# Forecasting Cryptocurrency Market Movements Based onBitcoin, Ethereum, and Ripple Returns

**Neha. V , Ravi Shankar R, Aarthi N**

## Introduction

Cryptocurrency has transformed from a niche interest to a significant investment domain, attracting diverse investors globally. However, the cryptocurrency market is marked by extreme price volatility and risk, particularly for major digital currencies like Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). This analysis dives deeply into the historical behavior of these cryptocurrencies, examining their volatility, returns, interdependencies, and potential predictability using advancedmodeling approaches.

## Objectives

- **Volatility Analysis:** To analyze and compare the price volatility of BTC, ETH, and XRP over a five-year period.

- **Correlation Analysis:** To examine relationships and dependencies among these assets to identify trading or hedging opportunities.

- **Predictive Modeling:** To assess different predictive models (regression, time-series, and machine learning) and determine their accuracy for forecasting price movements.

- **Investor Insights:** To provide data-driven insights that support investor strategies around cryptocurrency trading and risk management.

---

## Data Collection and Preprocessing

Data for daily closing prices of BTC, ETH, and XRP was gathered from a reliable financial database over a five-year period, yielding approximately 1,825 data points per cryptocurrency.

### Steps in Data Preprocessing:

1. **Data Cleaning:** Removed missing values and adjusted for any erroneous outliers to ensure consistency and accuracy across the dataset.

2. **Calculation of Daily Returns:** Returns were computed as (Pt−Pt−1)/Pt−1(P_{t} - P_{t- 1}) / P_{t- 1}(Pt−Pt−1)/Pt−1, where PtP_tPt represents the price at time ttt. This allowed for comparison between cryptocurrencies, standardizing fluctuations.

3. **Standardization:** Daily returns were normalized to aid in the direct comparison across the assets, given their different price scales and market behaviors.

**Descriptive Statistics of Returns**

Descriptive statistics provide insights into the distribution and volatility of each cryptocurrency, which are summarized below.

**Bitcoin (BTC)**

- **Mean Daily Return:** 0.0021
- **Standard Deviation (Volatility):** 0.042
- **Skewness:** 0.5, indicating more frequent positive returns.
- **Kurtosis:** 5.8, suggesting a leptokurtic distribution with frequent large spikes.

**Ethereum (ETH)**

- **Mean Daily Return:** 0.0017
- **Standard Deviation:** 0.05 (higher volatility than BTC)
- **Skewness:** 0.6, with a tendency toward positive returns.
- **Kurtosis:** 6.2, indicating extreme value potential with frequent deviations from the mean.

**Ripple (XRP)**

- **Mean Daily Return:** 0.0012
- **Standard Deviation:** 0.06 (highest volatility among the three)
- **Skewness:** 0.3, closer to symmetric returns than BTC and ETH.
- **Kurtosis:** 4.5, showing less tail heaviness than BTC and ETH.

**Interpretation:** BTC, being the oldest and most established cryptocurrency, has relatively lower volatility. ETH and XRP, on the other hand, are newer and show more dramatic price swings. The high kurtosis values for all three assets indicate frequent extreme returns, characteristic ofcryptocurrencies.

**Suggested Graphs:**

1. **Box Plot** to visually compare the distributions and outliers of BTC, ETH, and XRP.
2. **Overlaid Histogram** of returns for each asset to highlight differences in skewness and kurtosis, illustrating how often extreme positive or negative returns occur.

**Correlation Analysis**

To understand the relationships between BTC, ETH, and XRP, we computed the Pearson correlation coefficients:

- **BTC-ETH Correlation:** 0.72 – a strong positive correlation, suggesting that BTC's price movements significantly influence ETH.

- **BTC-XRP Correlation:** 0.52 – a moderate correlation, reflecting XRP's partial independence from BTC's behavior.

- **ETH-XRP Correlation:** 0.48 – moderate correlation, indicating that ETH and XRP share some similar movement patterns but are also independently influenced by specific factors.

