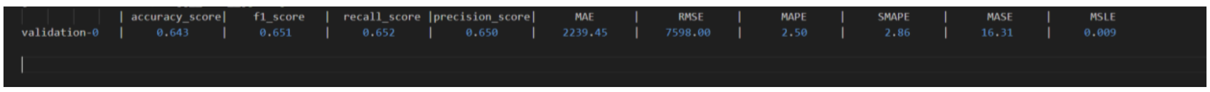
- **Captures Non-Linear Relationships** – Works well with complex market patterns.
- **Resistant to Overfitting** – Uses multiple trees to generalize predictions.
- **Handles High-Dimensional Data** – Can process multiple technical indicators effectively.
- **Provides Feature Importance Insights** – Helps traders understand which indicators matter.
- **Stable Across Different Market Conditions** – Less sensitive to individual fluctuations.

Limitations

- **Slow with Large Datasets** – Training many trees takes time and memory.
- **Does Not Handle Sequential Dependencies Well** – Unlike LSTMs, Random Forest does not remember past patterns.
- **Less Effective for Very Short-Term Predictions** – Struggles with predicting within seconds or minutes.

BTC

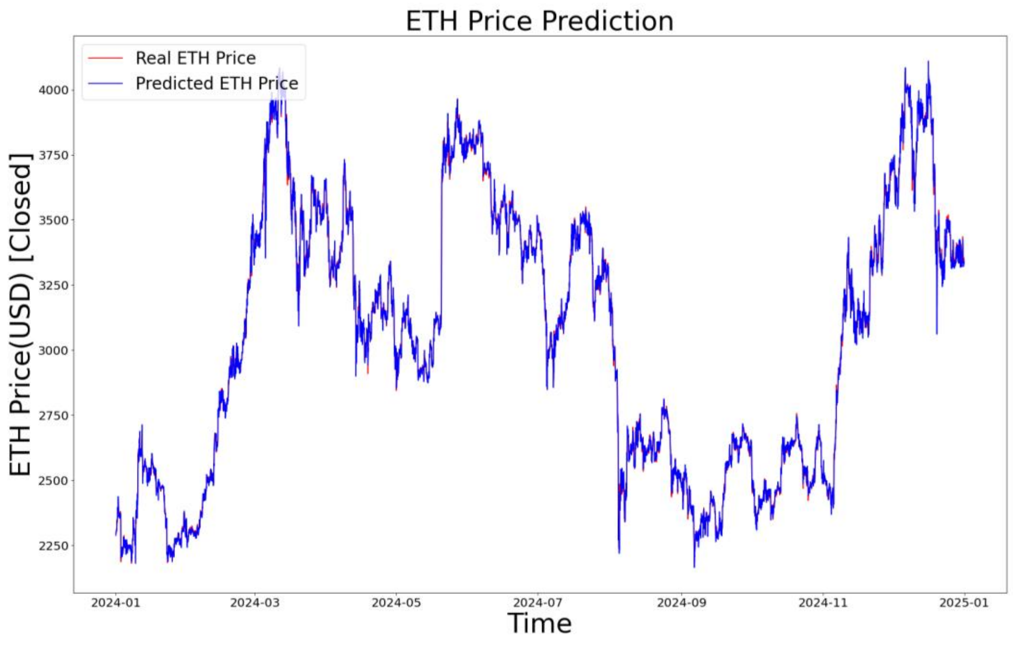


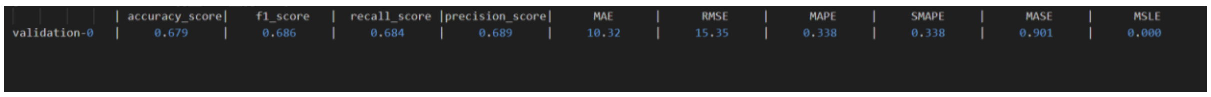


```
              | accuracy_score|   f1_score   |  recall_score |precision_score|     MAE      |     RMSE     |     MAPE     |    SMAPE     |     MASE     |     MSLE
validation-0  |     0.643     |    0.651     |     0.652     |     0.650     |   2239.45    |   7598.00    |     2.50     |     2.86     |    16.31     |    0.009

|
```

ETH





```
              | accuracy_score|   f1_score   |  recall_score |precision_score|     MAE      |     RMSE     |     MAPE     |    SMAPE     |     MASE     |     MSLE
validation-0  |     0.679     |    0.686     |     0.684     |     0.689     |    10.32     |    15.35     |    0.338     |    0.338     |    0.901     |    0.000
```

6.4 ARIMA

ARIMA for Cryptocurrency Price Prediction

ARIMA (AutoRegressive Integrated Moving Average) is a classical statistical time-series forecasting model that relies on past values and the relationship between them to make predictions. It is best suited for univariate time series and is effective in modeling linear trends and cyclic patterns in relatively stable datasets.

