Crypto Currency Price Prediction on Ethereum Using Time Series Forecasting Models Arima and Facebook Prophet Models

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Abstract. Crypto currencies have emerged as a popularinvestment option in recent years, with Ethereum being one of the most prominent ones. Accurate price prediction of Ethereum can provide valuable insights to investors andtraders for making informed decisions. In this study, we utilized two time series prediction models, ARIMA (AutoRegressive Integrated Moving Average) and Facebook Prophet, to predict the price of Ethereum. This research focuses on collecting legacy price data of Ethereum from a reliable source. The data was preprocessed to handle missing values and outliers. ARIMA and Facebook Prophet models were then implemented on the preprocesseddata to generate Ethereum price forecasts. The models weretrained using a time period of historical data and validatedusing a hold-out set of data. The MSE, which measures the squared discrepancies between predicted and real Ethereum prices, was used to assess the models' performance. Lower MSE values indicate better model performance. The resultsrevealed that Facebook Prophet outperformed ARIMA interms of MSE, indicating superior accuracy in Ethereumprice prediction. The higher accuracy of Facebook Prophetmay be attributed to it's ability to handle seasonality, trend changes, and outliers, which are common characteristics of crypto currency price data. In conclusion, this study demonstrates the effectiveness of time series forecasting models, specifically ARIMA and Facebook Prophet, in predicting Ethereum prices. The findings suggest thatFacebook Prophet may be a more accurate model compared to ARIMA for Ethereum price prediction, as evidenced by lower MSE values. The study provides valuable insights forinvestors and traders interested in utilizing forecastingmodels for Ethereum price prediction, and may serve as abasis for further research in this area.

Keywords: Ethereum, ARIMA ,Facebook prophet, MSE

1 Introduction

With the rise of crypto currencies as a global phenomenon,accurate forecasting of their prices has become a critical task for investors, traders, and researchers. Ethereum, being one of the leading crypto currencies, presents unique challenges and opportunities for price prediction due to its complex andvolatile nature. In this

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_102

research, we utilized two popular time series forecasting methods - ARIMA and Facebook Prophet to forecast the price of Ethereum and compared their performance. We conducted an in-depth analysis of historical Ethereum price data, preprocessing it to handle missing values and outliers. We then implemented ARIMA and Facebook Prophet models, training them on the historical data and using them to forecast Ethereum prices. Our findings highlight the superior performance of Facebook prophet findings in predicting the Ethereum prices compared to ARIMA. Facebook Prophet demonstrated its ability to capture non-linear patterns and seasonality in the data, as well as its robustness in handling missing values and outliers, resulting in more accurate forecasts. The system aims to provide reliable predictions for making sensible decisions.

The suggested approach tries to overcome the limits of existing algorithms for Ethereum price prediction by adding more advanced machine learning techniques, notably ARIMA and Facebook Prophet. By utilizing these advanced models, the proposed system aims to provide more accurate and reliable predictions for Ethereum prices. Section 2 refers analysis of literature describes prior research methodologies on crypto currency prediction. Section 3 refers to proposed models to predict the crypto currency and the evaluation of the performance of these models. Section 4 refers to results of ARIMA and Facebook Prophet models prediction.

2 Literature Review

This section contains previous studies focused on crypto currency price prediction using machine learning algorithms. In paper [1] the authors used machine learning algorithms to predict Bitcoin cryptocurrency. In paper [2-4] authors utilized a linear regression model using LSTM and RNN to accurately forecast bitcoin price. In paper [5],[12] to anticipate Bitcoin's future price, the ARIMA and LSTM were utilized. In paper [8][15] performed short-terms prediction model for crypto currency. According to studies, updated Binary Auto Regressive Tree (BART) outperforms ARIMA. In paper [9] authors used KryptoOracle in order to predict crypto currency rely on social web like Twitter. In paper[6] suggested Ensemble models were evaluated using cutting-edge technologies tested to estimate price for the next hour. In paper [7] RNN and LSTM outperformed standard models and to predict the crypto currency price. In paper [10],[13] in order to forecast concentric pricing linear regression, ANN & SVM are employed to forecast crypto currency time series. In paper[11] authors evaluated and proved LightGBM model as more robust than GBDT technique to estimate the cryptocurrency market. In paper[14] surveys and compares current mining strategies utilized by major Crypto currencies. They assessed each mining strategy's strengths, shortcomings, and potential risks.

