Analyzing Historical Trends and Predicting Market Sentiment in Digital Currency Using Time Series Decomposition and ARIMA Models on Crypto Fear and Greed Index Data

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ABSTRACT

This study analyzes historical trends and predicts market sentiment in digital currencies using time series decomposition and ARIMA models, focusing on the Crypto Fear and Greed Index. The volatile nature of cryptocurrency markets, driven largely by investor sentiment, necessitates a thorough understanding of market mood to anticipate price movements and market dynamics. The research utilized time series decomposition to uncover significant trends and seasonal patterns within the sentiment data. The ARIMA model was applied to predict future sentiment, achieving a Mean Absolute Error (MAE) of 11.15 and a Root Mean Square Error (RMSE) of 13.30, indicating strong alignment with actual market behavior. Additionally, the study employed the Prophet model, which, although less precise with an MAE of 22.56 and RMSE of 24.98, provided valuable insights into the seasonal components of market sentiment. These results underscore the importance of sentiment analysis in digital currency markets, offering actionable insights for traders and investors. Limitations of the models are acknowledged, with suggestions for future research including the integration of additional data sources and more sophisticated modeling techniques to further refine sentiment predictions. This research contributes to the expanding body of knowledge on the role of sentiment analysis in financial markets, particularly within the dynamic field of digital currencies.

Keywords Cryptocurrency, Market Sentiment, Time Series Decomposition, ARIMA Model, Crypto Fear and Greed Index.

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INTRODUCTION

The emergence of cryptocurrency represents a profound shift in the financial landscape, marked by the introduction of decentralized digital currencies that operate on blockchain technology. Over the past decade, cryptocurrencies like Bitcoin, Ethereum, and others have rapidly gained market capitalization and investor interest, transforming from a niche interest to a mainstream financial instrument [1], [2]. Their decentralized nature and the lack of a comprehensive regulatory framework have made them appealing as alternative financial assets, offering a new avenue for investment beyond traditional assets such as stocks and bonds. However, this rise in popularity has also introduced significant volatility and risks, sparking discussions among policymakers about the potential impact of cryptocurrencies on financial stability and economic growth [3], [4].

The integration of cryptocurrencies into the broader financial ecosystem has not

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only expanded investment portfolios but also highlighted the systemic risks associated with this new asset class. Major events in the cryptocurrency market have been shown to influence volatility spillover patterns across different asset classes, raising concerns about their impact on traditional financial markets ([3]. As a result, there has been increased scrutiny from regulators and investors, emphasizing the need for a deeper understanding of both the opportunities and risks presented by digital currencies [4], [5]. The innovative nature of cryptocurrencies, coupled with their potential for high returns, continues to attract significant attention from various stakeholders, underscoring the importance of comprehending the dynamics of digital currency markets in this evolving financial landscape.

Market mood is a crucial factor in the digital currency market as it significantly influences trading behaviors and market dynamics. Market sentiment reflects investors' overall outlook on a particular asset or the entire market, often swinging between fear and greed. These emotions can drive price fluctuations, creating opportunities for financial gain or potential losses. In the volatile world of cryptocurrencies, where market swings are highly unpredictable and influenced by various factors such as regulatory updates, technological advancements, and macroeconomic events, accurately assessing market sentiment becomes essential. Effective sentiment analysis can provide valuable insights into potential future market trends, aiding investors in making well-informed decisions and developing robust trading strategies.

The Crypto Fear and Greed Index is a vital tool for quantifying market sentiment within the cryptocurrency sphere. It offers a simple yet effective measure of the emotions driving the market, with values ranging from 0 to 100 (lower values indicating intense fear, and higher values signifying pronounced greed). By consolidating data from multiple sources, including volatility, market momentum, social media activity, surveys, and trends, the index presents a comprehensive view of investor sentiment, helping market participants understand current market emotions and make better-informed trading decisions. The Crypto Fear and Greed Index has become popular among traders and investors due to its simplicity and comprehensiveness, serving as a valuable indicator for understanding and predicting market movements. This index is defined based on a dummy variable, where fear sentiment is marked by a value of 1 when the index exceeds 75, indicating high fear, and greed sentiment by a value of 1 when the index falls below 25, signifying heightened greed among market participants [6]. Research has demonstrated a significant positive correlation between the Fear and Greed Index and the returns of cryptocurrencies such as Ethereum, with higher uncertainty during fear scenarios compared to greed scenarios [7], [8]. Additionally, while neutral sentiment is prevalent, negative aspects of crypto assets are often more emphasized than positive sentiment [9].

