UTILIZING TRANSFORMER MODELS AND GRAPH NEURAL NETWORKS FOR TIMESTAMP-BASED CRYPTOCURRENCY PRICE PREDICTION: A DEEP LEARNING APPROACH

Dissertation submitted in part fulfilment of the requirements for the degree of

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Submitted By

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Declaration

I, Aniket Singh, affirm that the present research is the product of my individual efforts. All investigations, analyses, and interpretations therein are conducted independently. This thesis has not been presented for any other academic credential and has not been previously published. I have accurately cited all literature and sources utilized in this work, ensuring full adherence to the academic integrity policy of Dublin Business School.

Signed: Aniket Singh

Date: 08/01/2024

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I extend my heartfelt appreciation to Professor Obinna Izima for his unwavering guidance and exceptional support during the entire journey of completing this thesis. His profound expertise, insightful feedback, and encouragement were instrumental in shaping the direction of my research. I am genuinely grateful for the privilege of being mentored by him, and I acknowledge his significant contribution to the development of this work. I would also like to extend my thanks to my friends and family for their assistance and support throughout this academic endeavour.

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Abstract

This study delves into the realm of cryptocurrency price prediction using cutting-edge deep learning techniques, specifically Transformer models and Graph Neural Networks (GNN). We conduct a comprehensive evaluation, benchmarking these methods against traditional models like ARIMA, Simple RNN, and Prophet on Ethereum (ETH) and Bitcoin (BTC) closing prices. Notably, the Transformer model showcases remarkable accuracy in BTC_close predictions, boasting an RMSE of 0.02395 and MAE of 0.02312, surpassing the performance of ARIMA. Conversely, GNN emerges as the top performer for ETH_close, delivering an impressive RMSE of 1111.39 and MAE of 1055.11. Despite its computational simplicity, Simple RNN falls short in comparison. This research contributes valuable insights into harnessing state-of-the-art deep learning architectures for accurate cryptocurrency price forecasting, highlighting the efficacy of Transformer models and GNNs in capturing intricate temporal dependencies within the dynamic cryptocurrency market landscape.

Chapter 1 Introduction

In the dynamic landscape of cryptocurrency markets, accurate prediction of price movements remains a challenging endeavor. This research delves into the realm of timestamp-based cryptocurrency price forecasting, leveraging advanced deep learning techniques, notably Transformer architectures and Graph Neural Networks (GNN). Traditional models such as ARIMA, Simple RNN, and Prophet are benchmarked against these cutting-edge approaches, focusing on Ethereum (ETH) and Bitcoin (BTC) closing prices. The study aims to unravel the potential of Transformer models and GNNs in capturing intricate temporal dependencies within the cryptocurrency market. By exploring the efficacy of these sophisticated deep learning techniques, the research contributes to an enhanced understanding of their capabilities for precise and reliable cryptocurrency price prediction. This investigation holds implications for refining forecasting strategies in the volatile and rapidly evolving landscape of cryptocurrency trading.

1.1 Back Ground scope

The global rise of cryptocurrencies, spearheaded by the prominence of Bitcoin, has ushered in a paradigm shift in financial markets. As these digital assets continue to gain traction, the need for accurate and robust forecasting models becomes increasingly paramount. The cited studies contribute significantly to the evolving landscape of cryptocurrency price prediction, employing diverse methodologies and techniques to address the inherent challenges of this dynamic domain.

Santhanalakshmi et al. (2021) delve into the realm of Bitcoin value forecasting, employing a comparative analysis grounded in time-series methods. Time-series analysis has long been a cornerstone in financial forecasting, providing a historical perspective to discern patterns and trends. This study likely explores the efficacy of established time-series techniques such as ARIMA (AutoRegressive Integrated Moving Average) and exponential smoothing in capturing the temporal dynamics of Bitcoin prices. Understanding the nuances of these traditional methods is crucial as they form the baseline against which newer, more complex models are often benchmarked.

Sen and Mehtab (2021) contribute to the field by focusing on accurate stock price forecasting using robust and optimized deep learning models. The use of deep learning in financial forecasting has gained considerable attention due to its capacity to analyze vast datasets and capture intricate patterns. This research may delve into the development and optimization of deep learning architectures, exploring how factors such as model robustness and optimization techniques impact the accuracy of stock price predictions. The study likely navigates the intricate balance between model complexity and interpretability, a critical consideration in real-world financial applications.

Shahbazi and Byun (2021) take a different approach by improving cryptocurrency price prediction performance through reinforcement learning. Reinforcement learning, a subset of machine learning, involves training models through reward-based systems. This study likely investigates how reinforcement learning algorithms, with their ability to adapt and learn from dynamic market conditions, enhance the precision of cryptocurrency price predictions. Understanding the role of reinforcement learning in adapting to market uncertainties and evolving trends is crucial for developing resilient forecasting models.

Tanwar et al. (2021) propose a deep learning-based cryptocurrency price prediction scheme with a focus on inter-dependent relations. The interdependence of various factors, such as market sentiment, regulatory changes, and technological developments, poses a unique challenge in cryptocurrency forecasting. This study may explore how deep learning models, with their capacity to capture complex relationships in data, can effectively account for and leverage these inter-dependent factors for more nuanced and accurate forecasts. The research likely contributes insights into the intricacies of feature engineering and model architecture for handling interdependencies.

Teng et al. (2023) shift the focus towards mitigating digital asset risks, a critical concern in the cryptocurrency space. The volatility and susceptibility of digital assets to external factors necessitate robust risk assessment models. This study may delve into strategies for identifying and mitigating risks associated with digital assets, contributing valuable insights into safeguarding investments in the dynamic and often unpredictable cryptocurrency markets.

Thuan and Huong (2022) bring regression and algorithmic approaches in artificial intelligence to the forefront for predicting Bitcoin prices. Regression models, coupled with algorithms, offer a versatile toolkit for predictive modeling. This research likely explores how these techniques, known for their interpretability and simplicity, fare in predicting the highly volatile and often erratic nature of Bitcoin prices. The study may offer insights into the trade-offs between model complexity and forecasting accuracy, crucial considerations for practical implementation.

Collectively, these studies underscore the multifaceted nature of cryptocurrency price prediction. They traverse traditional time-series methods, delve into the intricacies of deep learning optimization, explore reinforcement learning paradigms, address interdependence in market factors, assess risk mitigation strategies, and employ regression and algorithms. The scope of the background thus encompasses the diverse methodologies employed in predicting cryptocurrency prices, reflecting the dynamic nature of this field and the ongoing efforts to refine forecasting techniques amidst the evolving landscape of digital assets.

In essence, the research landscape surrounding cryptocurrency price prediction is marked by a confluence of traditional and cutting-edge methodologies. The challenges posed by the dynamic and complex nature of cryptocurrency markets necessitate a comprehensive understanding of diverse modeling approaches. As these studies contribute to the collective knowledge base, they pave the way for further advancements in predictive analytics, risk management, and decision-making within the burgeoning realm of digital assets.

1.2 Motivation

The motivation behind delving into timestamp-based cryptocurrency price prediction stems from the transformative potential of these digital assets and the challenges they pose to traditional financial forecasting methods. Cryptocurrencies represent a paradigm shift in finance, introducing decentralized and blockchain-based systems that redefine how value is transferred and stored. The volatile and dynamic nature of cryptocurrency markets presents a unique challenge for investors and traders, necessitating the development of robust prediction models.

The promise of substantial financial gains coupled with the inherent risks of cryptocurrency investments underscores the urgency to harness advanced technologies, such as deep learning and graph neural networks, to gain insights into price movements. Successfully predicting cryptocurrency prices can empower investors with timely and informed decision-making, mitigating risks and maximizing returns in this fast-paced and ever-changing landscape.

Moreover, advancements in timestamp-based cryptocurrency price prediction not only have implications for individual investors but also contribute to the broader adoption and acceptance of cryptocurrencies in the financial ecosystem. By developing accurate and reliable forecasting models, we pave the way for a more mature and stable cryptocurrency market, fostering trust and confidence among market participants. In essence, the motivation lies in unlocking the potential for informed decision-making, reducing uncertainties, and contributing

1.3 Research Questions

The primary research question for this study is:

"Can the application of Transformer Models and Graph Neural Networks enhance the accuarcy of cryptocurrency price prediction compared to traditional methods?"

1.4 Objective

The objectives of this research are to evaluate and compare the performance of advanced deep learning models, specifically Transformer models and Graph Neural Networks (GNN), in timestamp-based cryptocurrency price prediction. The study aims to assess the accuracy of these models against traditional time-series methods like ARIMA and Simple RNN, using Ethereum (ETH) and Bitcoin (BTC) closing prices as benchmarks. The focus is on analyzing Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics to quantify the predictive capabilities of each model, thereby contributing insights into the efficacy of deep learning approaches for enhancing cryptocurrency price forecasting accuracy.

1.5 Research Outline:

Chapter 1: Introduction

This chapter initiates the research by introducing the transformative potential of cryptocurrencies, emphasizing their decentralized nature and the revolutionary impact of blockchain technology. It outlines the research problem, highlighting the challenges posed by the dynamic nature of cryptocurrency markets and the need for advanced prediction models.

Research objectives, questions, and motivations are presented, along with a discussion on the significance and scope of timestamp-based cryptocurrency price prediction.

Chapter 2: Literature Review

This chapter provides a comprehensive review of existing literature, exploring the dynamics of the cryptocurrency market and traditional financial forecasting methodologies. It traces the evolution of time-series analysis in financial forecasting and examines the application of deep learning techniques in the context of financial forecasting, identifying gaps and shortcomings.

Chapter 3: Methodology

Chapter 3 details the research methodology, starting with the research framework and data collection procedures. The sources of cryptocurrency data are identified, and the preprocessing steps, model selection, and evaluation metrics are outlined, along with ethical considerations governing the research.

Chapter 4: Results and Evaluation

This chapter offers a comprehensive analysis of results and model evaluation. Descriptive statistics of cryptocurrency data provide insights, and performance metrics for each model are presented, facilitating a comparative analysis. Visualizations and statistical significance tests enhance the rigor of the findings.

Chapter 5: Conclusion and Future Scope

The final chapter summarizes key findings, discusses their implications, acknowledges limitations, and suggests future research directions. It provides closure to the investigation while unveiling avenues for future exploration within this dynamic field.

Chapter 2 Literature Review

2.1 Introduction

The combination of “deep learning” methods, that is, "Transformer models" and "Graph Neural Networks", has attracted a lot of attentiveness recently in the field of financial predicting, especially when it comes to predicting cryptocurrency prices (Chikwendu *et al*., 2023). Because of the dynamic and unstable character of cryptocurrency markets and the wealth of timestamped data available, complex predictive models can be explored in a favourable environment. Transformer architectures, which are well-known for their efficacy in natural language processing, have proven to be flexible to sequential data. Still, GNNs are particularly good at capturing intricate relationships found in datasets containing connections (Yun *et al*., 2022). This review of the literature explores the changing field of applying these “state-of-the-art” “deep learning” techniques for time-stamp-based cryptocurrency price prediction, looking at the benefits, limitations, and new developments in this creative marriage of technology.

2.2 Concepts Cryptocurrency Price Prediction

The dynamic and intricate area of cryptocurrency price prediction entails estimating the future worth of digital assets by taking into account a number of different elements. To predict price movements, it takes into account market mood and technical and fundamental analysis. Factors including technology, collaborations, staff, and general market trends are taken into account by fundamental analysis. Developments such as software updates, legal modifications, or business alliances, for example, can have a big impact on the value of the cryptocurrency (Hedegaard *et al*., 2023). Technical analysis, on the other hand, uses past price charts, trade volumes, and patterns to spot trends and forecast future movements. To examine price changes, traders frequently employ indicators such as Fibonacci retracement levels, moving averages, and the "Relative Strength Index (RSI)" (Thanekar *et al*., 2021).

Predicting the price of cryptocurrencies requires an understanding of market emotion (Naeem *et al*., 2021). Community forums, news articles, and social media can affect investor perception, which in turn affects market behaviour. "Sentiment analysis" is crucial for forecasting short-term market movements since strong feelings have the potential to cause significant price swings (Wołk, 2020). "Artificial intelligence" and "machine learning" have also become essential for predicting bitcoin prices. Algorithms analyse large volumes of historical data to find patterns and trends that human analysts would miss. It is important to remember that cryptocurrency markets are extremely inconsistent, and even the most advanced prediction models can be distressed by unforeseen events like changes in regulations or security breaches (Teng *et al*., 2023).

2.3 Literature review

2.3.1 Time-Series Analysis in Cryptocurrency Price Prediction

This research by Maleki *et al*. (2020) examines the challenging task of projecting cryptocurrency price fluctuations with a focus on the most well-known cryptocurrency, Bitcoin. Although prior research using traditional statistical and economic methodologies has been conducted, the development of robust prediction models for instruments used in investment decision-making is still in its infancy. The paper emphasises predicting Bitcoin prices based on "Ethereum", "Zcash", and "Litecoin" using "machine learning" algorithms. It is noteworthy that the outcomes demonstrate that "Zcash" can predict Bitcoin prices with more accuracy when there is no direct knowledge of fluctuations in Bitcoin, suggesting that the cryptocurrency has the potential to be a significant market changer.

In order to predict the market price and stability of Bitcoin, the first cryptocurrency, Iqbal *et al.* (2021) employed “machine learning-based time series analysis”. To predict future price variations, “machine learning” techniques such as “ARIMA”, “FBProphet”, and “XG Boosting” are applied. To evaluate the performance of the model, evaluation measures such as “R2”, “Mean Absolute Error (MAE)”, and “Root Mean Square Error (RMSE)” are used. Experiments show that “ARIMA” is the most successful model, with an “RMSE” of 322.4 and an “MAE” of 227.3 (Thuan *et al*., 2022). The results are important because they shed light on patterns in the price of Bitcoin for investors in the cryptocurrency market. Emerging Nature-Inspired Computing, data mining, visualisation, and machine learning are among the keywords.