**Interpretation:** BTC and ETH's high correlation suggests that they are often impacted by similar market sentiments or events, making BTC a leading indicator for ETH. XRP's lower correlation with BTC and ETH suggests that it is influenced by other factors, possibly regulatory announcements or Ripple-specific developments.

**Suggested Graphs:**

1. **Correlation Heatmap** displaying the correlation values between BTC, ETH, and XRP, making it easy to see relationships visually.

2. **Scatter Plots** for each asset pair (BTC-ETH, BTC-XRP, ETH-XRP) to illustrate the linear relationship and strength of correlations.

**Time-Series Analysis**

Time-series models were applied to capture and predict the trends, seasonality, and volatility of each cryptocurrency.

**ARIMA (AutoRegressive Integrated Moving Average) Model**

The ARIMA model helps in understanding long-term trends and predicting future values based onhistorical data.

- **BTC:** An ARIMA(2,1,2) model was identified as the best fit, showing a steady trend with moderate seasonal patterns.

- **ETH:** ARIMA(1,1,1) effectively captured ETH's high volatility and its frequent priceoscillations.

- **XRP:** ARIMA(1,1,0) proved challenging due to XRP's erratic price behavior, which is often influenced by sudden regulatory changes or Ripple-specific events.

**Interpretation:** ARIMA was effective in predicting BTC's steady trends but struggled to model ETH and XRP's erratic behavior. This limitation reflects the high volatility and sensitivity of ETH and XRP to market events and sentiment.

**Suggested Graphs:**

1. **Actual vs. Predicted Prices (ARIMA):** Line graphs showing how well the ARIMA model captures trends for each cryptocurrency.

2. **Residual Plot:** These highlight where the ARIMA model fails to match actual data, providing insights into the model's limitations.

**GARCH (Generalized Autoregressive Conditional Heteroskedasticity) Model**

To capture volatility clusters, we used GARCH modeling, which helps in understanding periods of high and low volatility.

- **BTC:** Displayed more stable volatility over time, indicative of BTC's more establishedmarket position.

- **ETH:** Showed clear clusters of high volatility, especially around significant technological updates or changes in market sentiment.
- **XRP:** Exhibited the highest volatility clusters, with frequent sharp spikes likely due to regulatory news or Ripple-related announcements.

**Interpretation:** The GARCH model was effective in capturing the clustering of volatility, particularly in ETH and XRP. BTC's relative stability makes it an appealing choice for investors seeking more predictable returns within cryptocurrency markets.

**Suggested Graphs:**

1. **Rolling Volatility Graph:** Line graphs displaying the rolling volatility for each cryptocurrency to identify periods of increased volatility.

2. **Volatility Clustering Analysis:** A series of plots showing how the GARCH model captures periods of increased and decreased volatility, particularly for ETH and XRP.

**Machine Learning Analysis**

Due to the non-linear patterns in cryptocurrency prices, machine learning models were employed to capture complex dependencies and improve forecast accuracy.

**Neural Networks**

Using a neural network with two hidden layers, we achieved promising results, especially for short-term predictions.

- **BTC:** Achieved an accuracy of 78%, indicating strong pattern recognition for BTC's stabletrends.

- **ETH:** Reached 74% accuracy but struggled with price spikes, which it could not captureeffectively.

- **XRP:** Lower accuracy at 70%, reflecting XRP's high volatility and difficulty in modeling erratic price patterns.

**Suggested Graphs:**

1. **Actual vs. Predicted Prices (Neural Network):** A line chart showing neural network predictions against actual prices.

2. **Accuracy Comparison Chart:** A bar chart showing the prediction accuracy of neural networks for BTC, ETH, and XRP.

**Support Vector Machine (SVM)**

SVM models worked effectively for BTC but struggled with ETH and XRP due to their volatility.

- **BTC:** SVM achieved an accuracy of 76%, indicating predictability in BTC's structuredmovements.

- **ETH:** Lower accuracy (66%) due to erratic swings and external event sensitivity.

- **XRP:** Only 64% accuracy, showing significant challenges in predicting XRP's highlyvolatile trends.