Table 1. Comparison on Crypto currency price prediction models

Ref. No	Year	Crypto Cur-	Model	Evaluation Parameter	Performance

		rency			
[1]	2021	Bitcoin(BTC)	ARIMA, FBProphet, XG Boosting	Root Mean Square Error(R MSE), MAE,R Sqaured	ARIMA provides best forecasting priceprediction with RMSE- 322.4 & MAE- 227.3
[2]	2021	Bitcoin(BTC) LiteCoin(LTC) Ethereum (ETH)	GRU, LSTM, bi- LSTM	MAPE	GRU providesmore accurateperformance. MAPE for BTC-0.2454% MAPE for LTC-0.2116% MAPE for ETH-0.8267%
[3]	2021	Bitcoin(BTC)	RNN, Gradient Boosting Classifier	MSE	Accuracy ranging from 50.9%-56.0%
[4]	2020	Bitcoin(BTC)	LR, RNN, LSTM	Mean SquaredError	LR-69.9% RNN-76.7% LSTM-96.2%
[8]	2019	Bitcoin(BTC) Ethereum Ripple	BART, ARIM A	Root Mean Square Error(RMSE)	Slow raising ARIMA- 16.40% ARFIMA- 9.26% BART-5.60% Transition Dynamic ARIMA-18.5% ARFIMA-8.7% BART-7.61%
[11]	2018	Crypto Currency	GBDT, LGBM	Confusion matrix	LGBM is morerobust than GBDT
[12]	2018	Bitcoin(BTC)	ARIMA, LSTM	MAPE	MAPE with ARIMA- 11.86% MAPE with LSTM-1.40%

3 Methodology

ARIMA is a widely used time series model that can capture linear dependencies in the data, while Facebook Prophet is a more advanced model that is designed to handle seasonality, trends, and outliers in time series data. By utilizing these advanced models as shown in Figure 1, the proposed system aims to provide more accurate and reliable predictions for Ethereum prices. This contributes to the advancement of cryptocurrency price prediction research and provides insights for stakeholders interested in leveragingmachine learning for cryptocurrency analysis.

- Data Collection and stationarity check: Collecting historical Ethereum price data from reliable sources and stationarizing the data to have a constant mean, constant variance, and no apparent trends or patterns.
- Model Implementation: ARIMA is a well-known time series forecasting method that captures linear dependencies, while Facebook Prophet is a more advanced model designed to handle seasonality, trends, and outliers. Model parameters, such as order for ARIMA and hyperparameters for Facebook Prophet, may be tuned to optimize model performance.

Performance Evaluation: Evaluating the performance of ARIMA and Facebook Prophet models using mean square error (MSE) as the evaluation metric. MSE measures the squared difference between the predicted and actual values, and a lower MSE indicates better accuracy.

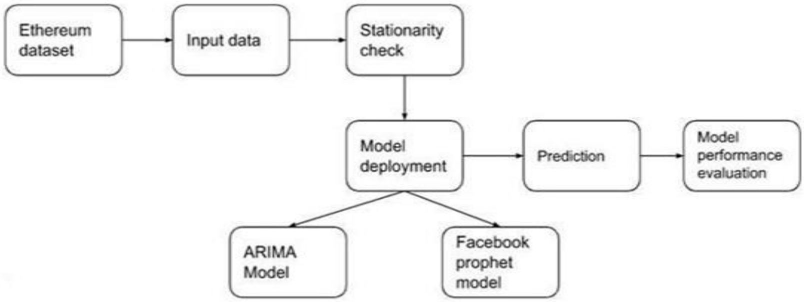

Fig. 1. Ethereum Price Prediction

3.1 ARIMA Model

The ARIMA model is a prominent time series forecasting technique used to evaluate and predict data with temporal dependencies, such as crypto currency prices. It provides insights into anticipated future price trends, but it has limits and should be used in conjunction with other analysis approaches for a more complete forecast.

ARIMA Model Components

- Auto Regression(AR): The AR component simulates the time series' linear regression against its own lagged data. 'p' represents auto regression. Higher 'p' values suggest a greater reliance on prior values.
- Integration: The I component entails differencing the time series data in order to render it stationary, which eliminates trends and seasonality. 'd' represents the order of differencing.
- Moving Average(MA): The MA component represents the error term as a series of lagged error terms. 'q' represents the moving average order.