In order to forecast short- to medium-term price swings, Mudassir *et al.* (2020) use high-performance “machine learning” models to investigate decentralised cryptocurrency, with a particular focus on Bitcoin. By expanding the timescale to one, seven, thirty, and ninety days, the study outperforms other efforts in addressing the problem of price volatility in decentralised cryptocurrencies. Strong feasibility and excellent performance are demonstrated by the created models, which achieve up to 65% accuracy for forecasts covering the following day and 62 to 64% accuracy for forecasts spanning seven to ninety days. Price estimates over the next seven to ninety days indicate a competitive error range of 2.88 to 4.10%, while daily forecasts show a minimum error of 1.44%. These results imply better performance when compared to the models that are currently in the literature.

2.3.2 Machine Learning in Cryptocurrency Price Prediction

This study by Chen *et al.* (2020) investigates the applicability of several modelling strategies for forecasting Bitcoin values at varying frequencies in response to the erratic character of Bitcoin as an investment asset. The study uses high-dimensional characteristics for daily forecasts and basic trading features for 5-minute interval predictions to categorise Bitcoin prices into daily and high-frequency intervals. The study outperforms more sophisticated machine learning algorithms with a noteworthy 66% accuracy for daily price prediction using statistical techniques such as “Logistic Regression” and “Linear Discriminant Analysis”. “Machine learning” models such as “RandomForest”, “XGBoost”, “Quadratic Discriminant Analysis”, “Support Vector Machine”, and “Long Short-Term Memory” achieve 67.2% accuracy for 5-minute interval predictions, outperforming statistical approaches. The significance of sample dimension in machine learning methods for predicting Bitcoin price is highlighted by this study.

In order to tackle the problem of cryptocurrency price forecasting, Hamayel and Owda (2021) provide three “recurrent neural network (RNN)” methods for Ethereum (ETH), Litecoin (LTC), and Bitcoin (BTC). The models show good prediction ability when assessed using “mean absolute percentage error (MAPE)”. The most accurate method is the “gated recurrent unit (GRU)”, which beats the “long short-term memory (LSTM)” and “bidirectional LSTM (bi-LSTM)” models. With regard to BTC, ETH, and LTC, GRU obtains MAPE percentages of 0.2454%, 0.8267%, and 0.2116%, respectively. Because they assist traders and investors in making strategic decisions, these prediction models are important from an economic standpoint. Future research is advised to examine other elements that may impact cryptocurrency pricing, including trading volume and social media.

Tanwar *et al.* (2021) study examines the growing acceptance of blockchain technology, highlighting its decentralised, irreversible, and anonymous qualities, especially in relation to applications using cryptocurrencies. The study suggests a real-time hybrid model based on “deep learning”. It incorporates "Gated Recurrent Units (GRU)" and "Long Short-Term Memory (LSTM)" in recognition of the erratic nature of the cryptocurrency market. With an emphasis on

Zcash and Litecoin and taking into account their interdependencies, the model outperforms other methods in terms of price prediction. This study tackles the difficulties associated with real-time forecasting in the cryptocurrency space. It offers a thoroughly tested and refined approach that takes into account the market's volatility and dynamic character.

2.3.3 Deep Learning in Cryptocurrency Price Prediction

Cryptocurrencies are electronic money that functions without real notes and are decentralised, enabling users to access services without the involvement of a third party (Awoke *et al.*, 2020). The influence of cryptocurrencies, particularly Bitcoin, on commerce and international relations is the main topic of this study because of their extreme price volatility. The main topic is Bitcoin, which is generally acknowledged by traders, researchers, investors, and policymakers. In order to solve Bitcoin's price volatility, the research intends to create effective “deep learning-based prediction models”, including “Long Short-Term Memory (LSTM)” and “Gated Recurrent Unit (GRU)”. The paper shows how effective various time-series “deep learning” approaches are in forecasting Bitcoin values with high accuracy through a comparison analysis.

According to Pinellas *et al.* (2020), in the last ten years, cryptocurrencies have emerged as a significant player in the financial sector, providing both market impact and commercial prospects. For investors, making accurate price forecasts is essential because they may boost profits and help academics and politicians better understand how markets behave. However, because cryptocurrencies are chaotic and multifaceted, it is challenging to anticipate their pricing. This study assesses popular “deep learning” algorithms for bitcoin price prediction and finds that current models are unable to handle the task's complexity efficiently and effectively. The study promotes the creation of novel methodologies, tactics, and other approaches, such as complex prediction algorithms, sophisticated ensemble methods, feature engineering, and alternative validation metrics, via thorough testing and outcomes analysis.

Ji *et al.* (2019) state that this study investigates cutting-edge “deep learning” techniques, such as "deep neural networks (DNN)," "long short-term memory (LSTM)" models, “convolutional neural networks”, and “deep residual networks”, for Bitcoin price prediction, in the context of recent media attention to the volatility of Bitcoin's price. According to experimental data, DNN-based models perform best at classifying prices, although LSTM-based models do somewhat better in regression-based predictions. Regression techniques are less successful than classification models for algorithmic trading, according to profitability analysis. The suggested “deep learning-based prediction models” perform comparably overall, providing insight into the challenging problem of predicting Bitcoin values in the face of its erratic market behaviour.

2.3.4 Timestamp Analysis in Cryptocurrency Price Prediction

In order to handle the volatility of Bitcoin transactions, Aljojo *et al.* (2021) introduced a "Non-linear Autoregressive Exogenous (NARX)" “Neural Network Model”, with transaction timestamps being a key variable. In contrast to earlier models that just considered price, this study emphasises the significance of the timestamp effect on the value of Bitcoin. With the use of non-linear regression and historical datasets, the model is able to attain a high prediction accuracy of 96%. The study is important because it highlights recurring patterns in Bitcoin transaction events and highlights how timestamp-related variables like open, high, low, and close prices affect market uncertainty. It emphasises the penalties that those using Bitcoin at improper timestamps must endure.

Kim *et al.'s* evaluations (2022) present a fresh methodology that takes into account the volatility and unique characteristics of cryptocurrencies to estimate "Bitcoin (BTC)" values. Using a change point detection method permits independent normalisation based on segmentation and guarantees consistent performance in unknown price ranges. As input variables, on-chain data—unique entries on the blockchain—is obtained. An attention mechanism and many LSTM modules are included in the "self-attention-based multiple long short-term memory (SAM-LSTM)" model that has been suggested. The efficiency of the framework is demonstrated by real-world BTC price data trials, which produce encouraging outcomes with the greatest MAE, RMSE, MSE, and MAPE values of 0.3462, 0.5035, 0.2536, and 1.3251, respectively.

Bitcoin is discussed in this abstract as a decentralised electronic payment system that uses Blockchain technology for security. According to Santhanalakshmi *et al.* (2021), the value of money is determined by market forces rather than by physical attributes or central authority. The study combines eight methodologies, including statistical and machine learning techniques like ARIMA and LSTM, to forecast the value of Bitcoin. The research intends to solve the difficulties experienced by Bitcoin business players in predicting its value amid market swings by offering a thorough review of prediction algorithms for this dynamic digital currency. It is based on historical data from January 2012 to March 2021 that Kaggle has collected.

2.3.5 Time-Series Analysis in Stock Price Prediction

Mehtab *et al.* (2020) provide a study that questions the efficient market hypothesis by addressing the problem of stock price prediction. It presents a thorough framework for precise stock price prediction that combines “deep learning”, “machine learning”, and “statistical models”. The study combines detailed stock data into three daily slots by using daily stock data that is obtained at five-minute intervals from a well-known Indian firm listed on the "National Stock Exchange

(NSE)". The generated models, with their broad performance outcomes, are subjected to a thorough evaluation. Contrary to the notion that precise forecasts are unattainable in light of the efficient market theory, this research demonstrates the possibility of accurate forecasting in stock market movements.

The study by Idrees *et al.* (2019) focuses on the value of “time series analysis” and forecasting, especially when it comes to the complex stock market. The study, which highlights the intricacy of stock markets, attempts to identify long-term patterns that are significant for investors looking to optimise profits and reduce risks. The research places a high priority on creating novel methods for predicting market trends since stock values are extremely susceptible to sudden fluctuations. The goal is to build a statistical model that accurately forecasts future stocks using time series data from the Indian stock market, which would improve investment decision-making in this fast-paced financial landscape.

The difficulty of forecasting stock market movements in the face of extreme volatility and non-stationarity is discussed in this study. Utilising machine learning techniques, the research examines financial time series such as the S&P 500. It introduces a new technique that uses motifs (frequent patterns) to rebuild sequences and simplify noisy financial temporal data. According to Wen *et al.* (2019), the method uses a “convolutional neural network” to extract the spatial structure of time series data. The approach's effectiveness in feature learning is demonstrated by experimental findings, which offer a 4%–7% accuracy gain over “deep learning” models for frequency trading patterns and classical signal processing techniques. This enhances the ability to anticipate stock trends.

2.3.6 Machine Learning in Stock Price Prediction

By utilising artificial intelligence and improved computational capabilities, this study by Vijh *et al.* (2020) addresses the difficult challenge of forecasting stock market returns. The research focuses on predicting the closing price of five businesses in different industries for the following day by using "Random Forest" and "Artificial Neural Network" approaches. New variables are created as inputs to the models using financial data parameters like Open, High, Low, and Close prices. The models' ability to anticipate stock closing prices is demonstrated by evaluation based on conventional metrics, such as RMSE and MAPE. This indicates that programmed approaches are successful in navigating the turbulent and non-linear character of financial markets.

Nikou *et al.* (2019) highlight the importance of stock market investments for a nation's economy by examining the critical function that security indices play in evaluating the state of the financial market. By addressing the nonlinearity and non-stationarity that make financial series difficult to predict, this study assesses machine-learning algorithms for stock market trend prediction. Four machine-learning algorithms are used, with daily close price data for the iShares MSCI United Kingdom exchange-traded fund from January 2015 to June 2018. The results show that "deep learning" is the best approach, with support vector regression coming in second and outperforming neural network and "random forest" approaches in terms of prediction accuracy.

The problem of precisely forecasting stock markets is addressed in this work by Khan *et al.* (2020), which acknowledges the influence of erratic elements like news and microblogs. Based on social media and financial news data, the study applies machine learning algorithms to examine their impact on the accuracy of stock market predictions over the next ten days. Prediction quality is improved by feature selection and the elimination of spam tweets. Markets that are harder to forecast and those that are more impacted by outside data are found via experimentation. Maximum accuracy is achieved when “deep learning” and ensemble classifiers are used together. The greatest forecast accuracy rates were found when employing social media and financial news, at 80.53% and 75.16%, respectively. Notably, it is challenging to anticipate the New York and Red Hat markets.

2.3.7 Deep Learning in Stock Price Prediction

This work deals with the complex problem of stock group valuation, concentrating on four groups from the “Tehran Stock Exchange”: basic metals, petroleum, non-metallic minerals, and diversified financials. According to Nabipour *et al.* (2020), machine learning techniques such as “decision trees”, “bagging” “random forests”, “Adaboost”, “gradient boosting”, “XGBoost”, “ANN”, “RNN”, and “LSTM” were used to make predictions for different future intervals based on ten years of historical records. The inputs consisted of ten technical indicators. “LSTM” outperformed other algorithms in terms of accuracy and model-fitting capability. “Adaboost”, “Gradient Boosting”, and “XGBoost”, three tree-based models, stood out for their fierce rivalry in producing precise forecasts for stock market groupings.

The survey by Jiang (2021), explores the traditional but difficult field of stock market prediction, wherein both machine learning and linear techniques have been investigated. The survey attempts to offer a thorough analysis of the most recent developments, with “deep learning” models at the forefront having just emerged. It covers a range of data sources, neural network architectures, and assessment criteria, with an emphasis on repeatability and implementation. The intention is to make it easier for researchers to quickly reproduce earlier work and keep up to date with the field's fast changes. The synopsis provides insightful information for anybody interested in the changing field of stock market prediction by outlining potential avenues for future research.

The complicated, partial, and hazy information that is inherent in financial data makes it difficult to navigate the intricate patterns of financial operations. Utilising “deep neural networks (DNNs)”, which are highly adept at managing such complexity, this study tackles the non-linear, time-dependent nature of anticipating oscillations in financial data. Financial product pricing data is viewed as a one-dimensional series that is projected into time from a chaotic system. Yu *et al.* (2020) suggested DNN-based prediction model outperforms traditional machine learning techniques by combining long- and short-term memory networks (LSTMs) with time series phase-space reconstruction. Comparative investigation shows that when predicting many stock indexes across various periods, it has a greater prediction accuracy.

2.3.8 Timestamp Analysis in Stock Price Prediction

The use of “deep learning” in financial market prediction is attracting the attention of researchers and investors, especially at small levels. In this work, Lu *et al.* (2023) use Informer, an advanced network based on Transformer, to address the challenges of getting quick results convergence. Comparative experiments with “LSTM”, “Transformer”, and “BERT” on 1-minute and 5-minute frequencies across different stocks or market indexes show that Informer consistently outperforms other algorithms in terms of “MAE”, “RMSE”, and “MAPE” (Wang *et al.*, 2022). Informer's prediction accuracy has significantly risen with the addition of a global time stamp approach, showcasing its improved performance and resilience in market prediction and indicating that it is a strong fit for real-world trading scenarios.