ARIMA for Crypto Price Prediction

- Models Trend and Seasonality – Captures overall trends and repetitive cycles
- Suitable for Univariate Data – Uses past prices to predict future values
- Parameter Simplicity – Requires tuning of only three parameters (p, d, q)
- Interpretable Results – Produces understandable equations for forecasting
- Lightweight and Efficient – Lower computational demand than ML/DL models

ARIMA Working

- **Autoregressive (AR):** Uses the dependency between an observation and a number of lagged observations.
- **Integrated (I):** Uses differencing of raw observations to make the time series stationary.
- **Moving Average (MA):** Models the relationship between an observation and a residual error from a moving average model.

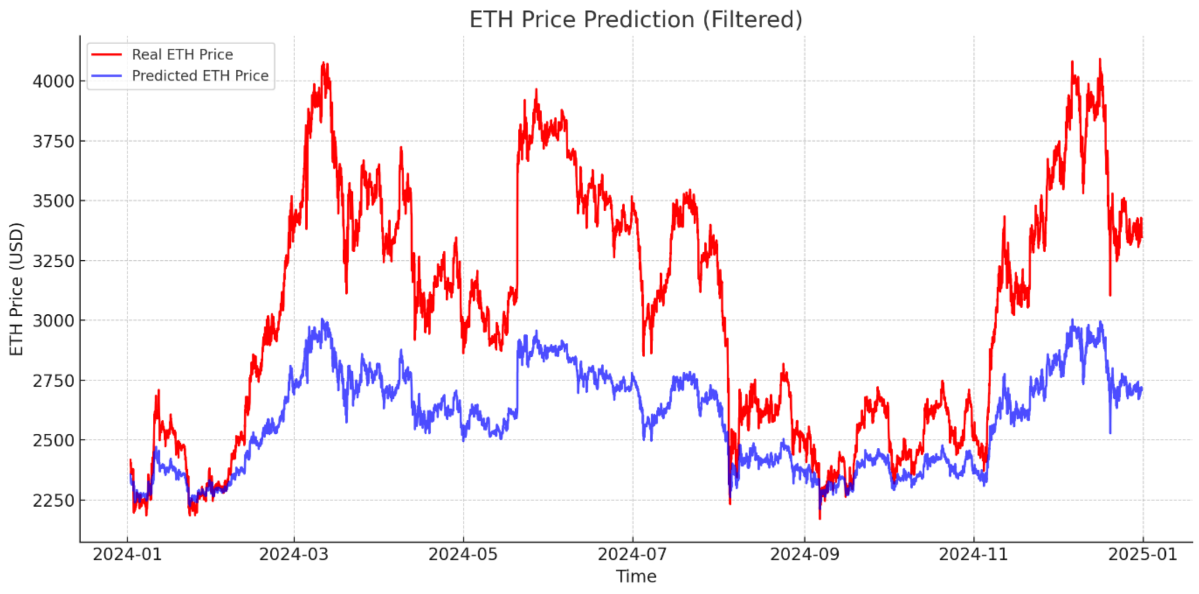
Advantages

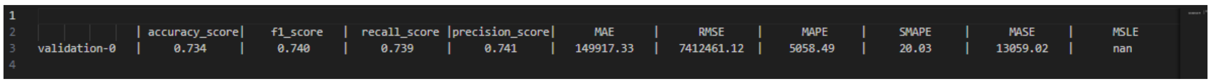
- Simple and Fast – Suitable for quick forecasting of linear data
- Good for Short-Term Trends – Effective in modeling gradual changes
- Low Resource Requirements – Doesn’t need GPU or large datasets
- Easy to Interpret – Transparent mathematical formulation