Higher 'q' values suggest a greater reliance on previous errors.

ARIMA Model Order Selection

Choosing the right order for the ARIMA model is critical for effective predictions. ACF aids in the identification of the MA order (q), whereas PACF aids in the identification of the AR order (p). The order of differencing (d) can be established by determining whether or not the differenced data is stationary.

Model Fitting

After determining the ARIMA model order, the model parameters are estimated using previous ethereum price data.

Model Forecasting

After fitting the ARIMA model, it can be used to make future price predictions for Ethereum. Forecasting involves generating forecasts using the estimated model parameters and assessing their accuracy using MSE.The forecast can bevisualized and interpreted to gain insights into potential future price trends.

3.2 Facebook Prophet Model

Facebook Prophet is an open-source time series forecasting model developed by Facebook is designed to forecast cryptocurrency prices like Ethereum.

Model Components

The Facebook Prophet model consists of several key components:

a. Trend Component: It captures the overall direction and pattern of the time series data, including any long-term upward or downward trends.

b. Seasonality Component: It captures recurring trends within the data to know the periodic data or seasonality.

c. Holidays/Events Component: It allows the model to incorporate information about known holidays

d. Error Component: It captures the residuals or errors that are not explained by the trend, seasonality and holidays/components

Model Fitting and Forecasting

After completing the training process, the model is capable of generating forecasts for Ethereum's future prices. The forecasts are generated by providing the model with future timestamps and the model will predict the corresponding Ethereum price The forecasts can be evaluated for accuracy using metrics such as MSE and visualized to gain insights into potential future price trends ARIMA and Facebook Prophet Models on Ethereum are implemented in python programming language using libraries Pandas, matploitlib, statsmodel, ARIMA, datetime, Prophet.

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4 Results and Discussions

The Ethereum price dataset is derived from a well- known and trustworthy financial data source. Yahoo Finance offers historical price data for Ethereum in the form of downloadable CSV files. Data pre-processing is accomplished by applying several transforms to the dataset shown in Table.2

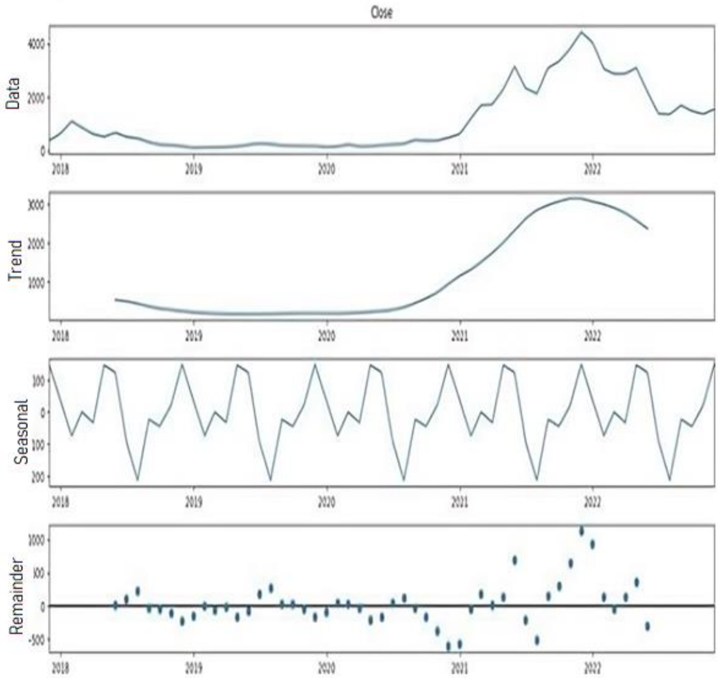

Fig. 2. Seasonal Decomposition

Fig.2. shows the trend and seasonality in our dataset. The statsmodels seasonal decomposition function assisted us in determining whether or not our given dataset was stationary.