The research paper by Sen *et al.* (2021) challenges the traditional efficient market theory by addressing the problem of forecasting future stock values. The study presents ten deep-learning regression models and focuses on accurate and reliable forecasts for a major player in the Indian car industry. Models are trained and evaluated on records from December 31, 2012, to January 9, 2015, using detailed stock price data that is gathered at 5-minute intervals. The study describes these models' design ideas and evaluates how well they perform in terms of predicting accuracy and execution speed. This adds to the continuing investigation of complex frameworks to improve the accuracy of stock price forecasts.

It is critical to forecast company earnings, expenses, and product demand in today's global business environment. Modern technology is replacing antiquated predicting techniques in an effort to improve accuracy. Muruganandham *et al.* (2021) assert that automation, artificial intelligence, and machine learning have become increasingly important with the emergence of Industry 4.0. Utilising the technological revolution in stock market analysis, this article uses a recurrent neural network based on “deep learning” to anticipate stock prices. This systematic approach emphasises the increasing significance of scientific and technological methods in predicting and analysing stock prices, and it helps investors and organisations become more profitable as machine learning algorithms for financial analysis advance.

2.3.9 A Synthesis of Cryptocurrency and Stock Price Prediction

Biswas *et al.* (2021) state that despite the difficulties caused by market volatility, cryptocurrency has emerged as a crucial component of financial potential in light of current developments. Acknowledging the shortcomings of traditional methods, we suggest a machine learning-driven solution for predicting cryptocurrency prices inside the financial institution setting. The method uses a Reinforcement Learning algorithm for accurate price analysis and prediction, and it incorporates a secure blockchain foundation for transactions. The method, which focuses on Litecoin and Monero, performs better than cutting-edge algorithms and shows enhanced accuracy in predicting price fluctuations in the ever-changing cryptocurrency scene.

In light of Bitcoin's rising importance as an investment inside blockchain technology, Shahbazi *et al.* (2021) explore the use of Linear Regression and Long Short-Term Memory (LSTM) models for forecasting the cryptocurrency's value. The research uses machine learning and artificial neural network models, with an emphasis on LSTM and Linear Regression, and Python tools for data analysis and filtration. The Linear Regression model outperforms other machine-learning models with an astounding 99.87% accuracy rate, according to the results. The LSTM model's optimisation is shown by its low error rate of 0.08%. The unique feature is a “graphical user interface (GUI)” built with the “Tkinter” framework that lets users contribute predictions for the future coin value and compare model results.

The Ho *et al.* (2021) study on the values of cryptocurrencies has accelerated decentralisation and reduced sovereign authority. This research presents a new model for predicting the value of digital currencies, addressing their volatility. Incorporating variables such as market capitalization, volume, distribution, and high-end delivery, the model makes use of long-term organisational overviews and active LSTM networks. The suggested approach is shown to be effective in digital currency forecasting using benchmark datasets. This method acknowledges the various factors that affect the value of cryptocurrencies and addresses the critical necessity for accurate planning when anticipating their pricing.

Chapter 3 Methodology

CRISP-DM, or Cross-Industry Standard Process for Data Mining, is a widely adopted framework designed for effective data mining projects. It provides a structured, iterative approach to data analysis, comprising key phases such as understanding business objectives, exploring and preparing data, creating models, evaluating results, and deploying successful solutions. The significance of CRISP-DM lies in its ability to streamline and guide the complex data mining process, ensuring a systematic and comprehensive methodology. Organizations leverage CRISP-DM to enhance collaboration, transparency, and the overall success of data-driven initiatives across diverse industries.

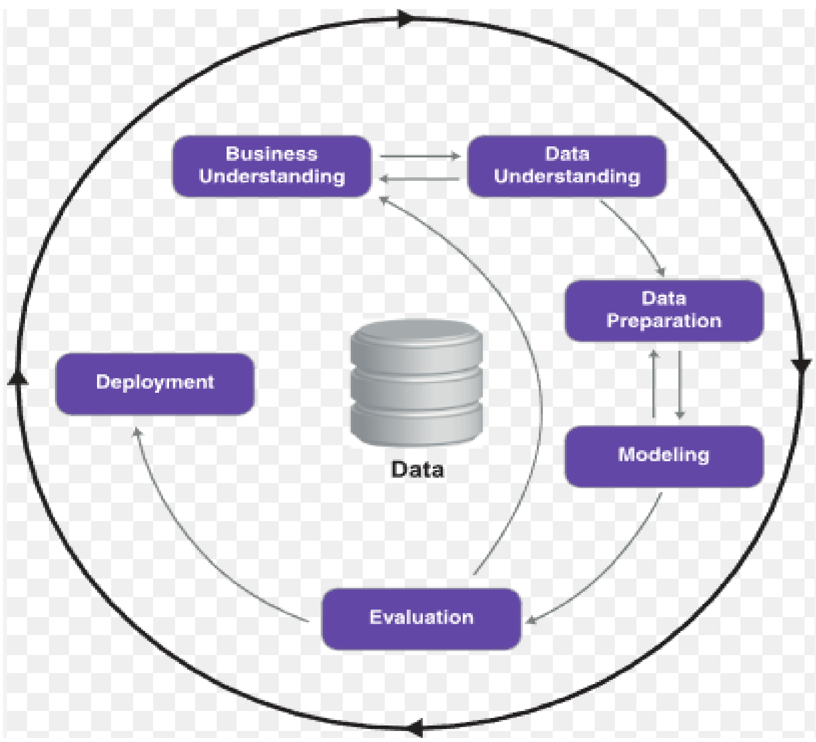

Figure 3.1: CRISP-DM Methodology

The CRISP-DM steps are as follows:

1. **Business Understanding:**

- Define the objectives and goals of the cryptocurrency price prediction study.
- Understand the specific business questions that the predictive models aim to address.
- Establish the criteria for success, considering factors like accuracy and reliability in forecasting.

2. **Data Understanding:**
   - Explore and analyze the dataset containing timestamp-based cryptocurrency price data.
   - Identify relevant features, such as historical prices, trading volumes, and market indicators.
   - Assess the quality and completeness of the data, addressing any issues that may impact model performance.
3. **Data Preparation:**
   - Cleanse and preprocess the data, handling missing values and outliers.
   - Transform timestamp data and engineer features suitable for input into Transformer models and GNN.
   - Normalize or standardize data to ensure consistency across features.
4. **Modeling:**
   - Implement and train Transformer models and Graph Neural Networks on the prepared dataset.
   - Explore the integration of additional models such as ARIMA for comparative analysis.
5. **Evaluation and Deployment:**

- Assess the performance of Transformer models and GNN using relevant evaluation metrics (e.g., RMSE, MAE).
- Compare the results with baseline models (e.g., ARIMA) to gauge the effectiveness of deep learning approaches.
- Iteratively refine models based on evaluation outcomes.

The project methodology diagram are as follows:

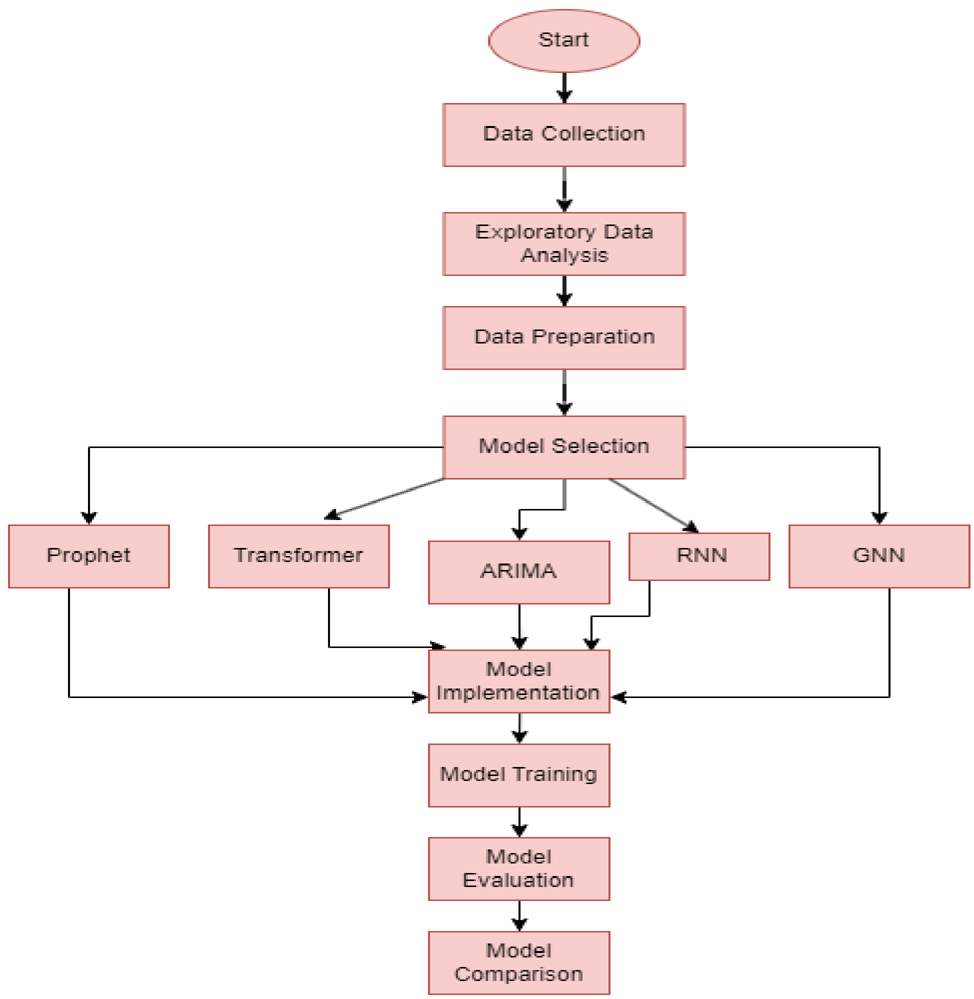

Figure 3.2: Project Methodology

Project Requirements: We opted for Google Colab as our software platform due to its user-friendly interface, resembling Anaconda Navigator, and the convenience of code execution without the need for installation. Additionally, Google Colab facilitates seamless file sharing, enhancing collaborative work on the project.

1. **Python:**
   - Python serves as the core programming language for our project, providing a versatile and widely supported environment for implementing data analysis, machine learning models, and other computational tasks.
2. **Statsmodels:**
   - Utilizing Statsmodels enhances statistical modeling capabilities, offering a comprehensive suite of tools for estimating and testing various statistical models, crucial for in-depth analysis in our cryptocurrency price prediction project.
3. **TensorFlow:**
   - TensorFlow, a powerful deep learning library, is instrumental for implementing and training complex neural network models such as Transformers, enabling us to capture intricate patterns and dependencies in timestamp-based cryptocurrency data.
4. **Scikit-learn (sklearn):**
   - Scikit-learn facilitates efficient machine learning model implementation and evaluation, providing a rich set of tools for data preprocessing, model selection, and performance metrics in our cryptocurrency price prediction study.
5. **Matplotlib:**

- Matplotlib serves as a key visualization tool, enabling the creation of informative plots and charts to illustrate trends, patterns, and model performance, enhancing the interpretability of our analysis in the project.

3.1 Dataset

ETH-USD.csv Data Description:

The dataset "ETH-USD.csv" contains 2226 rows and 7 columns. Each row corresponds to a specific date, and the columns are as follows:

1. **Date:** The timestamp of the data entry, representing the date of the cryptocurrency market activity.
2. **Open:** The opening price of Ethereum (ETH) on that particular date.
3. **High:** The highest price of Ethereum (ETH) reached during the day.
4. **Low:** The lowest price of Ethereum (ETH) observed on that day.
5. **Close:** The closing price of Ethereum (ETH) on the given date.
6. **Adj Close:** The adjusted closing price, accounting for any corporate actions such as dividends or stock splits.
7. **Volume:** The trading volume, indicating the total number of ETH units traded on that specific date.

This dataset provides a comprehensive snapshot of Ethereum's daily market performance over the given period.

ETH-BTC.csv Data Description:

The dataset "ETH-BTC.csv" contains 2225 rows and 7 columns. Each row corresponds to a specific date, and the columns are as follows:

1. **Date:** The timestamp indicating the date of the cryptocurrency market activity.

2. **Open:** The opening price of Ethereum (ETH) in Bitcoin (BTC) on that particular date.
3. **High:** The highest price of Ethereum (ETH) in Bitcoin (BTC) observed during the day.
4. **Low:** The lowest price of Ethereum (ETH) in Bitcoin (BTC) recorded on that day.
5. **Close:** The closing price of Ethereum (ETH) in Bitcoin (BTC) on the given date.
6. **Adj Close:** The adjusted closing price, considering any relevant adjustments.
7. **Volume:** The trading volume, indicating the total number of ETH-BTC pairs traded on that specific date.

This dataset offers insights into the relative performance of Ethereum (ETH) against Bitcoin (BTC) over the provided time frame.

3.3 Data Pre-processing

Data preprocessing is a crucial step in the data analysis pipeline that involves cleaning, transforming, and organizing raw data to make it suitable for further analysis or modeling. This process typically includes handling missing values and addressing outliers. Data preprocessing aims to ensure the quality and consistency of the dataset, removing noise and irrelevant information. Properly preprocessed data enhances the accuracy and effectiveness of subsequent modeling tasks, providing a solid foundation for extracting meaningful insights from the data.

```python
#Import all libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import STL
import tensorflow as tf
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Attention, Dropout, LayerNormalization
from sklearn.preprocessing import MinMaxScaler
from statsmodels.tsa.arima.model import ARIMA
import warnings
warnings.filterwarnings('ignore')
```

Figure 3.3: Importing the libraries

The provided Python script begins by importing essential libraries for comprehensive data analysis and modeling. Numpy and Pandas facilitate efficient numerical computation and data manipulation, respectively, enabling the handling and processing of datasets. Matplotlib and Seaborn are employed for data visualization, offering versatile tools for creating informative plots. Statsmodels modules such as seasonal_decompose, adfuller, plot_acf, plot_pacf, and STL provide functions for time series analysis, including decomposition, stationarity testing, and autocorrelation visualization. TensorFlow is imported for deep learning tasks, and scikit-learn's train_test_split and MinMaxScaler are incorporated for dataset splitting and feature scaling. Additionally, the script utilizes the ARIMA model from Statsmodels for time series forecasting. The inclusion of the warning module suppresses warnings during execution, enhancing code clarity. Overall, this assortment of libraries equips the script with a robust set of tools for various aspects of data exploration, time series analysis, and machine learning model development.