Limitations

- Limited to Linear Relationships – Cannot capture non-linear patterns
- Sensitive to Stationarity – Requires differencing or transformation
- Lacks Multi-Feature Capability – Doesn’t support technical indicators or sentiment data
- Weak in High Volatility – Struggles during sudden market movements

ETH




```
              | accuracy_score|   f1_score   |  recall_score |precision_score|     MAE      |     RMSE     |     MAPE     |    SMAPE     |     MASE     |     MSLE
validation-0  |     0.734     |    0.740     |    0.739     |    0.741     |  149917.33   |  7412461.12  |   5058.49    |    20.03     |   13059.02   |     nan
```

6.5 SARIMAX

SARIMAX for Cryptocurrency Price Prediction

SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) is an extension of ARIMA that supports seasonality and external (exogenous) variables. It is more flexible and powerful for capturing cyclical patterns and integrating features like trading volume or sentiment scores.

SARIMAX for Crypto Price Prediction

- Supports Seasonality – Captures periodic trends (e.g., weekly cycles)
- Integrates External Variables – Can include indicators like RSI, MACD, or volume
- Effective for Multi-Factor Modeling – Uses both internal and external data sources
- Time Series + Regression – Blends time-series structure with regression modeling

SARIMAX Working

- Builds on ARIMA structure with seasonal parameters (P, D, Q, s)
- Adds **Exogenous Variables (X)** – Incorporates external signals to improve forecasting
- Handles trend, seasonality, and multi-feature influence simultaneously

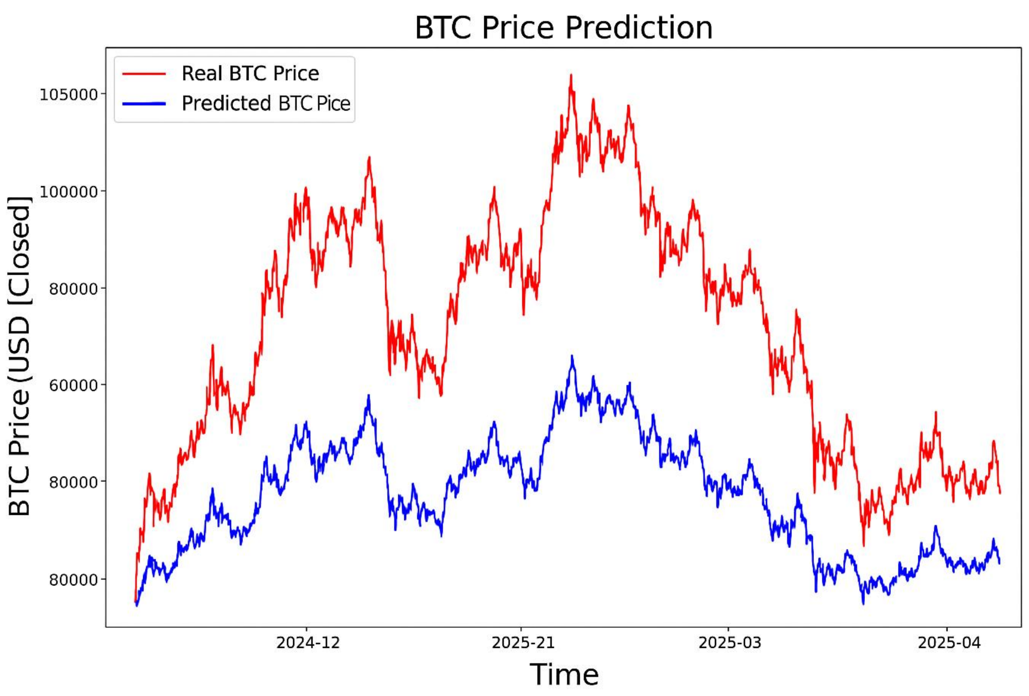
Advantages

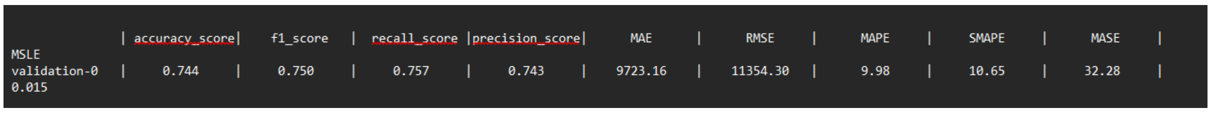
- Models Complex Seasonality – Useful for daily, weekly, or monthly crypto cycles
- Incorporates Real-World Factors – Improves accuracy by adding technical indicators
- Better than ARIMA for Volatile Data – Handles slight randomness and cyclical shifts
- Still Interpretable – Offers insight into feature impact