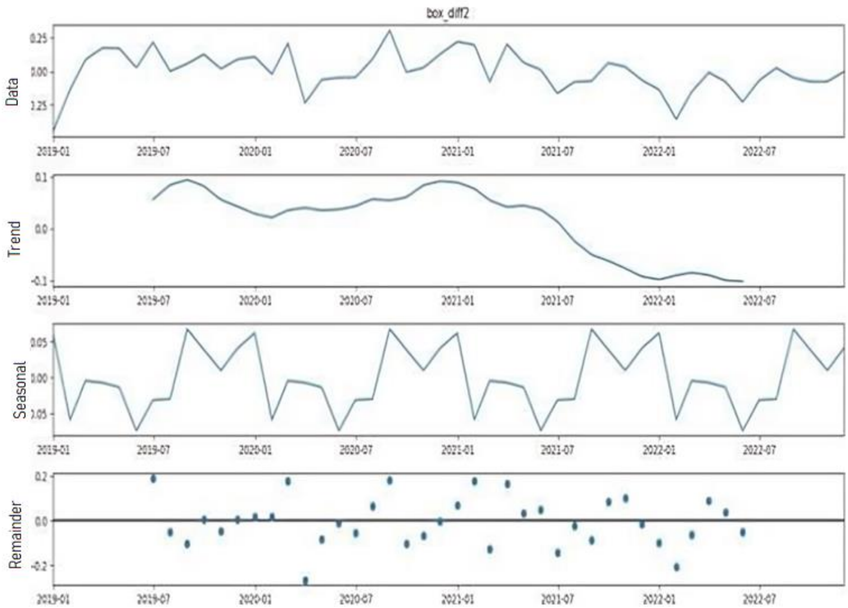

Fig.3. Regular Differentiation

If the Dickey-Fuller test indicates that our time series is non-stationary, we applied differencing to make it stationary. It calculates the difference between value of the time series at a certain time point and its value at an earlier time point. We applied regular differencing or seasonal differencing, depending on whether there is a seasonal pattern in the data as shown in Figure 3.Results of Arima model are shown in Fig.4. Fig.5 describes Ethereum price prediction using ARIMA. We also used the inverse_boxcox() function to reverse the earlier Box-Cox modification. Finally, we use Matplotlib to plot the actual and forecasted values. The resulting plot compares the accuracy of our ARIMA model to the real and expected Ethereum prices over time. Fig.6 shows the graphicalreprsentation of Ethereum price prediction using the Facebook prophet model. The Prophet() function from the fbprophet package was used to fit the Prophet model to the Ethereum dataset. We established a new dataframe with two columns: ds, which holds the dates of the Ethereum prices, and y, which has the corresponding closing prices. We forecasted these dates using the predict() method. The periods input defines the number of future periods for which we wish to make forecasts (in this case, 365 days or one year).