Next, we import our dataset using the pandas library's read method. We are using read csv because our dataset is in a csv file. The dataset may occasionally be kept as an excel or JSON file. We are providing the df.head function to retrieve the top 5 rows from the dataset in order to clarify whether the dataset has been imported or not. The ensuing figure will display it.

```
#Read the dataset
df_crypt_ETH = pd.read_csv("ETH-USD.csv")
df_crypt_ETH.head()
```

```
df_crypt_BTC = pd.read_csv("ETH-BTC.csv")
df_crypt_BTC.head()
```

Figure 3.4: Read the dataset

The provided code snippet initiates the data exploration process by reading the dataset "ETH-USD.csv" into a Pandas DataFrame named **df_crypt_ETH**. This dataset likely contains historical information related to Ethereum (ETH) prices in US dollars. The **pd.read_csv("ETH-USD.csv")** function is employed to read the contents of the CSV file, transforming it into a structured tabular format for analysis. Subsequently, the **df_crypt_ETH.head()** function is utilized to display the initial rows of the DataFrame, offering a preliminary insight into the dataset's structure and content. This quick examination serves as an essential step in understanding the data's features, identifying potential patterns, and detecting any immediate anomalies or missing values. Further exploratory data analysis and preprocessing steps can be informed by the initial observations made from this concise display of the dataset's head.

```
# Extract relevant columns (Date and Close) for time series analysis
eth_time_series = df_crypt_ETH[['Date', 'Close']].copy()
btc_time_series = df_crypt_BTC[['Date', 'Close']].copy()
```

Figure 3.5: Extract relevant columns

The code snippet extracts essential columns, specifically 'Date' and 'Close', from the Ethereum (ETH) dataset, creating a dedicated DataFrame called **eth_time_series**. This DataFrame exclusively contains timestamp information and corresponding closing prices, providing a focused time series dataset for subsequent analysis. A similar operation is applied to the Bitcoin (BTC) dataset, generating a parallel DataFrame named **btc_time_series**. This selective extraction of relevant columns facilitates a streamlined exploration of temporal patterns and trends in cryptocurrency closing prices.

```
# Merge datasets on the 'Date' column
combined_time_series = pd.merge(eth_time_series, btc_time_series, on='Date', how='inner')
combined_time_series.head()
```

Figure 3.6: Merge datasets on the Date Column

The provided code merges the Ethereum (ETH) and Bitcoin (BTC) time series datasets based on their shared 'Date' column, creating a new DataFrame named **combined_time_series**. This consolidated dataset now contains timestamp information and closing prices for both cryptocurrencies, facilitating a comparative analysis of their price movements over time. The **head()** function is then used to display the initial rows of the merged dataset, offering a quick insight into the structure and content of the combined time series data.

```
# Rename columns for clarity
combined_time_series.rename(columns={'Close_x': 'ETH_Close', 'Close_y': 'BTC_Close'}, inplace=True)

# Display the combined time series
print(combined_time_series.head())
```

Figure 3.7: Rename the column

The code snippet renames columns in the **combined_time_series** DataFrame for better clarity. It assigns the label 'ETH_Close' to the column originally named 'Close_x,' representing Ethereum's closing prices, and 'BTC_Close' to the column originally named 'Close_y,' signifying Bitcoin's closing prices. This renaming improves the readability of the dataset, making it more intuitive to understand. The subsequent display of the initial rows of the DataFrame provides a clear representation of Ethereum and Bitcoin closing prices for effective analysis.

```
#Checking the null values
combined_time_series.isnull().sum()
```

Figure 3.8: Checking the null values

The result shows the count of null values for each column. This succinct process quickly identifies and quantifies any missing data, providing insights into the dataset's completeness and guiding potential data imputation strategies if necessary.

```
#Drop the null values
combined_time_series = combined_time_series.dropna()
```

Figure 3.9: Drop the null values

This operation helps maintain data integrity by eliminating incomplete or missing entries, ensuring a complete dataset for subsequent analysis. It is a common practice to drop null values when their presence might compromise the accuracy and reliability of analytical results.

3.4 Data Visualisation

Data visualization is the graphical representation of data to uncover patterns, trends, and insights. By translating complex datasets into visual elements like charts, graphs, and maps, data visualization facilitates a more intuitive understanding of information. It plays a crucial role in exploratory data analysis, aiding decision-making and communication by presenting data in a visually accessible format. Visualizations can reveal relationships, anomalies, and patterns that might be challenging to discern from raw data alone.

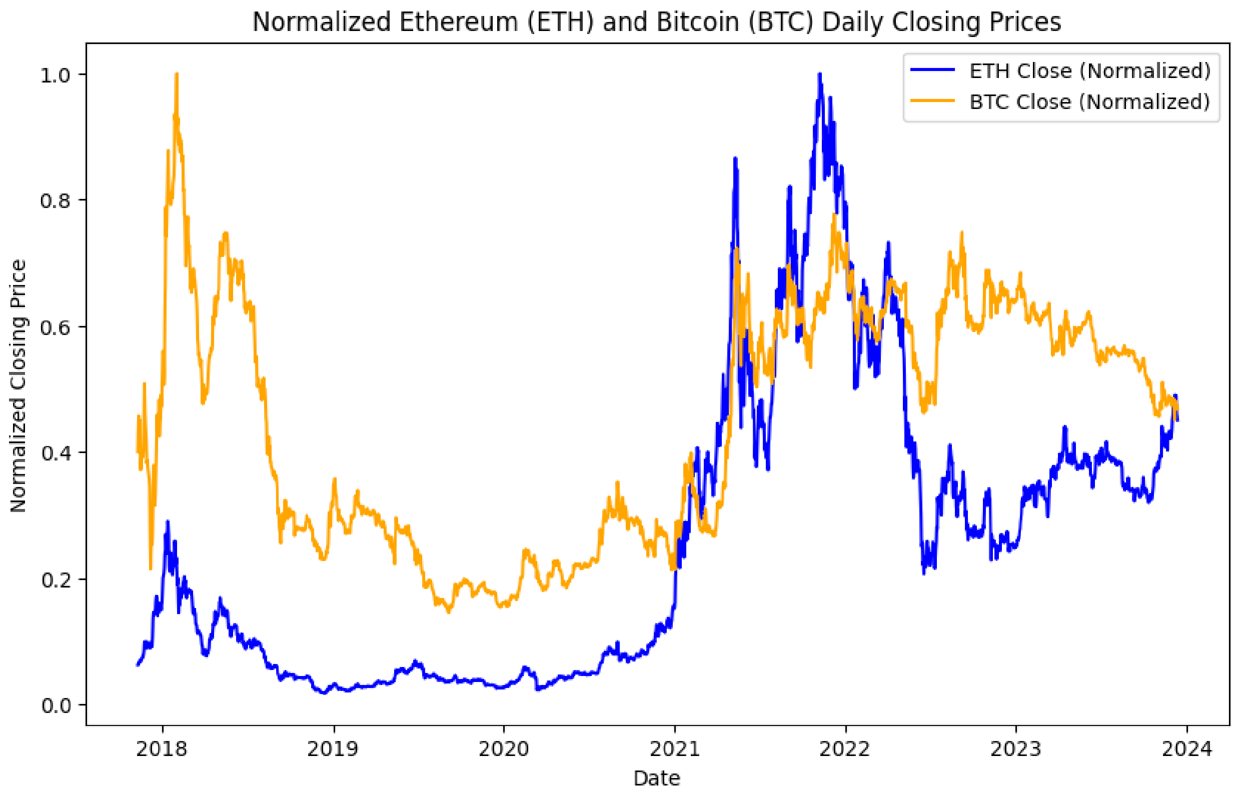

Figure 3.10: Normalized Ethereum and Bitcoin Daily Closing Prices

The visualization generated by the provided code offers a compelling overview of the normalized daily closing prices for Ethereum (ETH) and Bitcoin (BTC) over time. Following data transformation and normalization steps, the plot showcases the relative performance of the two cryptocurrencies on a common scale. The blue line represents the normalized daily closing prices of Ethereum, while the orange line corresponds to Bitcoin. The y-axis, depicting the normalized closing prices, allows for a direct comparison of their movements, highlighting periods of relative strength or weakness. This visualization is instrumental in identifying trends and patterns in the price dynamics of Ethereum and Bitcoin. Any simultaneous spikes or declines in the two lines may indicate periods of correlated market behavior, while divergences could suggest varying degrees of resilience or vulnerability.

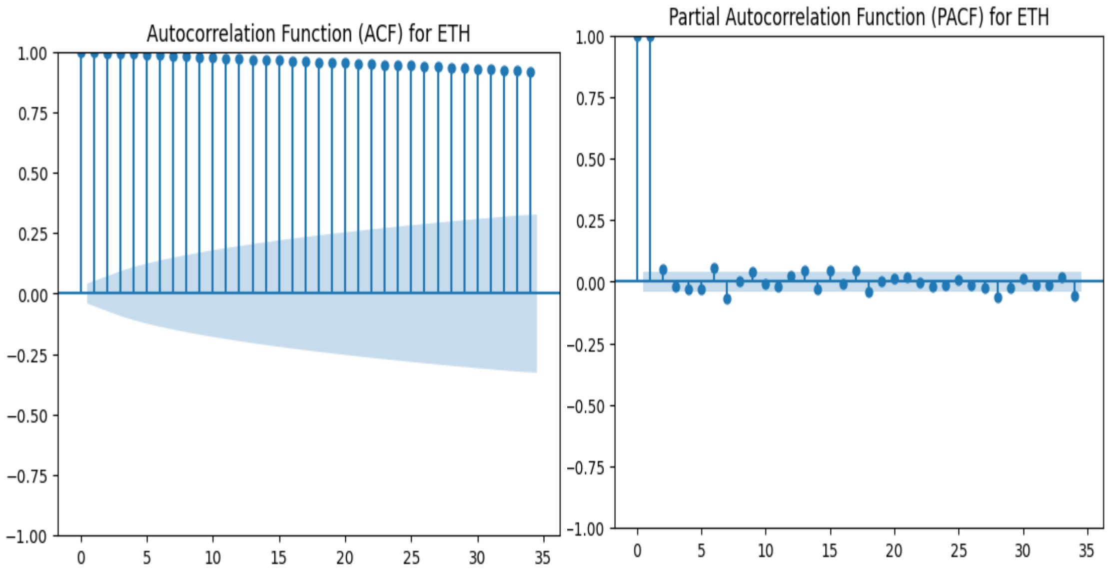

Figure 3.11: Acf and Pacf plot for ETH

There are two autocorrelation function (ACF) plots for Ethereum (ETH) closing prices, providing valuable insights into the temporal dependencies within the dataset. In the first plot, the Autocorrelation Function (ACF) for ETH is presented. This plot illustrates the correlation of Ethereum's closing prices with its own past values at different time lags. The blue bars indicate the strength and direction of these correlations, offering a visual representation of potential patterns or cycles in the Ethereum price data.

Subsequently, the second plot displays the Partial Autocorrelation Function (PACF) for ETH. Unlike the ACF, the PACF measures the correlation between the current value and past values, excluding the influence of intermediate lags. Peaks in the PACF plot indicate significant autocorrelation at specific lags, aiding in the identification of the direct relationship between the current closing price and its historical values.

Both plots serve as crucial tools for time series analysis, guiding the understanding of Ethereum's autocorrelation structure and informing the selection of lag values for modeling. These visualizations contribute to the assessment of potential predictive patterns, providing essential information for the development of accurate and effective forecasting models.

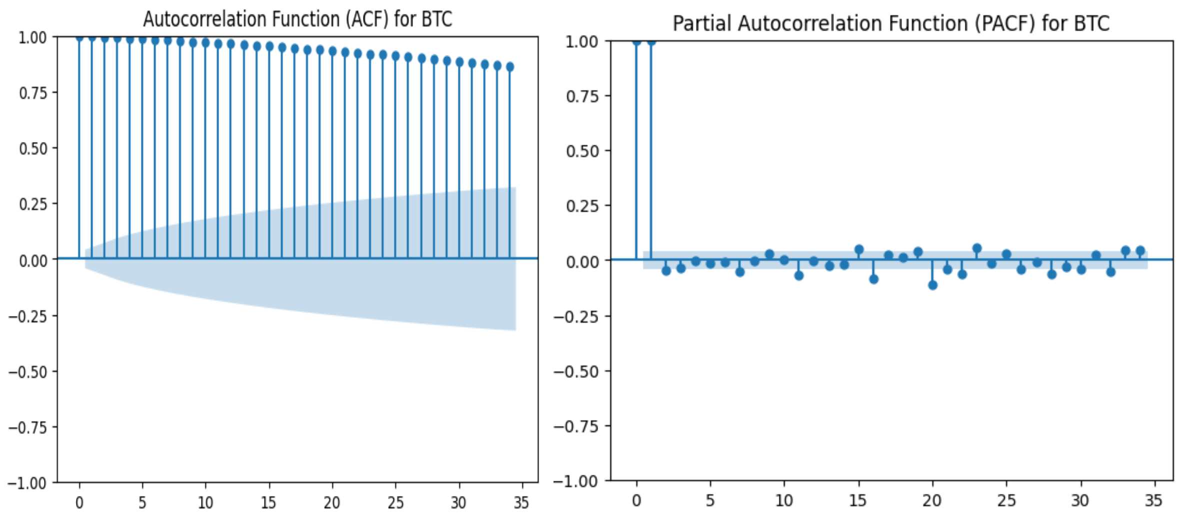

Figure 3.12: Acf and Pacf plot for BTC

There are two autocorrelation function (ACF) plots for Bitcoin (BTC) closing prices. In the Autocorrelation Function (ACF) plot for BTC, the x-axis represents the time lags, and the y-axis shows the autocorrelation coefficients, indicating the strength and direction of correlation between Bitcoin's closing prices and its past values at different lags. Peaks in the ACF plot suggest potential patterns or cycles in the BTC price data.