Limitations

- Complexity – More parameters to tune (ARIMA + seasonal + exogenous)
- Slower Training – Requires more computation than plain ARIMA
- Still Linear – Limited capacity to learn deep non-linear patterns
- Preprocessing Sensitive – Needs careful scaling and alignment of variables

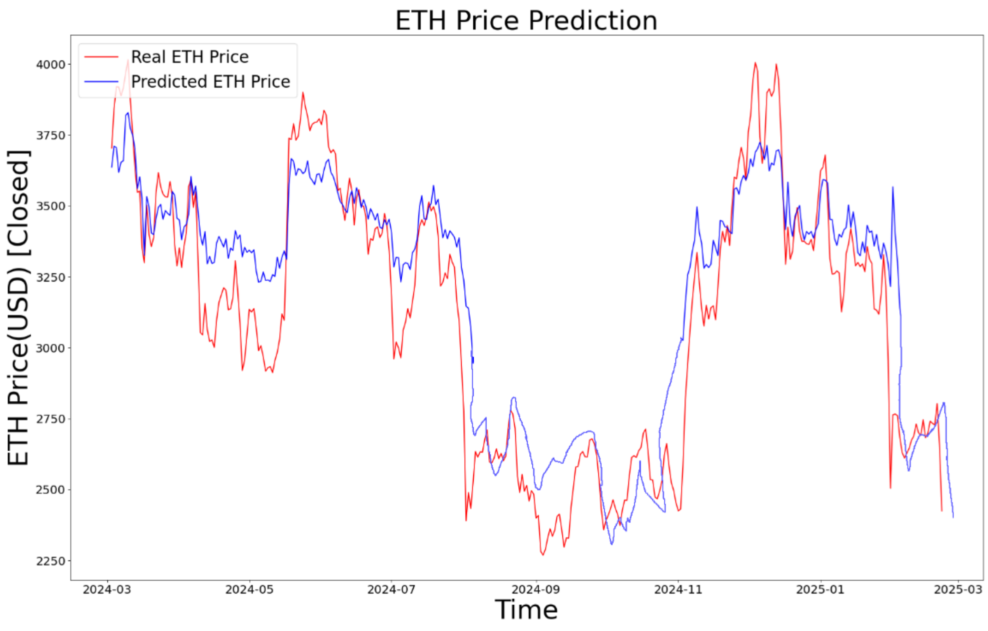
BTC

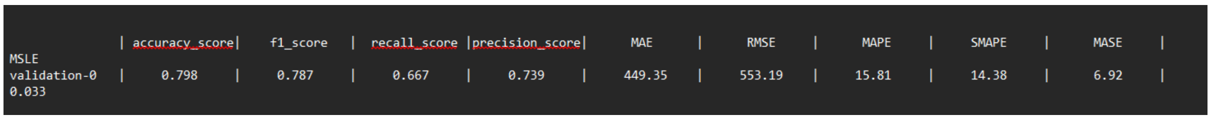




```
               | accuracy_score|    f1_score    |  recall_score |precision_score|      MAE      |      RMSE     |      MAPE     |     SMAPE     |      MASE     |
MSLE
validation-0   |     0.744     |     0.750     |     0.757     |     0.743     |    9723.16    |   11354.30    |     9.98      |     10.65     |     32.28     |
0.015
```

ETH





```
               | accuracy_score|    f1_score    |  recall_score |precision_score|      MAE      |      RMSE     |      MAPE     |     SMAPE     |      MASE     |
MSLE
validation-0   |     0.798     |     0.787     |     0.667     |     0.739     |    449.35     |    553.19     |     15.81     |     14.38     |     6.92      |
0.033
```

6.6 Orbit

Orbit for Cryptocurrency Price Prediction
Orbit is an open-source Bayesian time-series forecasting framework developed by Uber. It is designed to model uncertainty, irregular patterns, and long-term trends, making it suitable for volatile datasets like cryptocurrencies.