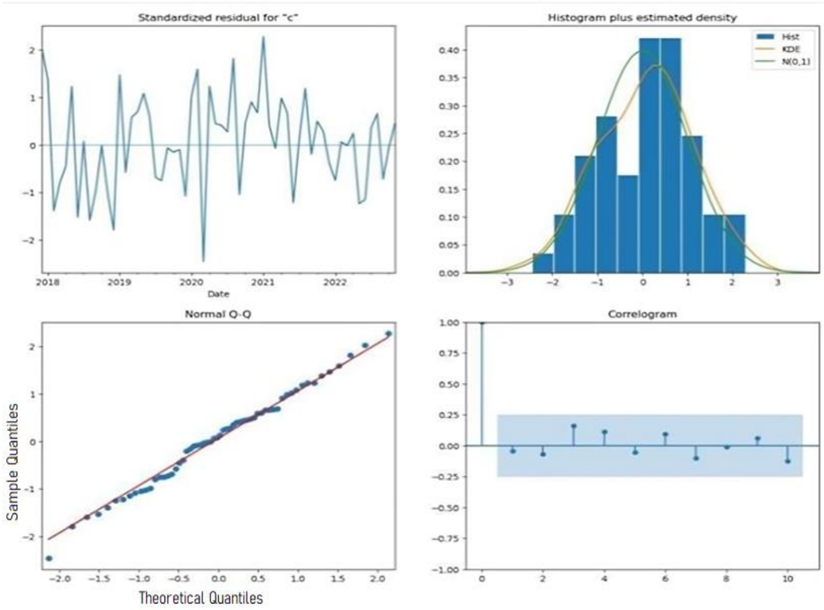

Fig. 4. Analysis of ARIMA Results

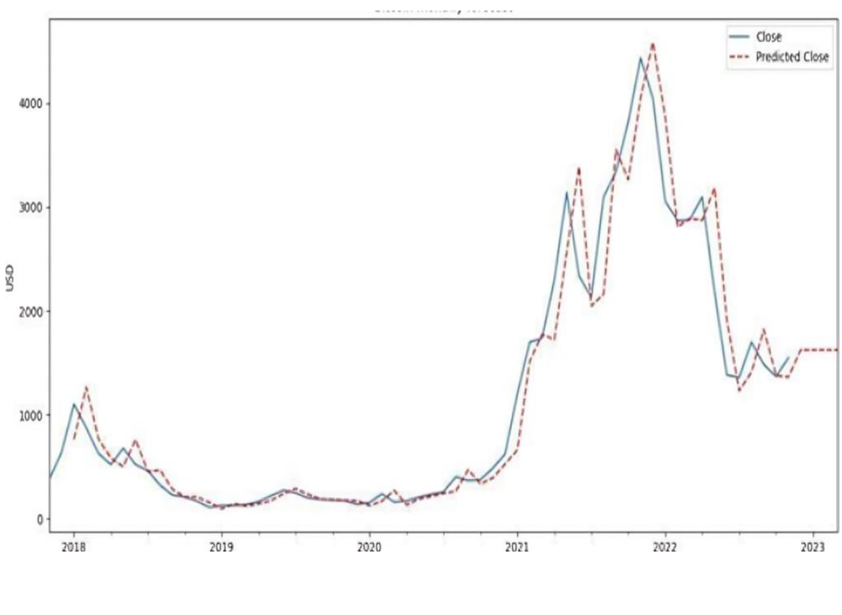

Fig. 5. Ethereum price prediction using ARIMA

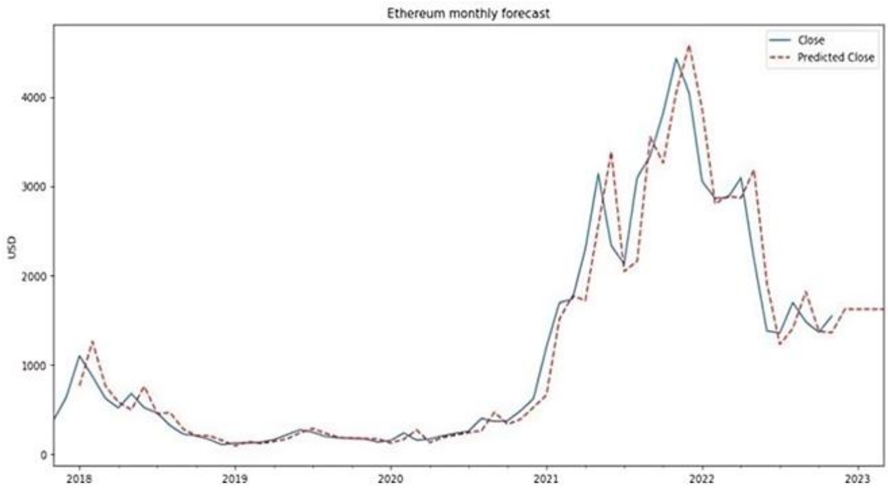

Fig. 6. Ethereum price prediction using Facebookprophet model

Table.2. depicts the Mean Squared Error (MSE) of ARIMA and Facebook Prophet model.

Table 2. Evaluation of Mean Squared Error

Model	MSE
ARIMA	332.17
Facebook Prophet	196.280897

5 Conclusion

With cryptocurrencies becoming a global phenomenon, accurate price forecasting has become crucial for investors, traders, and academics. Due to its complicated and volatile nature, Ethereum, as one of the top cryptocurrencies, presents unique challenges and potentials for price prediction. In this study, we predicted the price of Ethereum using two well-known time series forecasting algorithms - ARIMA and Facebook Prophet - and compared their results.In our study, ARIMA and Facebook Prophet models were implemented to predict Ethereum price and mean square error (MSE) was used as an evaluation measure. This study shows how time series prediction algorithms, ARIMA and Facebook Prophet, can accurately predict Ethereum values.

Based on the MSE values obtained, the ARIMA model has an MSE of 332.17 for predicting Ethereum price, while the Facebook Prophet model achieved a lower

MSE value of 196.280897. The results suggest that Facebook Prophet is accurate for Ethereum price prediction than ARIMA, as indicated by the lower MSE values. The work is useful for investors and traders interested in using predictive models to forecast the Ethereum price, and it can serve as a basis for future research in this area.

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