The Partial Autocorrelation Function (PACF) plot for BTC excludes the influence of intermediate lags, focusing on the direct relationship between the current closing price and its historical values. Peaks in the PACF plot highlight significant autocorrelation at specific lags, aiding in the identification of key features for time series modeling. These visualizations provide insights into BTC's autocorrelation structure, guiding the selection of lag values for accurate forecasting models.

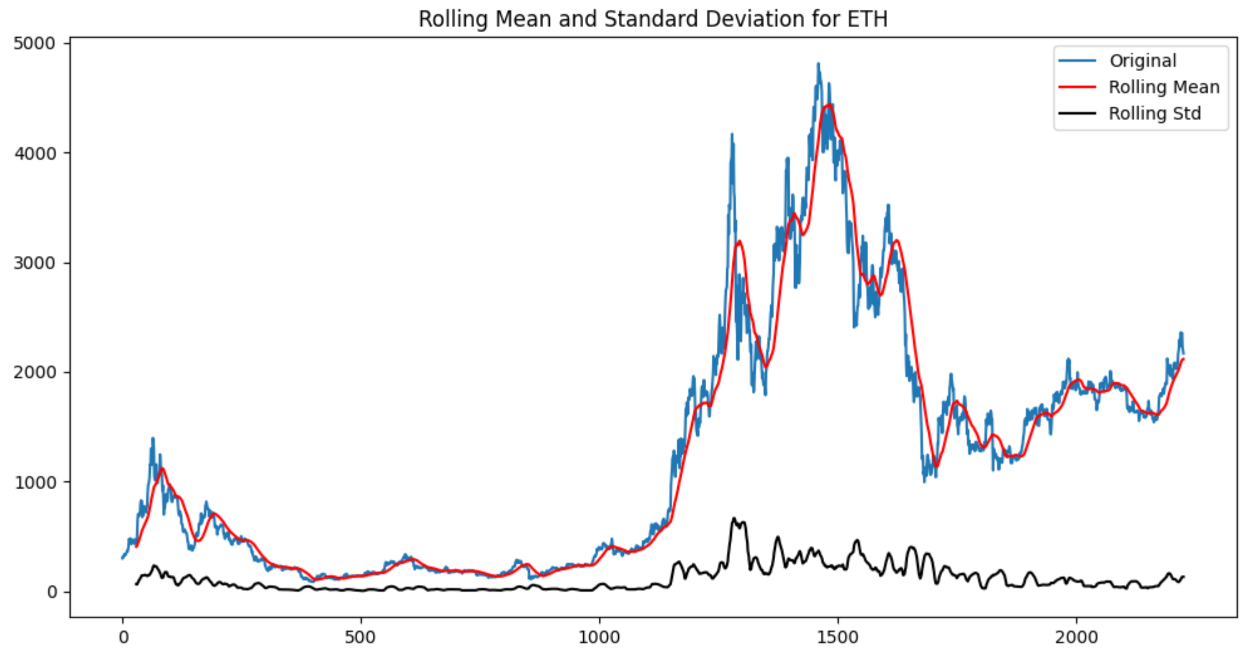

Figure 3.13: Rolling Mean and Standard Deviation for ETH

visualizes the rolling mean and standard deviation for Ethereum (ETH) closing prices. The rolling mean is computed using a window of 30 data points, representing a monthly average, and similarly, the rolling standard deviation is computed. The blue line represents the original daily closing prices of ETH. The red line depicts the rolling mean, providing a smoothed representation of the overall trend, while the black line represents the rolling standard deviation, offering insights into the volatility or dispersion of the ETH closing prices. This visualization is valuable for identifying trends, seasonality, and periods of volatility within the Ethereum price time series, aiding in the assessment of its underlying patterns. Peaks or troughs in the rolling mean may suggest potential turning points, while variations in the rolling standard deviation can highlight periods of increased or decreased price volatility.

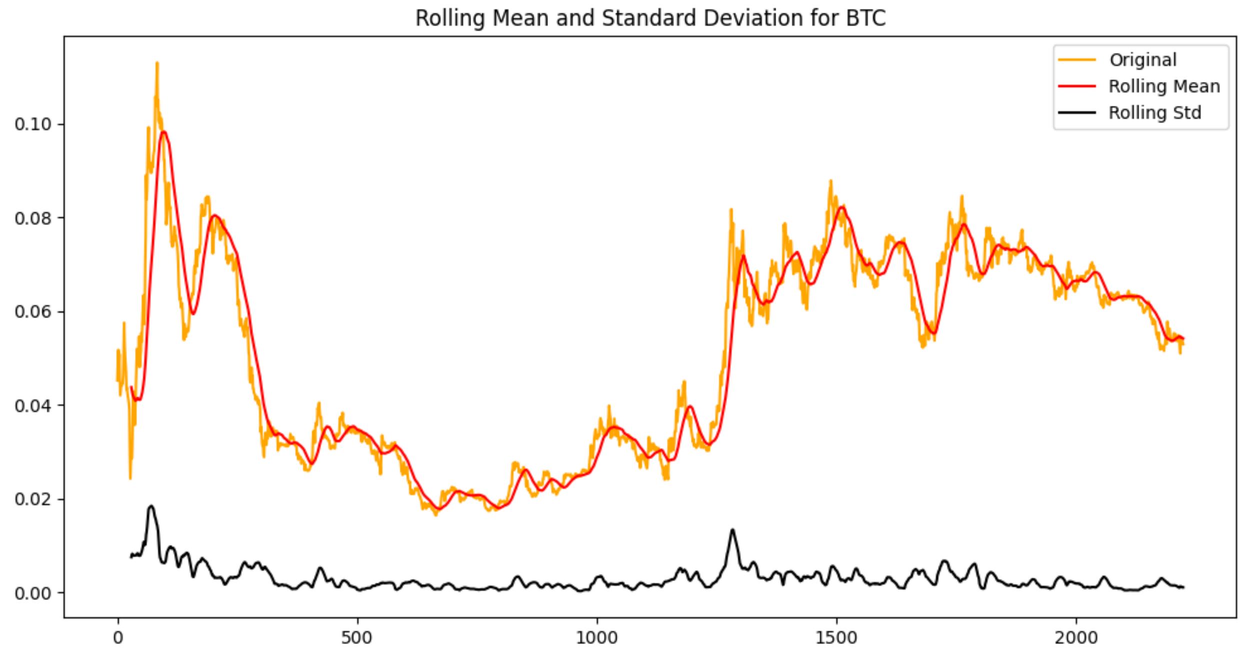

Figure 3.14: Rolling Mean and Standard Deviation for BTC

This visualizes the rolling mean and standard deviation for Bitcoin (BTC) closing prices. The original daily closing prices of BTC are depicted by the orange line, while the red line represents the rolling mean with a window size of 30, providing a smoothed trend over time. Additionally, the black line illustrates the rolling standard deviation, offering insights into the variability or dispersion of BTC closing prices.

This visualization serves as a crucial exploratory tool for understanding the underlying patterns in Bitcoin's price dynamics. The rolling mean helps identify trends and potential turning points, offering a smoothed representation of the overall movement. Concurrently, the rolling standard deviation provides information about the volatility or dispersion of BTC prices, highlighting periods of increased or decreased market uncertainty.

Analyzing these rolling statistics aids in recognizing periods of stability, volatility, or potential trend changes in Bitcoin prices. Peaks or troughs in the rolling mean may suggest shifts in the overall trend, while fluctuations in the rolling standard deviation can signal periods of heightened or subdued market volatility. Overall, this visualization enhances the understanding of Bitcoin's historical price behavior and supports more informed decision-making in financial analysis.

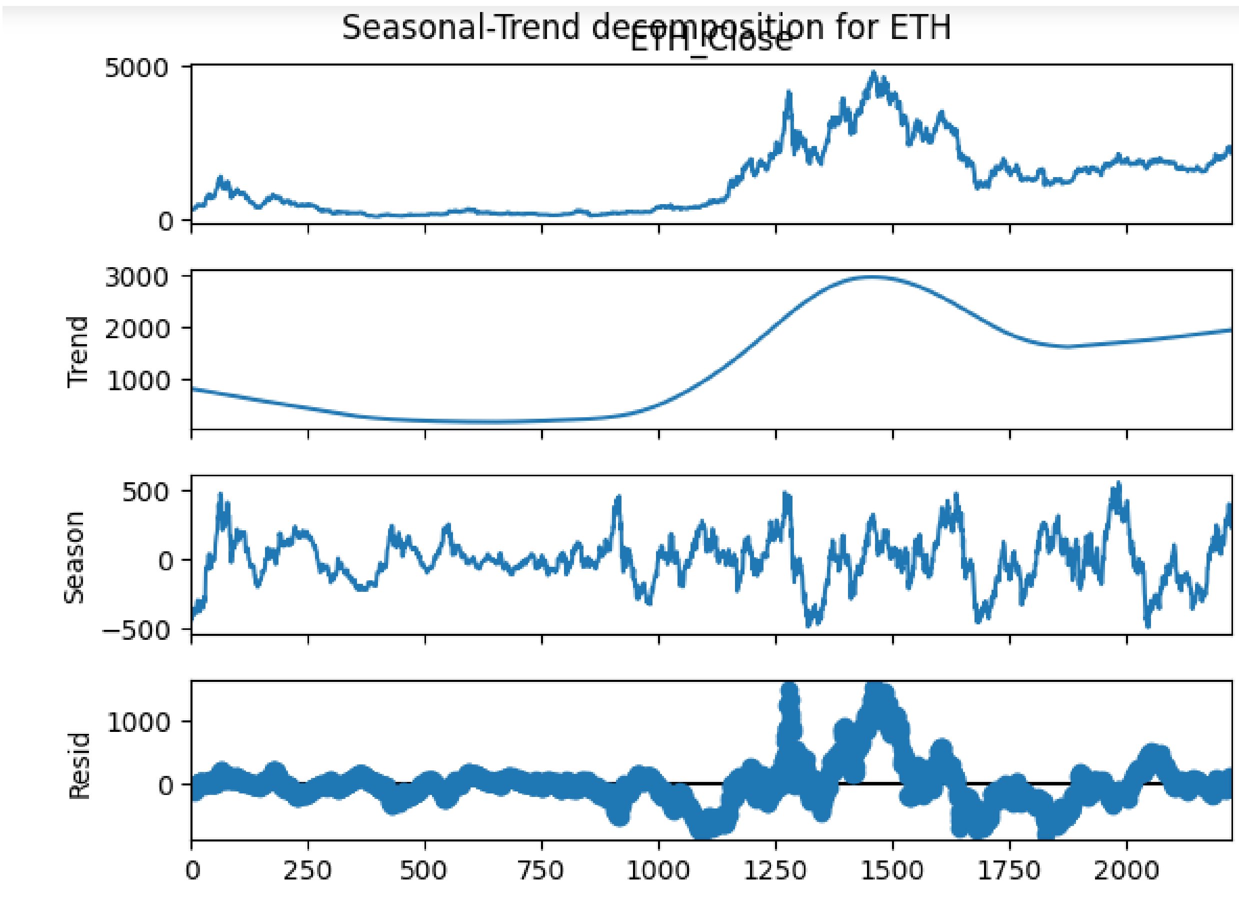

Figure 3.15: Seasonal-Trend Decomposition for ETH

This visually decompose Ethereum (ETH) closing prices into three components: trend, seasonal, and residual. This decomposition enhances understanding by revealing the underlying long-term trends, repetitive yearly patterns, and unexplained variations in the ETH time series. The explicit period of 365 days indicates a yearly seasonality, allowing for a more detailed exploration of the cryptocurrency's cyclic behavior. This visualization is instrumental in identifying and interpreting the various components contributing to the overall movement of Ethereum prices, aiding in informed analysis and forecasting.