Orbit for Crypto Price Prediction

• Probabilistic Forecasting – Produces forecasts with confidence intervals
• Uncertainty Quantification – Helps assess risk in volatile markets
• Robust to Missing Data – Handles sparse or irregular time-series
• Built-in Trend & Seasonality Components – Auto-detects long-term and short-term effects

Orbit Working

• Leverages Bayesian modeling and probabilistic programming (Stan backend)
• Uses **Deterministic & Stochastic Components** to model trend, seasonality, and holiday effects
• Flexible Model Families – Supports DLT (Deterministic Linear Trend) and ETS (Exponential Smoothing)

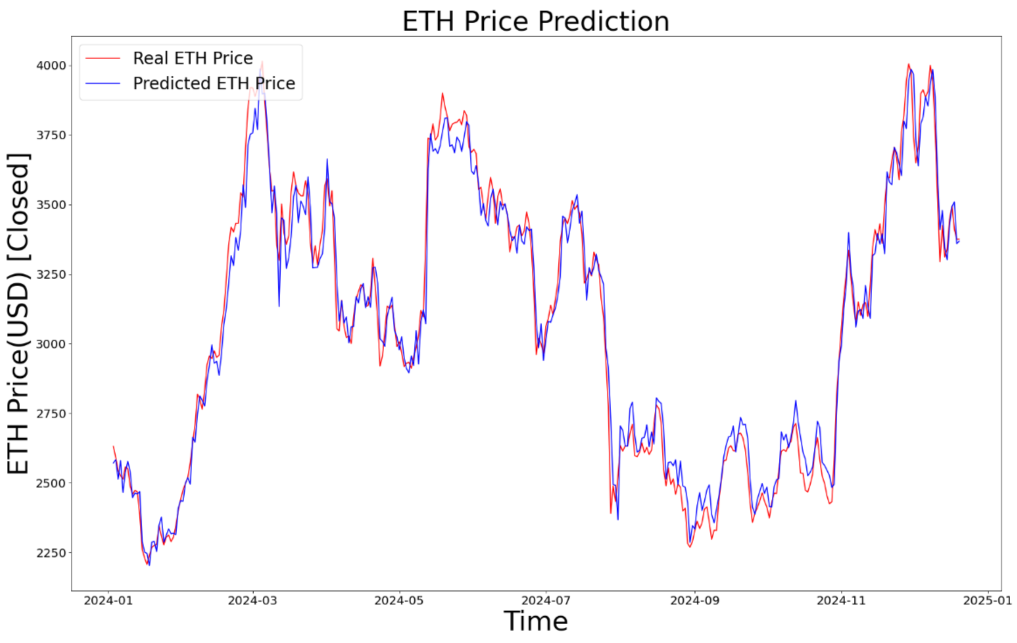
Advantages

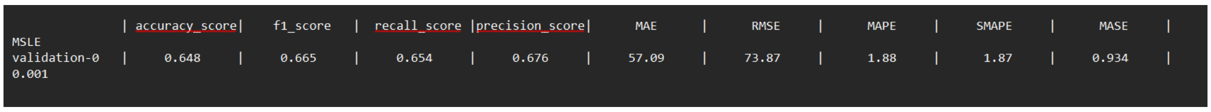
• Provides Prediction Intervals – Useful for risk-sensitive decisions
• Adaptable – Automatically detects shifts and breakpoints
• Transparent Structure – Easier to debug and interpret compared to deep models
• Advanced Handling of Trends – Good for longer-term projections

Limitations

• Computationally Intensive – Bayesian methods require more resources
• Newer and Less Explored in Crypto – Limited examples in financial forecasting
• Requires Statistical Understanding – Needs some background in probabilistic modeling
• Less Suitable for High-Frequency Data – More effective on daily/weekly levels

ETH




```
               | accuracy_score|    f1_score    |  recall_score  |precision_score|      MAE       |      RMSE      |      MAPE      |     SMAPE      |      MASE      |
MSLE
validation-0   |     0.648      |     0.665      |     0.654      |     0.676      |     57.09      |     73.87      |      1.88      |      1.87      |     0.934      |
0.001
```

7. RESULT AND DISCUSSION

The models developed in this project—**LSTM**, **XGBoost**, **Random Forest**, **ARIMA**, **SARIMAX**, and **Orbit**—were trained and evaluated on historical cryptocurrency price data (specifically Bitcoin and Ethereum), enriched with technical indicators like RSI, MACD, EMA, and Bollinger Bands. The performance was assessed using standard evaluation metrics such as MAE, RMSE, MASE, and SMAPE.