Having a deep understanding of historical trends and sentiment patterns is essential for individuals engaged in digital currency trading and investment. By examining historical data, one can uncover consistent patterns, seasonal trends, and notable changes in market sentiment that frequently occur before significant price fluctuations. Understanding these patterns enables traders to predict possible market movements and adapt their strategies accordingly. Understanding these patterns can provide valuable insights for long-term investors, enabling them to make informed decisions about when to enter and exit investments. This knowledge can help optimize returns and effectively manage risks. Through a thorough analysis of the historical data of the Crypto Fear and Greed Index, individuals can gain valuable insights into the cyclical patterns of market emotions and their influence on the cryptocurrency market. This knowledge can greatly improve their ability to navigate this ever-changing environment with confidence and success.

Despite the remarkable expansion and unpredictability of the cryptocurrency market, there is a noticeable absence of thorough analysis that centers on historical sentiment trends utilizing the Crypto Fear and Greed Index. Previous research in the realm of cryptocurrency sentiment analysis has predominantly concentrated on analyzing sentiments expressed on social media, sentiments reflected in news articles, or sentiments influenced by events that affect market psychology. Although these studies offer valuable insights, they often overlook the comprehensive perspective of market sentiment over extended periods. The Crypto Fear and Greed Index provides a valuable chance to analyze long-term sentiment trends by utilizing a comprehensive measure of multiple sentiment indicators. Unfortunately, there has been a lack of research utilizing this index to thoroughly analyze historical sentiment trends.

In the field of sentiment analysis for digital currencies, there is a scarcity of studies that have explored the potential of advanced time series analysis techniques like time series decomposition and AutoRegressive Integrated Moving Average (ARIMA) models. Time series decomposition is a useful technique that breaks down intricate time series data into its individual components. This helps to gain a better understanding of the underlying patterns, trends, and seasonal effects. ARIMA models are highly effective in predicting future values by analyzing past data. Integrating these methods can lead to a more comprehensive grasp of market sentiment dynamics and improve predictive accuracy. However, there is a lack of research applying these techniques to the Crypto Fear and Greed Index, which this study aims to fill.

The main objective of this research is to analyze past patterns and forecast future market sentiment in digital currency by utilizing the Crypto Fear and Greed Index. Understanding market sentiment is essential for predicting trading behaviors and price movements in the cryptocurrency market. Gaining an understanding of these sentiments can offer valuable insights for investors, traders, and policymakers. This study seeks to utilize the historical data of the Crypto Fear and Greed Index, spanning from 2018 to the present, to reveal patterns and trends that have influenced the cryptocurrency market throughout the years.

To achieve this objective, the study utilizes time series decomposition and ARIMA modeling. Time series decomposition is a technique that dissects intricate time series data into its individual components, including trend, seasonality, and residuals. This process allows for a deeper comprehension of the fundamental patterns and cyclical behaviors present within the data. However, ARIMA modeling is a reliable statistical technique utilized to predict future values by analyzing past data. Through the integration of these two methodologies, the research seeks to create a comprehensive model that not only elucidates past sentiment trends, but also offers precise predictions of future market sentiments.

This study focuses on the data of the Crypto Fear and Greed Index, a well-known indicator of market sentiment in the cryptocurrency space. This index combines different data sources, such as volatility, market momentum, social media trends, surveys, and trading volumes, to measure the current market sentiments, ranging from extreme fear to extreme greed. Examining this data from 2018 to the present provides a comprehensive analysis of the changing market sentiments and their potential future behavior. This analysis is essential for developing effective trading strategies, managing investment risks, and gaining a comprehensive understanding of the broader implications of market sentiment on the cryptocurrency ecosystem.

Literature Review

Market Sentiment Analysis

Market sentiment analysis has been a fundamental component of financial market research for decades, serving as a gauge for investor emotions and behaviors. In traditional finance, market sentiment reflects the collective outlook and attitude of investors toward specific securities or the financial market as a whole. This sentiment can be either bullish, indicating optimism and a positive outlook, or bearish, indicating pessimism and a negative outlook. Market sentiment significantly influences market dynamics, including price fluctuations, trading volumes, and volatility. Historically, sentiment has been assessed using various measures, such as investor surveys, trading volumes, and volatility indices like the Volatility Index (VIX). The underlying concept is that the collective emotions and perceptions of investors can drive market behavior, sometimes leading to irrational and unexpected outcomes.