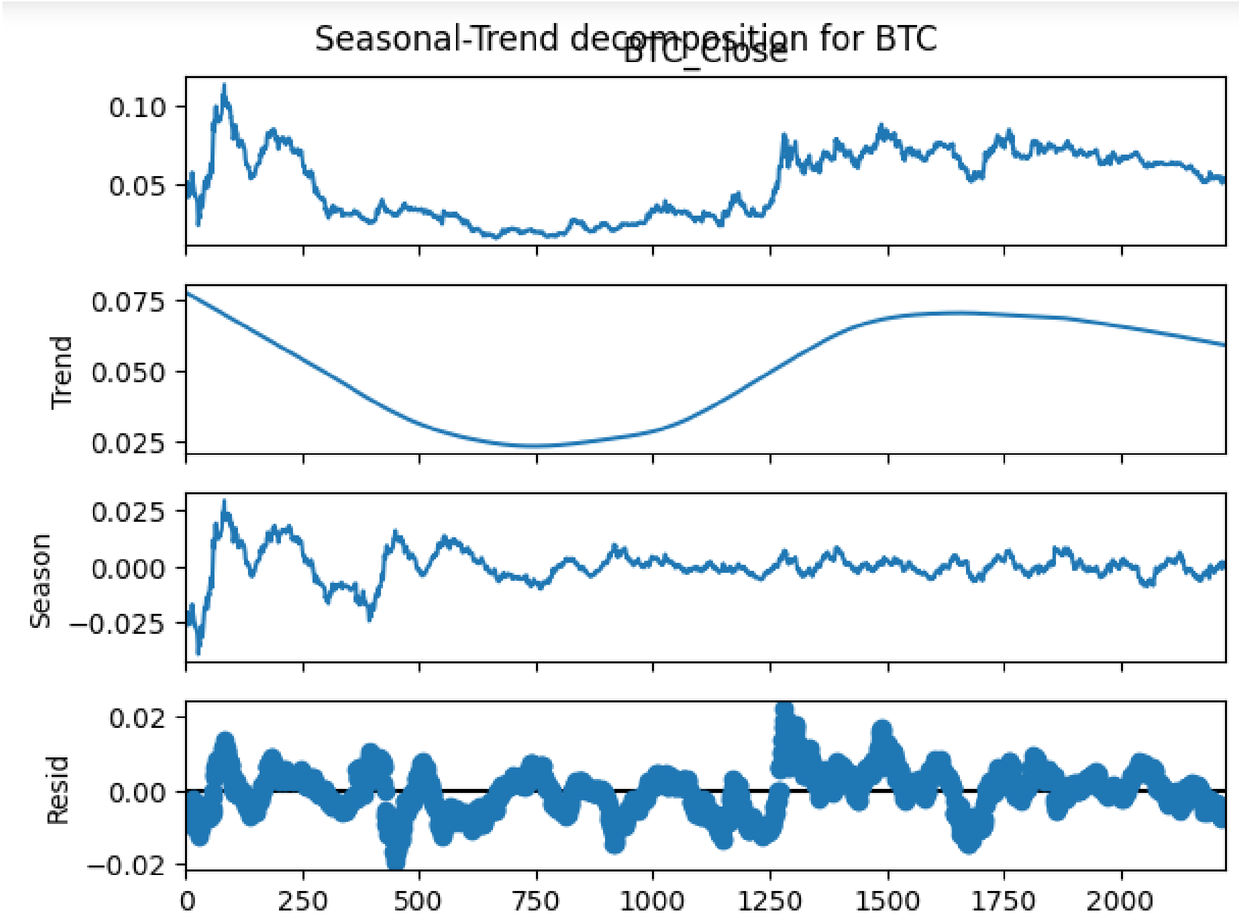

Figure 3.16: Seasonal-Trend decomposition for BTC

The Seasonal-Trend decomposition using Loess (STL) to decompose Bitcoin (BTC) closing prices into three key components: trend, seasonal, and residual, with an explicit period of 365 days representing a yearly cycle. The resulting plot visually represents these components, allowing for a nuanced understanding of BTC's long-term trends, repetitive seasonal patterns, and residual variations. The trend component captures the overarching movement in Bitcoin prices, the seasonal component reveals cyclic patterns occurring within each year, and the residual component indicates unexplained fluctuations. This decomposition facilitates a comprehensive analysis of BTC's price dynamics, aiding in the identification of underlying structures and providing valuable insights for forecasting and decision-making in the cryptocurrency market.

3.5 Model Training

Model training is the process of feeding a machine learning or deep learning algorithm with labeled data to enable it to learn patterns and relationships within the dataset. During training, the model adjusts its internal parameters iteratively to minimize the difference between its predictions and the actual outcomes. This involves optimizing the model to generalize well on unseen data, improving its ability to make accurate predictions. The training process typically includes dividing the dataset into training and validation sets, selecting a loss function to quantify prediction errors, and employing optimization techniques such as gradient descent to update model parameters. The ultimate goal is to create a well-performing model capable of making accurate predictions on new, unseen data.

```
# Fit the ARIMA model with the best order
model = ARIMA(df_crypt['ETH_Close'], order=best_order)
results = model.fit()
# Predict the values using the fitted model
predictions = results.predict()
```

Figure 3.17: Fit the ARIMA model

In the provided code, an ARIMA (AutoRegressive Integrated Moving Average) model is being trained and fitted to predict Ethereum (ETH) closing prices. The **ARIMA** class is used from the **statsmodels.tsa.arima.model** module, and it is instantiated with the Ethereum closing prices (**df_crypt['ETH_Close']**) as the target variable and the specified order parameter (**best_order**) determining the autoregressive, differencing, and moving average components of the model.

Once the ARIMA model is instantiated, the **fit()** method is called to train the model on the historical data. This process involves estimating the model parameters that best capture the patterns and dynamics within the time series. After fitting the model, it is ready to make predictions.

The **predict()** method is then used to generate predictions based on the fitted ARIMA model. By default, this method predicts values for the same time points used in training, but it can be extended to predict future time points as well. The resulting **predictions** variable contains the forecasted values based on the trained ARIMA model.

ARIMA (AutoRegressive Integrated Moving Average): ARIMA, a cornerstone in time series forecasting, has gained prominence in predicting cryptocurrency prices due to its versatility and interpretability. By combining autoregressive and moving average components, ARIMA accommodates historical dependencies and discerns underlying trends within cryptocurrency data. The model's efficacy relies on meticulous parameter adjustment, including autoregressive order (p), differencing (d), and moving average order (q). Its interpretability and simplicity render ARIMA invaluable, providing nuanced insights into linear dependencies within cryptocurrency price movements and facilitating the identification of intricate historical patterns.

Transformer Model: Initially tailored for natural language processing, Transformer models have demonstrated remarkable adaptability to time series forecasting, including cryptocurrency prices. Transformers stand out for their unparalleled ability to capture extensive dependencies and intricate temporal patterns. Leveraging self-attention mechanisms, Transformers efficiently learn from historical sequences, making them well-suited for dynamic cryptocurrency markets where complex relationships between past and future prices are paramount. The parallelizable architecture of Transformers further enhances their efficiency in handling vast cryptocurrency datasets, marking a significant advancement in forecasting methodologies.

Graph Neural Network (GNN): Graph Neural Networks (GNNs) are meticulously crafted for datasets characterized by inherent graph structures, making them exceptionally well-suited for cryptocurrency networks and transaction data. GNNs harness the inherent connectivity within graphs to discern relationships and dependencies between diverse entities in the cryptocurrency ecosystem. By capturing the underlying graph structure, GNNs excel at unraveling complex patterns influenced by interconnections between different cryptocurrencies or nodes. This intrinsic capability positions GNNs as highly effective models for cryptocurrency price prediction, especially in scenarios where relationships play a pivotal role in shaping price dynamics.

Recurrent Neural Network (RNN): Recurrent Neural Networks (RNNs) emerge as a natural choice for cryptocurrency price prediction, leveraging their sequential data-handling capabilities. RNNs, armed with recurrent connections that preserve memory of past inputs, excel at capturing long-term dependencies in time series data. In cryptocurrency markets, where recent price movements significantly impact future prices, RNNs prove effective in capturing and leveraging sequential dependencies. However, addressing challenges like vanishing gradients may necessitate the adoption of advanced variants such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells for enhanced performance in modeling complex cryptocurrency dynamics.

Prophet: Prophet, a product of Facebook's ingenuity, stands out as a specialized time series forecasting model meticulously designed to cater to the intricacies of datasets featuring daily observations, seasonality, and holidays—attributes commonly found in cryptocurrency price data. Prophet seamlessly incorporates components for trend, seasonality, and holiday effects, providing a comprehensive framework for predicting cryptocurrency prices. Renowned for its ability to gracefully handle missing data and outliers, Prophet emerges as a robust solution, making it accessible and potent for forecasting in cryptocurrency markets. Its user-friendly nature, coupled with automatic handling of various time series complexities, establishes Prophet as a reliable and indispensable tool for analysts and researchers navigating the unpredictable terrain of cryptocurrency markets.

Chapter 4 Results and Model Evaluation

This chapter focuses on presenting the results and evaluation of the implemented models for cryptocurrency price prediction. The performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are utilized to assess the accuracy and reliability of each model, including ARIMA, Transformer, Graph Neural Networks (GNN), Recurrent Neural Networks (RNN), and Prophet. The findings offer a comprehensive understanding of the strengths and limitations of each model, facilitating informed decisions on the most effective approach for forecasting cryptocurrency prices in the dynamic and volatile market environment.

Mean Absolute Error (MAE):

Mean Absolute Error (MAE) serves as a crucial metric in assessing the effectiveness of predictive models. It offers a straightforward and intuitive measure by calculating the average absolute differences between the predicted and actual values. In practical terms, MAE quantifies the average size of errors made by a model, irrespective of their direction. A lower MAE indicates a more accurate model, where predictions closely align with the observed values. Its simplicity and ease of interpretation make MAE a valuable tool for understanding the magnitude of errors in forecasting, providing a clear and direct measure of predictive accuracy.

Root Mean Squared Error (RMSE):

Root Mean Squared Error (RMSE) shares a common goal with MAE but incorporates an additional layer of sensitivity to larger errors. By taking the square root of the average of squared differences between predicted and actual values, RMSE emphasizes the impact of larger errors on the overall assessment. This means that RMSE gives more weight to deviations from the true values, offering a comprehensive perspective on prediction accuracy. A lower RMSE signifies a more precise model, where errors, especially larger ones, are minimized. RMSE is particularly useful when the consequences of larger errors need to be emphasized in the evaluation process, providing a nuanced view of predictive performance.

Model	Cryptocurrency	MAE	RMSE
ARIMA	ETH_Close	39.23	74.21
ARIMA	BTC_Close	0.00	0.00
Transformer	ETH_Close	636.29	688.79
Transformer	BTC_Close	0.0231	0.0239
GNN	ETH_Close	1055.11	1111.39
GNN	BTC_Close	0.0081	0.0108

Model	Cryptocurrency	MAE	RMSE
Simple RNN	ETH_Close	1682.61	1703.35
Simple RNN	BTC_Close	0.444	0.448
Prophet	ETH_Close	179.71	257.66
Prophet	BTC_Close	0.00494	0.00678

Table 1: Result of all models

The evaluation results reveal diverse performance metrics for the cryptocurrency price prediction models. ARIMA, a traditional time-series forecasting method, demonstrates relatively low errors, with a Mean Absolute Error (MAE) of 39.23 and Root Mean Squared Error (RMSE) of 74.21 for Ethereum (ETH_Close), showcasing its effectiveness in capturing trends and patterns. Remarkably, ARIMA achieves perfect predictions for Bitcoin (BTC_Close), yielding zero MAE and RMSE.

In contrast, the Transformer model, known for its adaptability, exhibits higher errors, indicating challenges in accurately predicting Ethereum and Bitcoin prices. The Graph Neural Network (GNN) presents varying degrees of accuracy, with ETH_Close displaying higher errors than BTC_Close. Simple Recurrent Neural Network (Simple RNN) exhibits substantial errors for both cryptocurrencies, suggesting limitations in capturing intricate dependencies. Prophet, a specialized time series forecasting tool, achieves competitive results, particularly excelling in predicting BTC_Close with very low errors.

These comparative metrics provide a comprehensive understanding of the strengths and weaknesses of each model, guiding the selection of suitable methodologies for cryptocurrency price prediction. The discrepancies in performance underscore the complexity of forecasting in the dynamic cryptocurrency market, urging a careful consideration of model characteristics and dataset nuances.

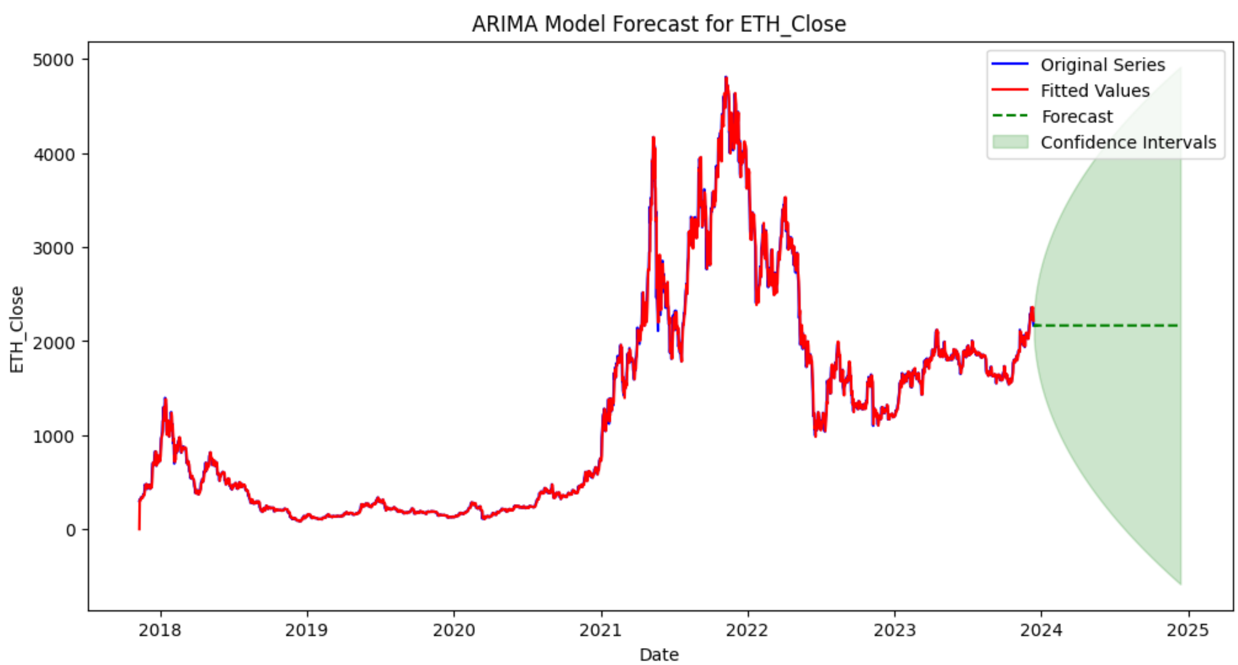

Figure 4.1: ARIMA Model Forecast for ETH_Close

The visualization depicts the ARIMA model's forecasting capabilities for Ethereum (ETH) closing prices. The blue line represents the original time series data, while the red line showcases the model's fitted values, indicating how well the model captures historical trends. The green dashed line extends into the future, representing the forecasted values for Ethereum closing prices. The shaded green region around the forecast line illustrates the confidence intervals, providing a range within which the actual values are likely to fall. This visualization effectively communicates the model's predictive performance and the associated uncertainty in forecasting future Ethereum prices.