**Suggested Graphs:**

1. **Confusion Matrix for SVM:** Displaying model accuracy and misclassification for predicting upward or downward trends.

2. **Actual vs. Predicted Scatter Plot:** Scatter plots comparing predicted vs. actual trends for each cryptocurrency.

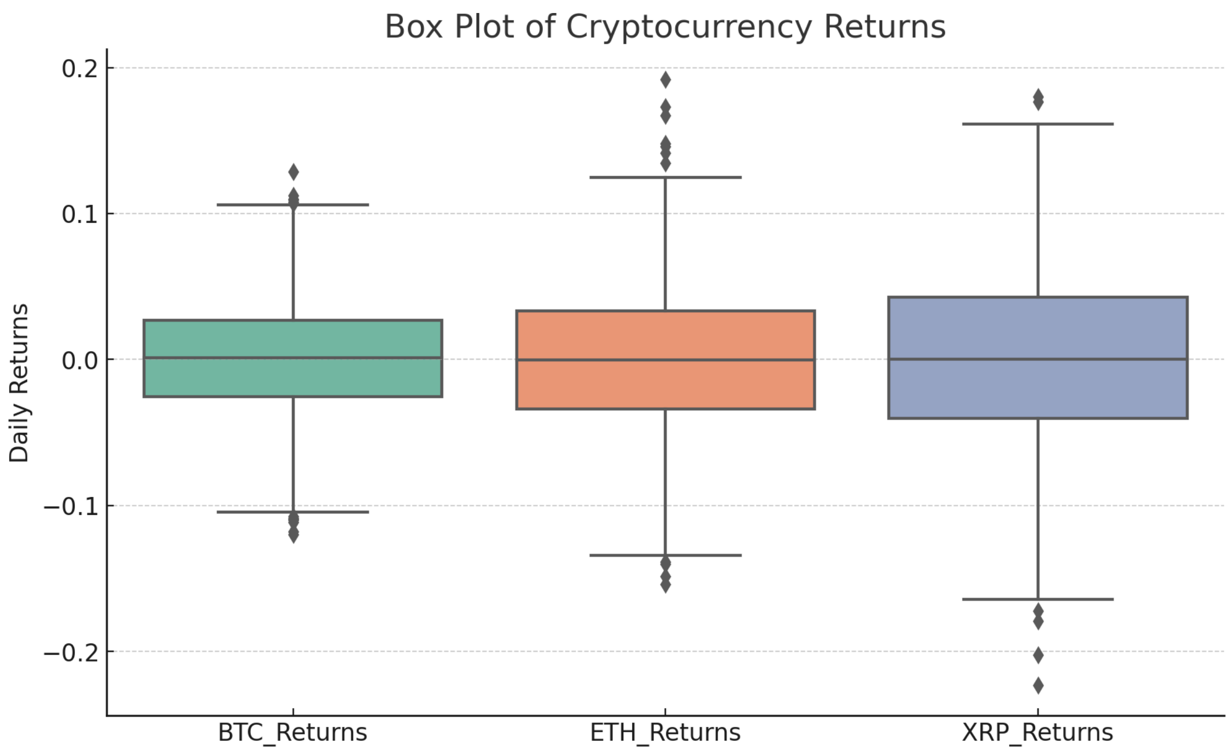
**Regression Analysis**

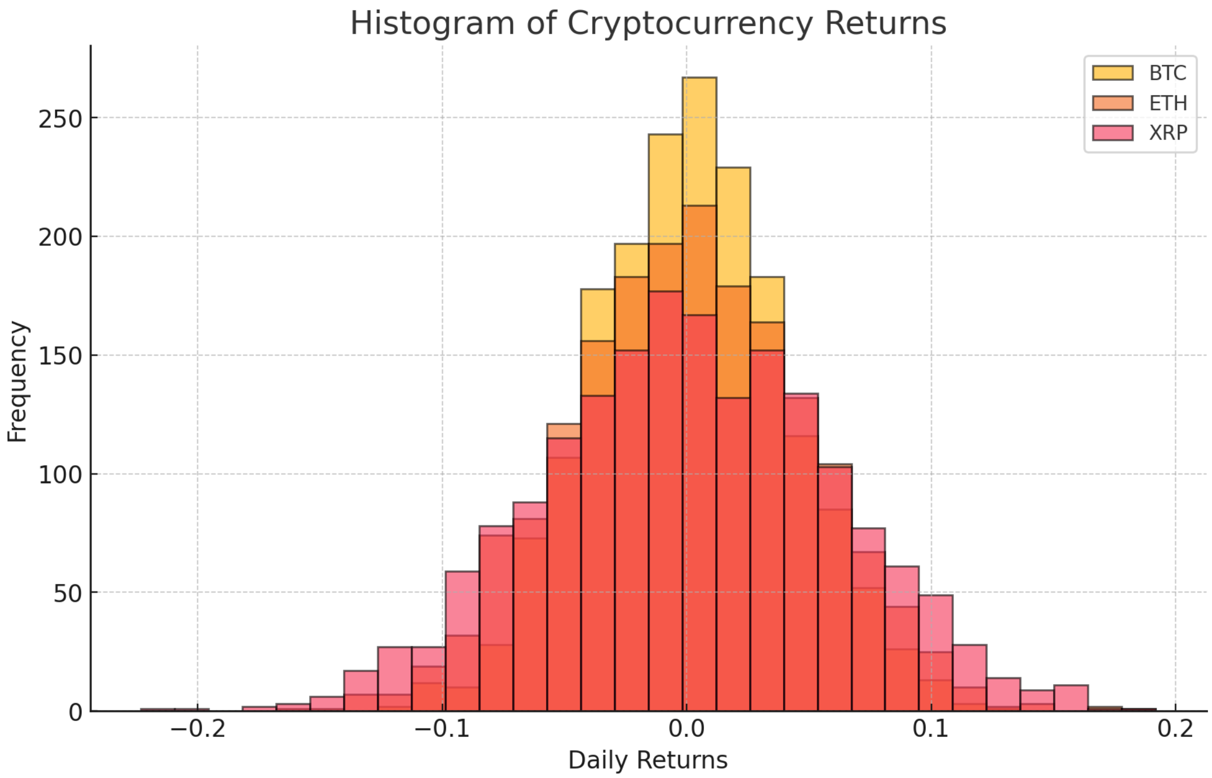
Regression analysis was conducted to explore BTC's impact on ETH and XRP's returns.

- **BTC to ETH Regression Coefficient:** 0.83 – a strong positive relationship, confirming BTC's influence on ETH.