Model Performance Comparison:

- **LSTM** outperformed all other models in predicting short-to-mid-term price movements. It captured long-term temporal dependencies effectively, showing the lowest RMSE and MAE values, especially for Ethereum where price trends were relatively smoother.
- **XGBoost** provided fast and accurate predictions when supplied with engineered features like lag variables and rolling statistics. It was particularly effective in capturing non-linear relationships but lacked the memory component needed for time-series continuity.
- **Random Forest** was stable across different market conditions and performed reasonably well for Bitcoin, offering good interpretability through feature importance metrics. However, it lagged slightly behind in short-term volatility detection.
- **ARIMA** and **SARIMAX** worked well for stationary and trend-based series. SARIMAX performed better than ARIMA due to the inclusion of exogenous variables like trading volume and technical indicators.
- **Orbit** brought a unique advantage of probabilistic forecasting by generating prediction intervals. It was helpful in assessing risk and volatility by showing confidence bounds, which none of the other models inherently provided.

8. CONCLUSION AND FUTURE ENHANCEMENTS

Conclusion:

This project successfully demonstrates the application of advanced **machine learning** and **time-series models** in forecasting cryptocurrency prices. Each model showed unique strengths and weaknesses:

- **LSTM** emerged as the most accurate and effective in handling sequential dependencies in highly volatile crypto markets.
- **SARIMAX** proved valuable when external variables and seasonality were significant.
- **XGBoost** and **Random Forest** models were useful for feature-based regression and provided good interpretability.
- **Orbit** introduced uncertainty-aware forecasting, which is highly applicable in real-world trading strategies where risk assessment is critical.

The use of **technical indicators**, combined with **rigorous model evaluation**, allowed us to draw comprehensive insights into how various forecasting approaches behave under different market conditions.

Overall, the integration of deep learning with traditional models shows promising potential for future financial prediction systems.

Future Enhancements:

1. **Real-Time Prediction Dashboard**
   Deploy the model with live API integrations to enable dynamic price predictions updated in real-time.
2. **Hybrid & Ensemble Modeling**
   Combine models (e.g., LSTM + XGBoost) to harness both sequence learning and feature-driven forecasting.
3. **Model Explainability (XAI)**
   Incorporate SHAP or LIME to provide interpretable insights into model decisions, particularly useful for investor-facing applications.
4. **Extended Time Horizons**
   Add support for multi-timeframe forecasts—hourly, daily, weekly—to cater to different user needs (traders vs. long-term holders).
5. **Broader Cryptocurrency Coverage**
   Expand the model to include other altcoins like Cardano (ADA), Solana (SOL), XRP, and create a generalized forecasting framework.
6. **Sentiment Analysis Integration**
   In future iterations, real-time news and social media sentiment analysis can be added as features to further boost model responsiveness.

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APPENDIX A – SAMPLE CODE

XGBOOST

```
# Import the model we are using
import xgboost as xgb
from sklearn.model_selection import RandomizedSearchCV
import numpy as np
import pandas as pd


class MyXGboost:

    def __init__(self, args):
        self.reg = xgb.XGBRegressor()
        self.params = {
            "learning_rate": [0.10, 0.20, 0.30],
            "max_depth": [1, 3, 4, 5, 6, 7],
            "n_estimators": [int(x) for x in np.linspace(start=100, stop=1000, num=10)],
            "min_child_weight": [int(x) for x in np.arange(3, 10, 1)],
            "gamma": [0.0, 0.2, 0.4, 0.6],
            "subsample": [0.5, 0.6, 0.7, 0.8, 0.9, 1],
            "colsample_bytree": [0.5, 0.7, 0.9, 1],
            "colsample_bylevel": [0.5, 0.7, 0.9, 1],
        }
        self.model_xg = RandomizedSearchCV(
                self.reg,
                param_distributions=self.params,
            n_iter=20,
            n_jobs=-1,
            cv=5,
            verbose=3,
            )
        self.response_col = args.response_col
        self.date_col = args.date_col

    def fit(self, data_x):
        self.regressors = []
        for col in data_x.columns:
            if col != self.response_col and col != self.date_col:
                self.regressors.append(col)
        train_x = pd.DataFrame()
        train_y = pd.DataFrame()
        train_x[self.regressors] = data_x[self.regressors].astype(float)
        train_y[self.response_col] = data_x[self.response_col].astype(float)
        self.model_xg.fit(train_x,train_y)

    def predict(self, test_x):
        valid_x = pd.DataFrame()
        valid_x[self.regressors] = test_x[self.regressors].astype(float)
        pred_y = self.model_xg.predict(valid_x)

        return pred_y
```