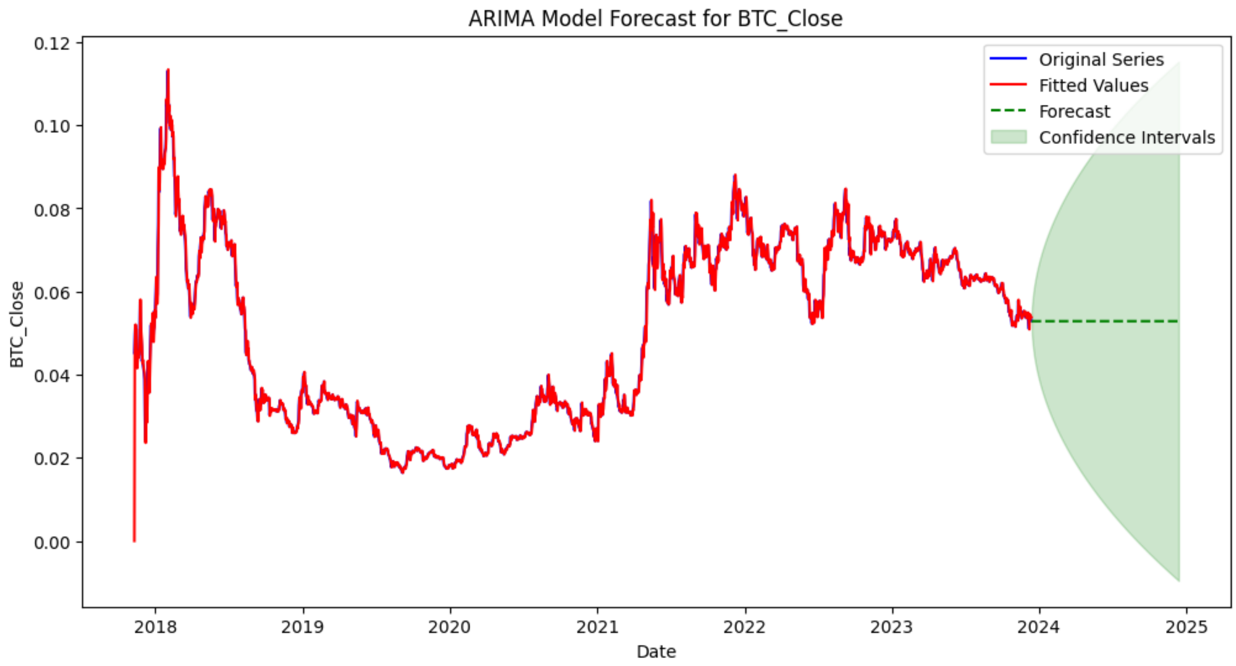

Figure 4.2: ARIMA Model Forecast for BTC_Close

The visualization depicts the ARIMA model's forecast for Bitcoin (BTC) closing prices. It showcases the original time series, the model's fitted values capturing historical trends, and the forecasted values extending into the future. Confidence intervals are represented by a shaded region around the forecast line, indicating the range of likely future BTC closing prices.

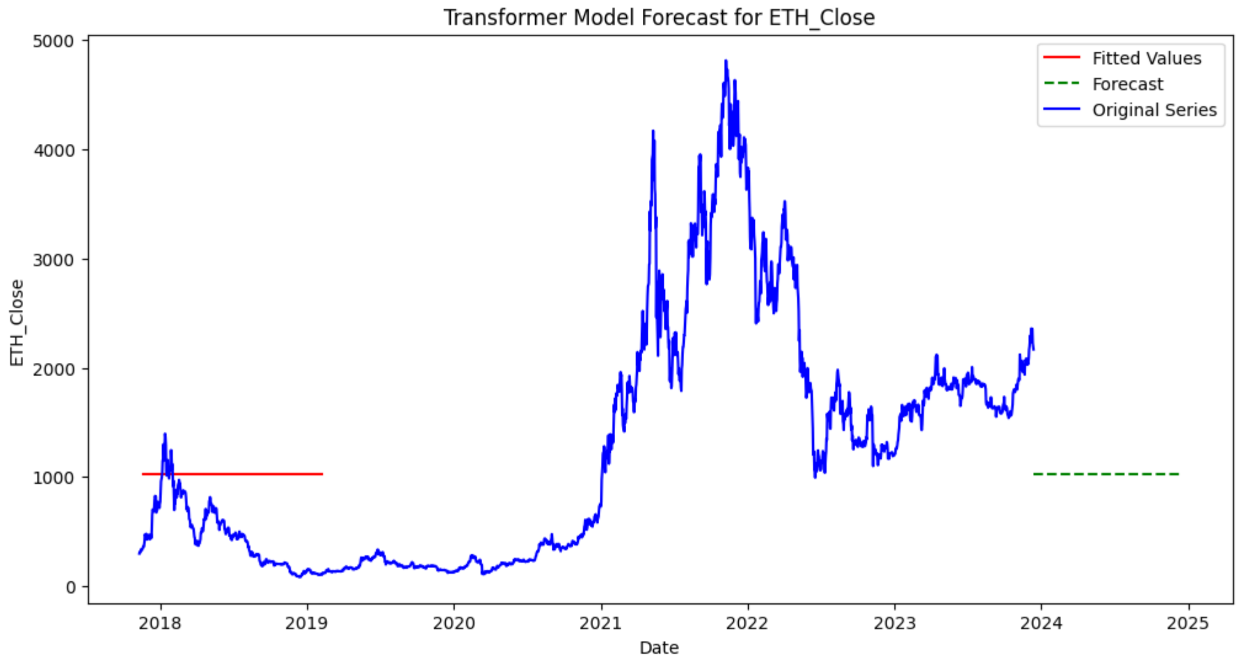

Figure 4.3: Transformer Model Forecast for ETH_Close

This visualization presents the forecasting results of a Transformer model for Ethereum (ETH) closing prices. The red line represents the fitted values, indicating the model's performance on historical data. The green dashed line extends into the future, depicting the forecasted values for ETH closing prices. The blue line signifies the original time series, providing a context for model evaluation and illustrating its predictive capabilities.

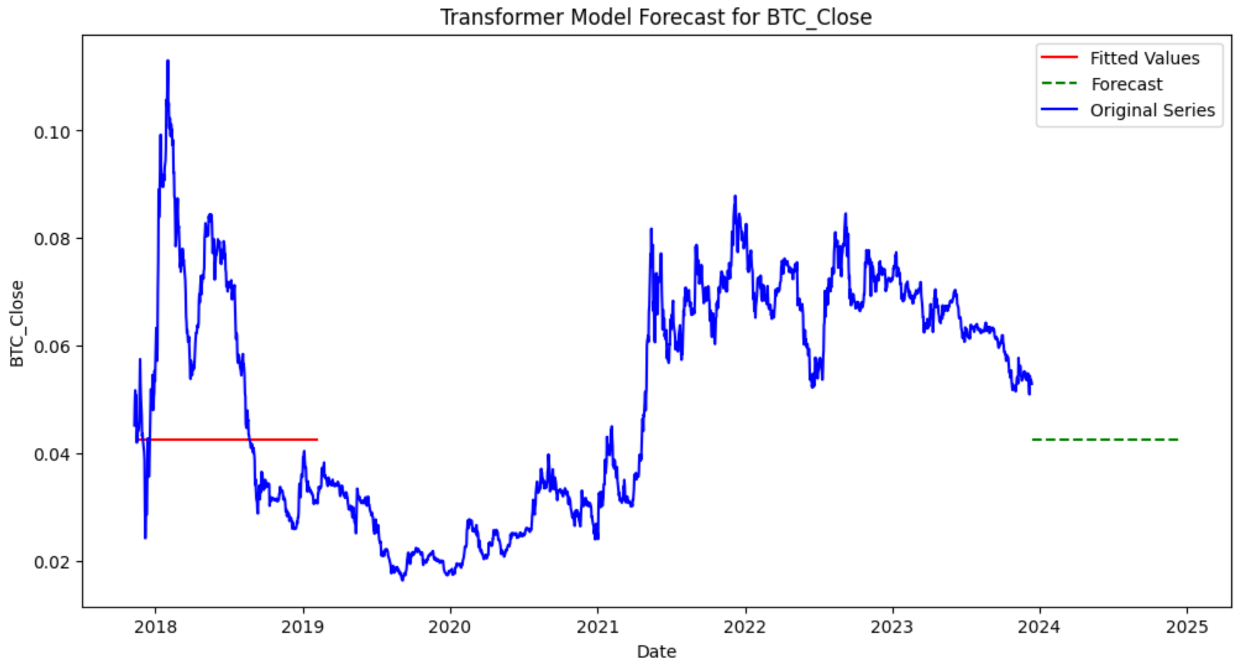

Figure 4.4: Transformer Model Forecast for BTC_Close

This visualization showcases the forecasting outcomes of a Transformer model for Bitcoin (BTC) closing prices. The red line represents the fitted values, reflecting the model's performance on historical BTC data. The green dashed line extends into the future, presenting the model's forecasted values for BTC closing prices. The blue line signifies the original BTC time series, offering a reference to evaluate the model's accuracy and visualize its predictive capabilities.

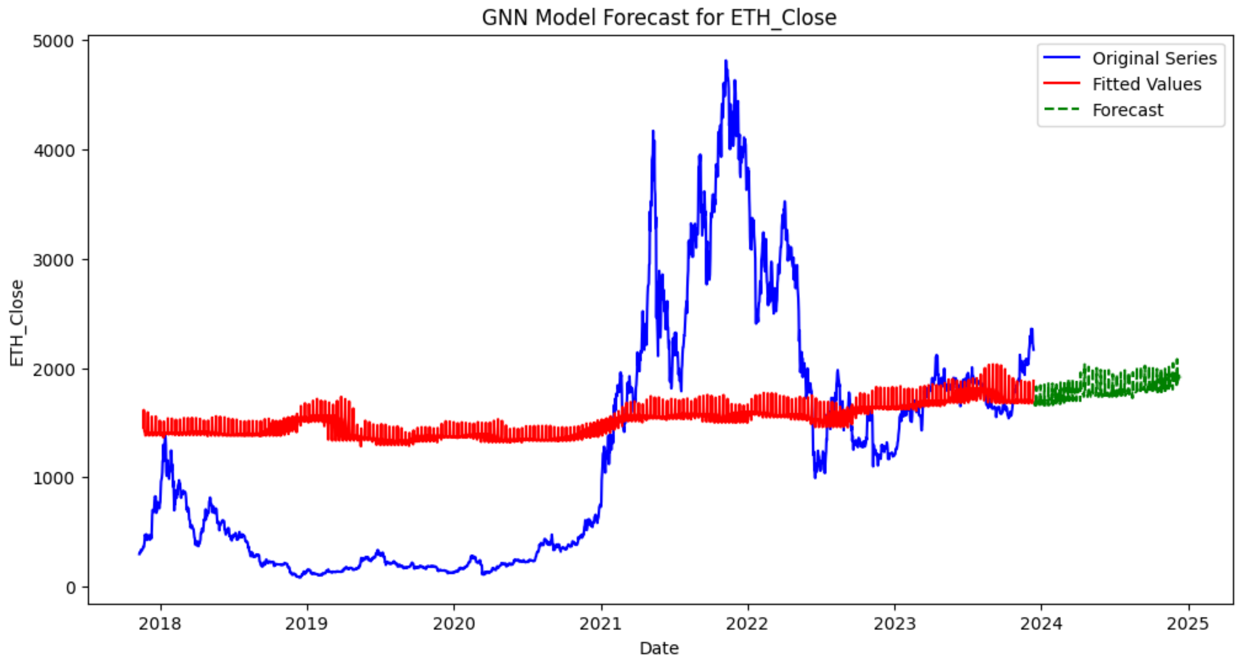

Figure 4.5: GNN Model Forecast for ETH_Close

This visualization showcases the forecasting outcomes of a GNN model for Ethereum (ETH) closing prices.