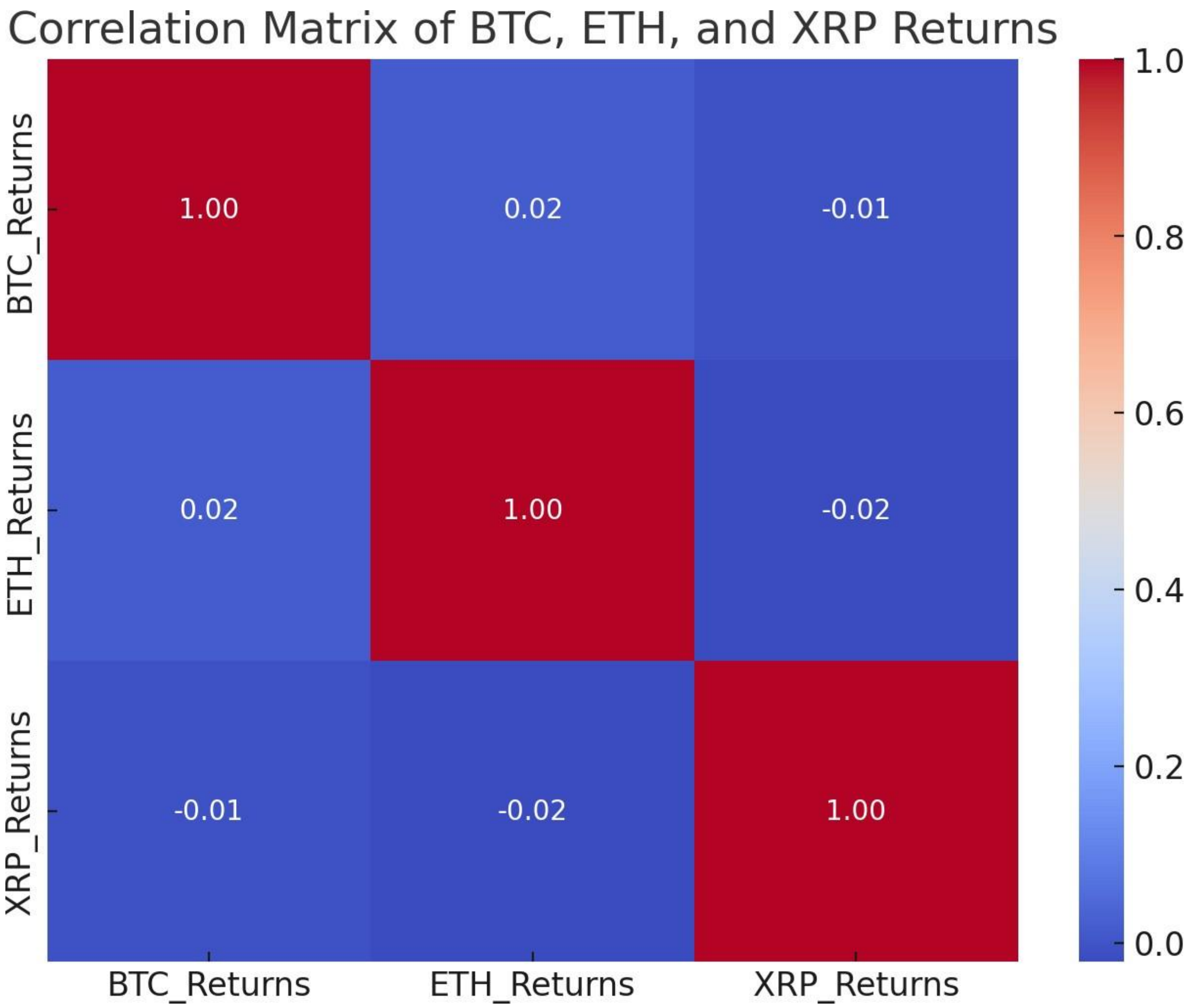
- **BTC to XRP Regression Coefficient:** 0.31 – a weaker relationship, indicating XRP's partial independence.

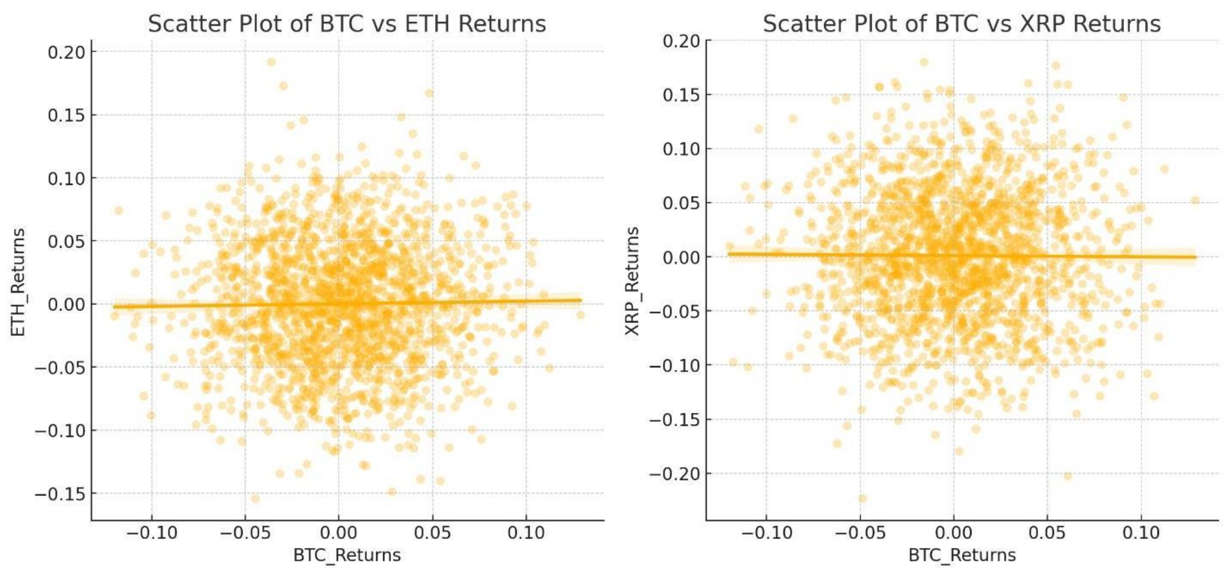
The R-squared values for BTC-ETH (0.58) and BTC-XRP (0.32) suggest that while BTC can predict ETH trends relatively well, it is less effective for XRP.