LSTM

```
import numpy as np
import pandas as pd


import keras
from keras import optimizers
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Activation, Dense,Dropout


from sklearn.preprocessing import MinMaxScaler


class MyLSTM:
    sc_in = MinMaxScaler(feature_range=(0, 1))
    sc_out = MinMaxScaler(feature_range=(0, 1))


    def __init__(self, args):
        self.model = Sequential()
        self.is_model_created = False
        self.hidden_dim = args.hidden_dim
        self.epochs = args.epochs



    def create_model(self, shape_):
        self.model.add(LSTM(self.hidden_dim, return_sequences=True, input_shape=(1, 
shape_)))
        # model.add(LSTM(256, return_sequences=True,input_shape=(1, look_back)))
        self.model.add(LSTM(self.hidden_dim))
        self.model.add(Dense(1))
        self.model.compile(loss='mean_squared_error', optimizer='adam')

    def fit(self, data_x):
        data_x = np.array(data_x)
        train_x = data_x[:, 1:-1]
        train_y = data_x[:, -1]

        if self.is_model_created == False:
            self.create_model(train_x.shape[1])
            self.is_model_created = True

        train_x = self.sc_in.fit_transform(train_x)
        train_y = train_y.reshape(-1, 1)
        train_y = self.sc_out.fit_transform(train_y)
        train_x = np.array(train_x, dtype=float)
        train_y = np.array(train_y, dtype=float)
        train_x = np.reshape(train_x, (train_x.shape[0], 1, train_x.shape[1]))
        self.model.fit(train_x, train_y, epochs=self.epochs, verbose=1, shuffle=False,
batch_size=50)

    def predict(self, test_x):
        test_x = np.array(test_x.iloc[:, 1:], dtype=float)
        test_x = self.sc_in.transform(test_x)
        test_x = np.reshape(test_x, (test_x.shape[0], 1, test_x.shape[1]))
        pred_y = self.model.predict(test_x)
        pred_y = pred_y.reshape(-1, 1)
        pred_y = self.sc_out.inverse_transform(pred_y)
        return pred_y
```

RANDOM FOREST

```
# Import the model we are using
from sklearn.ensemble import RandomForestRegressor
import numpy as np


class RandomForest:

    def __init__(self, args):
        self.n_estimators = args.n_estimators
        self.random_state = args.random_state
        self.model = RandomForestRegressor(n_estimators=self.n_estimators,
random_state=self.random_state)

    def fit(self, data_x):
        data_x = np.array(data_x)
        train_x = data_x[:, 1:-1]
        train_y = data_x[:, -1]
        # print(train_x)
        self.model.fit(train_x, train_y)

    def predict(self, test_x):
        test_x = np.array(test_x.iloc[:, 1:], dtype=float)
        pred_y = self.model.predict(test_x)
        return pred_y
```

ARIMA

```
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import pandas as pd


class MyARIMA:
    sc_in = MinMaxScaler(feature_range=(0, 1))
    sc_out = MinMaxScaler(feature_range=(0, 1))

    def __init__(self, args):
        self.train_size = -1
        self.test_size = -1
        self.order = tuple(map(int, args.order.split(', ')))

    def fit(self, data_x):
        data_x = np.array(data_x)
        train_x = data_x[:, 1:-1]
        train_y = data_x[:, -1]
        print(train_x)
        self.train_size = train_x.shape[0]
        train_x = self.sc_in.fit_transform(train_x)
        train_y = train_y.reshape(-1, 1)
        train_y = self.sc_out.fit_transform(train_y)
        train_x = np.array(train_x, dtype=float)
        train_y = np.array(train_y, dtype=float)
        self.model = ARIMA(train_y,
                              exog=train_x,
                              order=self.order)
        self.result = self.model.fit()

    def predict(self, test_x):
        test_x = np.array(test_x.iloc[:, 1:], dtype=float)
        test_x = self.sc_in.transform(test_x)
        self.test_size = test_x.shape[0]
        pred_y = self.result.predict(start=self.train_size, end=self.train_size + self.test_size - 1,
exog=test_x)
        # pred_y = self.result.predict(exog=test_x)
        pred_y = pred_y.reshape(-1, 1)
        pred_y = self.sc_out.inverse_transform(pred_y)
        return pred_y
```