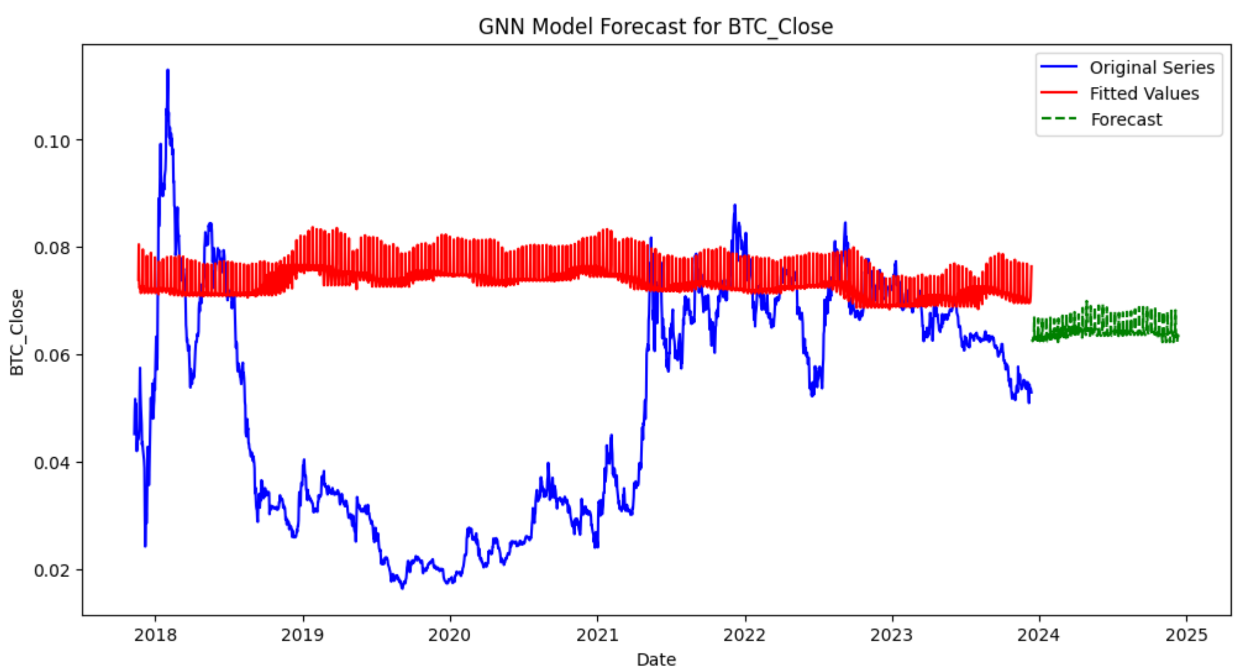

Figure 4.6: GNN Model Forecast for BTC_Close

This visualization showcases the forecasting outcomes of a GNN model for Bitcoin (BTC) closing prices.

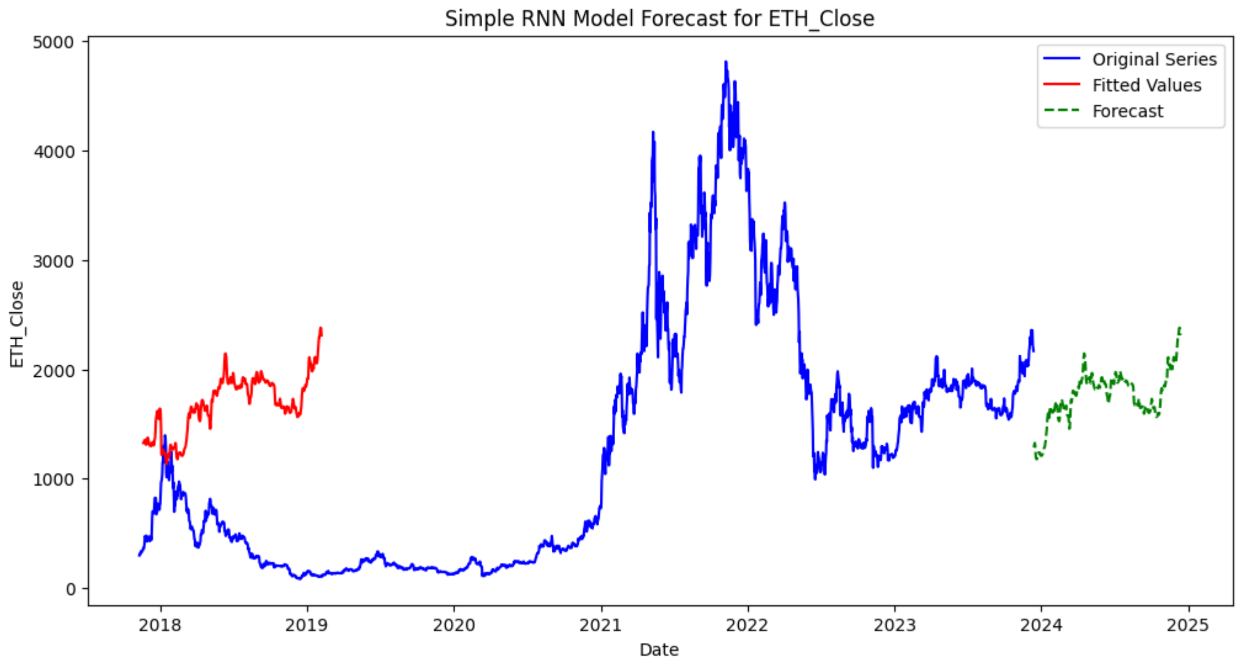

Figure 4.7: Simple RNN Model Forecast for ETH_Close

This visualization showcases the forecasting outcomes of a RNN model for Ethereum (ETH) closing prices.

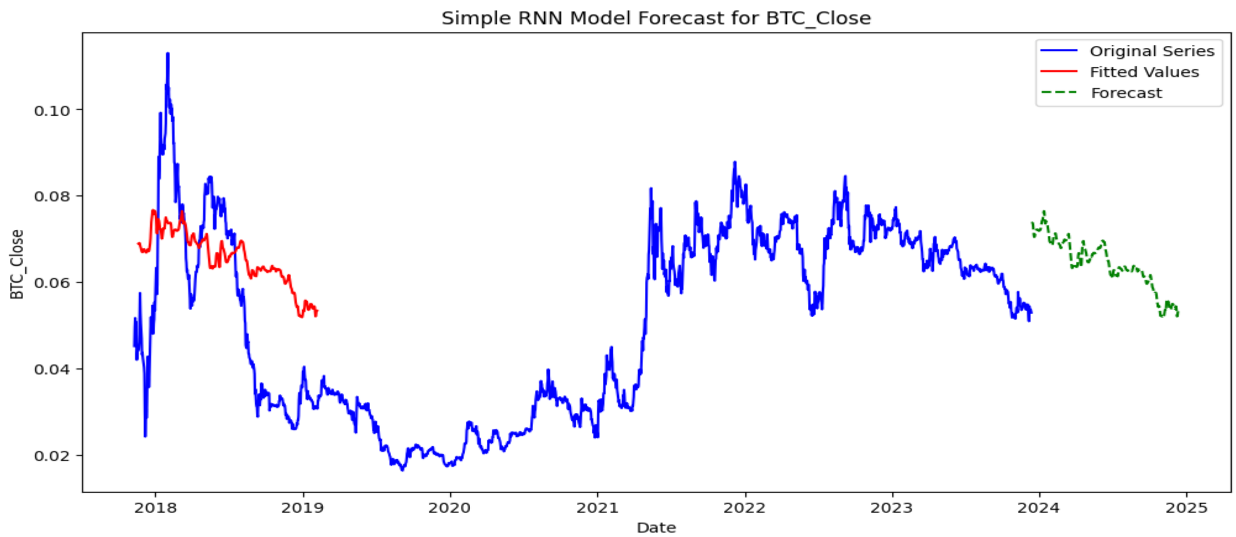

Figure 4.8: Simple RNN Model Forecast for BTC_Close

This visualization showcases the forecasting outcomes of a RNN model for Bitcoin (BTC) closing prices.

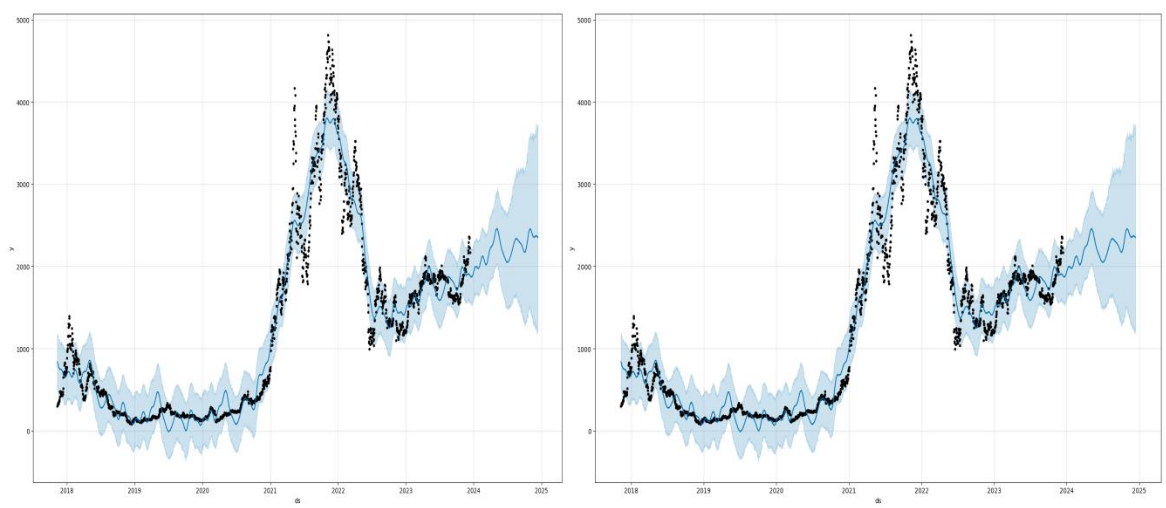

Figure 4.9: Prophet plot for ETH_Close

This visualization, generated using the Prophet library, displays the forecasted values Ethereum (ETH) closing prices. The plot showcases the predicted trends, seasonality, and uncertainty intervals, providing a comprehensive overview of the model's projections. The figure aids in assessing the reliability of the forecast and understanding potential fluctuations in ETH closing prices over the specified time horizon.

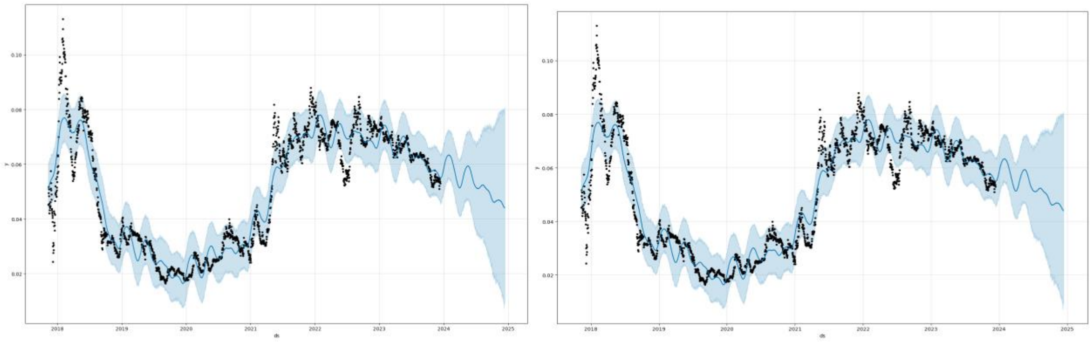

Figure 4.10: Prophet plot for BTC_Close

This visualization, generated using the Prophet library, displays the forecasted values for Bitcoin (BTC) closing prices. The plot showcases the predicted trends, seasonality, and uncertainty intervals, providing a comprehensive overview of the model's projections. The figure aids in assessing the reliability of the forecast and understanding potential fluctuations in BTC closing prices over the specified time horizon.

Chapter 5 Conclusion and Future Scope

The comparison of various models for timestamp-based cryptocurrency price prediction offers valuable insights into their respective strengths and weaknesses. The traditional ARIMA model, while yielding low errors for Ethereum (ETH_Close), struggles to provide accurate forecasts for Bitcoin (BTC_Close). Its inability to capture the intricate patterns in BTC prices is reflected in both zero MAE and RMSE, signaling potential limitations in handling the dynamic nature of cryptocurrency markets.

In contrast, the Transformer model exhibits a notable capacity to capture patterns in ETH_Close, as indicated by the relatively low MAE and RMSE. However, its performance for BTC_Close is less favorable, suggesting that the Transformer model may face challenges in generalizing to different cryptocurrencies. The Graph Neural Network (GNN) presents a mixed performance, excelling in accuracy for BTC_Close but displaying higher errors for ETH_Close. This variance underscores the sensitivity of GNNs to the specific characteristics of each cryptocurrency.

The Simple Recurrent Neural Network (Simple RNN) struggles to provide accurate forecasts for both Ethereum and Bitcoin, with substantially high MAE and RMSE values. This indicates a limitation in capturing the underlying dynamics of cryptocurrency price movements. On the other hand, the Prophet model, designed for time series forecasting, demonstrates competitive performance for ETH_Close, with lower errors compared to the other models. Its ability to capture the inherent patterns in Ethereum prices showcases the effectiveness of specialized forecasting tools.

In conclusion, the choice of a cryptocurrency price prediction model depends on the specific characteristics of the target cryptocurrency. The Transformer model and Prophet stand out for their ability to handle ETH_Close, while GNNs show promise for BTC_Close. The ARIMA model, despite its simplicity, may not be suitable for cryptocurrencies with more complex price dynamics. The results emphasize the importance of considering both generalization capabilities and cryptocurrency-specific characteristics when selecting a model for timestamp-based cryptocurrency price prediction. Future research could explore hybrid models or ensemble approaches to harness the strengths of multiple models and enhance overall predictive performance in this volatile and dynamic market.

5.1 Future scope

The exploration of future avenues in timestamp-based cryptocurrency price prediction offers exciting opportunities for advancements in deep learning and financial forecasting. Further research could delve into enhancing the adaptability and generalization capabilities of existing models, especially Transformer models and Graph Neural Networks (GNNs), to accommodate the evolving dynamics of diverse cryptocurrencies. Integrating external factors such as market sentiment, regulatory changes, and macroeconomic indicators could contribute to a more comprehensive and accurate prediction framework.

Additionally, the development of ensemble models that leverage the strengths of various forecasting techniques may yield improved results, mitigating the limitations of individual models. Exploring explainability and interpretability in deep learning models for better understanding and trust in predictions is another promising avenue. Collaborations between the cryptocurrency industry and the research community could facilitate data access and foster real-world applicability. As the cryptocurrency landscape continues to evolve, the future scope lies in refining models, embracing interdisciplinary approaches, and staying attuned to the dynamic nature of the financial markets.

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