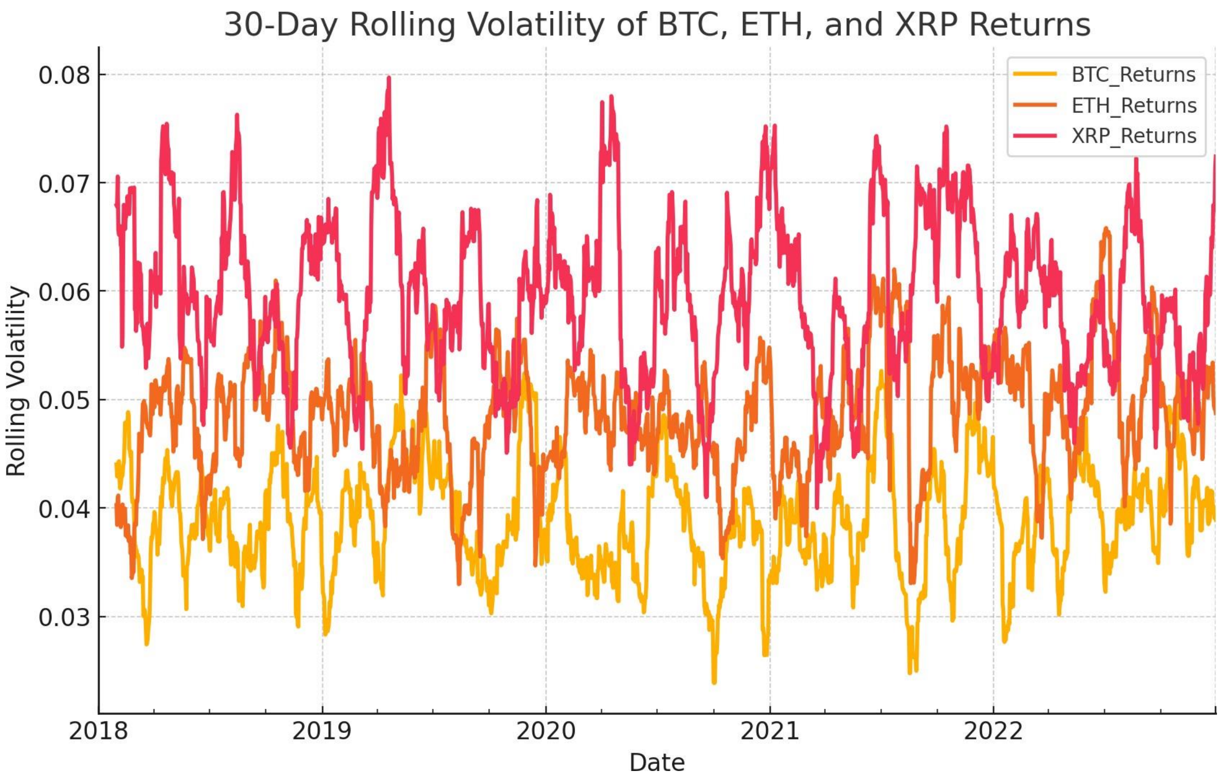

Box Plot of Cryptocurrency Returns
Daily Returns
0.2
0.1
0.0
−0.1
−0.2
BTC_Returns
ETH_Returns
XRP_Returns