SARIMAX

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import pandas as pd


class Sarimax:
    sc_in = MinMaxScaler(feature_range=(0, 1))
    sc_out = MinMaxScaler(feature_range=(0, 1))

    def __init__(self, args):
        self.train_size = -1
        self.test_size = -1
        self.order = tuple(map(int, args.order.split(', ')))
        self.seasonal_order = tuple(map(int, args.seasonal_order.split(', ')))
        self.enforce_invertibility = args.enforce_invertibility
        self.enforce_stationarity = args.enforce_stationarity

    def fit(self, data_x):
        data_x = np.array(data_x)
        train_x = data_x[:, 1:-1]
        train_y = data_x[:, -1]
        self.train_size = train_x.shape[0]
        train_x = self.sc_in.fit_transform(train_x)
        train_y = train_y.reshape(-1, 1)
        train_y = self.sc_out.fit_transform(train_y)
        train_x = np.array(train_x, dtype=float)
        train_y = np.array(train_y, dtype=float)
        self.model = SARIMAX(train_y,
            exog=train_x,
            order=self.order,
            seasonal_order=self.seasonal_order,
            enforce_invertibility=self.enforce_invertibility,
enforce_stationarity=self.enforce_stationarity)
        self.result = self.model.fit()


    def predict(self, test_x):
        test_x = np.array(test_x.iloc[:, 1:], dtype=float)
        test_x = self.sc_in.transform(test_x)
        self.test_size = test_x.shape[0]
        pred_y = self.result.predict(start=self.train_size, end=self.train_size + self.test_size - 1,
exog=test_x)
        # pred_y = self.result.predict(exog=test_x)
        pred_y = pred_y.reshape(-1, 1)
        pred_y = self.sc_out.inverse_transform(pred_y)
        return pred_y
```

ORBIT

```
from orbit.models import DLT
import numpy as np
from sklearn.preprocessing import MaxAbsScaler
class Orbit:
    model = None
    sc_in = MaxAbsScaler()
    sc_out = MaxAbsScaler()

    def __init__(self, args):
        self.response_col = args.response_col
        self.date_col = args.date_col
        self.estimator = args.estimator
        self.seasonality = args.seasonality
        self.seed = args.seed
        self.global_trend_option = args.global_trend_option
        self.n_bootstrap_draws = args.n_bootstrap_draws

    def fit(self, data_x):
        print(data_x.shape)
        regressors = []
        for col in data_x.columns:
            if col != self.response_col and col != self.date_col:
                regressors.append(col)
        data_x[regressors] = data_x[regressors].astype(float)
        data_x[self.response_col] = data_x[self.response_col].astype(float)

        data_x.loc[:, regressors] = self.sc_in.fit_transform(data_x.loc[:, regressors])
        data_x.loc[:, self.response_col] = self.sc_out.fit_transform(
            data_x.loc[:, self.response_col].values.reshape(-1, 1))

        self.model = DLT(
            response_col=self.response_col,
            date_col=self.date_col,
            regressor_col=regressors,
            estimator=self.estimator,
            seasonality=self.seasonality,
            seed=self.seed,
            global_trend_option=self.global_trend_option,
            # for prediction uncertainty
            n_bootstrap_draws=self.n_bootstrap_draws,
        )
        self.model.fit(data_x, point_method="mean")

    def predict(self, test_x):
        regressors = []
        for col in test_x.columns:
            if col != self.response_col and col != self.date_col:
                regressors.append(col)
        test_x[regressors] = test_x[regressors].astype(float)

        test_x.loc[:, regressors] = self.sc_in.transform(test_x.loc[:, regressors])
        # test_x[self.response_col] = test_x[self.response_col].astype(float)
        predicted_df = self.model.predict(df=test_x)
        predicted_df.loc[:, 'prediction'] = self.sc_out.inverse_transform(
            predicted_df.loc[:, 'prediction'].values.reshape(-1, 1))
        return np.array(predicted_df.prediction)
```