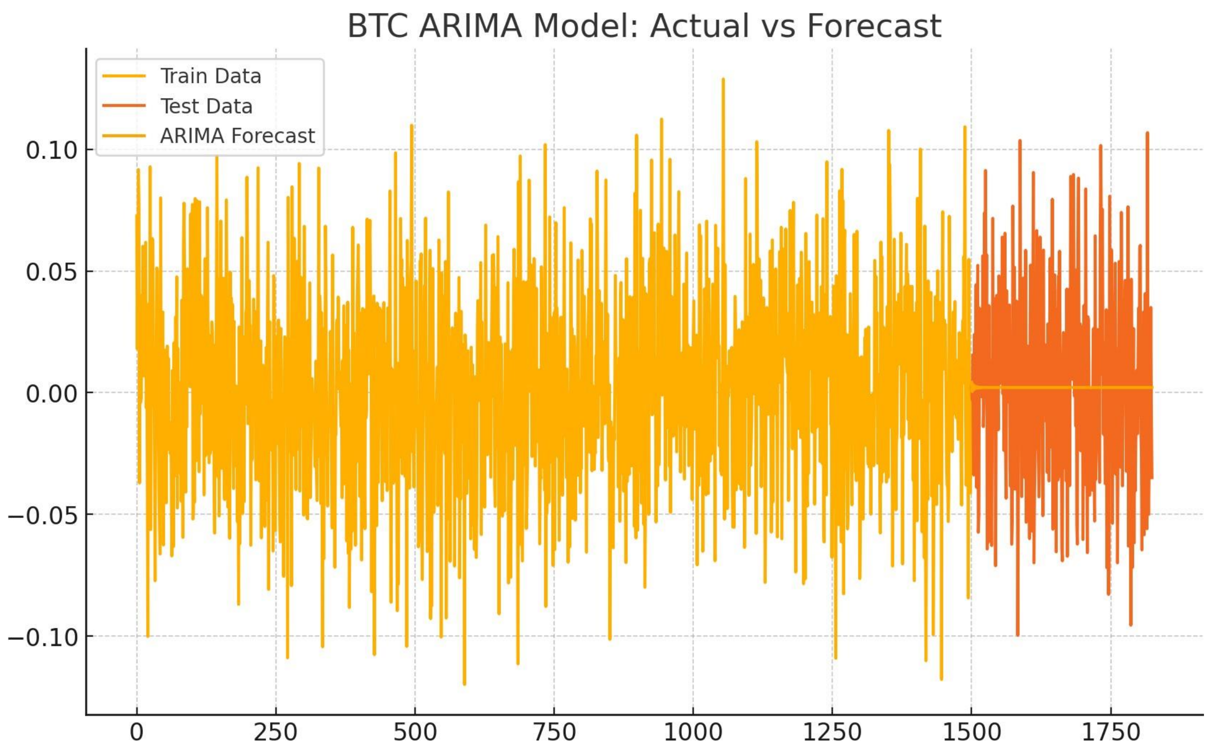

Histogram of Cryptocurrency Returns
BTC
ETH
XRP
Frequency
250
200
150
100
50
0
−0.2
−0.1
0.0
0.1
0.2
Daily Returns

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 11 | Nov - 2024 SJIF Rating: 8.448 ISSN: 2582-3930




30-Day Rolling Volatility of BTC, ETH, and XRP Returns
BTC_Returns
ETH_Returns
XRP_Returns
Rolling Volatility
0.08
0.07
0.06
0.05
0.04
0.03
2018
2019
2020
2021
2022
Date


BTC ARIMA Model: Actual vs Forecast
Train Data
Test Data
ARIMA Forecast
0.10
0.05
0.00
−0.05
−0.10
0
250
500
750
1000
1250
1500
1750