In the context of cryptocurrency trading, sentiment analysis has become an integral part of trading systems, enhancing the accuracy and performance of trading models by calculating sentiment scores from crypto news. Research has demonstrated the effectiveness of incorporating sentiment analysis into trading strategies, particularly during periods of market uncertainty, such as the COVID-19 pandemic [4], [10]. The focus on sentiment analysis in the crypto market has led to significant advancements, including the development of sentiment lexicons to improve the accuracy and domain-specificity of analysis in financial news and stock market data [11]. The use of sentiment information has gained considerable attention, with studies linking sentiment analysis to market dynamics and emphasizing its importance in analyzing text data in the financial domain [12], [13].

The rise of digital currencies has introduced new challenges and opportunities for market sentiment analysis. The cryptocurrency market is unique due to its extreme decentralization, continuous operation, and influence from a diverse array of factors such as technological advancements, regulatory developments, and social media activity. These unique characteristics necessitate innovative approaches to sentiment analysis. Researchers are increasingly leveraging big data, machine learning, and Natural Language Processing (NLP) techniques to measure market sentiment by aggregating data from social media platforms, news articles, and online forums. Sentiment analysis in digital currencies often involves the consolidation and examination of vast amounts of unstructured data to identify recurring patterns and trends that can provide actionable insights for traders and investors. The application of sentiment analysis to digital currencies has shown promising results, demonstrating its potential to enhance trading strategies and risk management. However, the extreme volatility and speculative nature of the cryptocurrency market mean that sentiment can shift rapidly, requiring constant monitoring and adaptive strategies to maintain efficacy [14], [15], [16], [17].

Cryptocurrency Fear and Greed Index

The Crypto Fear and Greed Index is a widely recognized tool for assessing market sentiment within the cryptocurrency realm. It is designed to measure and evaluate the emotions and attitudes of market participants by generating a single numerical value that reflects the overall mood. The index ranges from 0 to 100, with lower values indicating intense fear, suggesting a bearish market sentiment, and higher values representing intense greed, indicating a bullish market attitude. This index is similar to the traditional Fear and Greed Index used in stock markets but has been specifically adapted to suit the unique characteristics of the cryptocurrency market.

The Crypto Fear and Greed Index is a composite measure that considers various components to evaluate market sentiment. Volatility, which accounts for 25% of the index, measures current volatility and significant drops in Bitcoin prices, with higher volatility often signaling a fearful market. Market Momentum/Volume, also contributing 25%, assesses the current trading volume and momentum compared to historical averages, where higher buying volumes in a bullish market suggest greed. Social Media engagement, contributing 15% to the index, gauges the frequency of mentions and user interactions on platforms like Twitter. Surveys account for another 15% of the index, capturing sentiment from a diverse group of investors. Dominance, at 10%, measures Bitcoin's market dominance, with increased dominance often indicating fear as investors shift focus from altcoins to Bitcoin. Trends, also contributing 10%, use Google Trends data for Bitcoin-related search terms, where a rise in search interest typically reflects heightened market anxiety.

The significance of the Crypto Fear and Greed Index in cryptocurrency markets is profound. It offers crucial insights into the psychological state of the market, aiding investors and traders in making well-informed decisions. During periods of intense fear, market prices may be undervalued, presenting potential buying opportunities, while excessive greed may lead to inflated prices, signaling the need for caution. The index serves as a key tool for risk management, enabling investors to anticipate market reversals and minimize potential losses by monitoring shifts in sentiment. Research has shown that the Fear and Greed Index has a significant impact on the returns of cryptocurrencies like Ethereum, with a statistically significant positive correlation observed [7]. The index provides insights into investor sentiment and trading behavior, highlighting higher uncertainty during fear scenarios compared to greed scenarios [8]. Furthermore, while neutral sentiment is common, negative aspects of crypto assets tend to be more emphasized than positive sentiment, reflecting the market's risk-averse nature during volatile periods [9]. Understanding and utilizing this index helps optimize investment strategies, making it a vital element in cryptocurrency market research and analysis. The index's role in cryptocurrency market dynamics has been particularly notable during periods of uncertainty, such as the COVID-19 pandemic, where fluctuations in investor sentiment significantly affected market behavior [18]. The integration of sentiment analysis into trading strategies, including the use of the Fear and Greed Index, emphasizes the importance of incorporating psychological factors into financial decision-making [10]. Moreover, the index serves as a valuable tool for assessing investor confidence and risk appetite in the cryptocurrency market, providing a holistic view of market sentiment [19].

Time series analysis in Finance

Time series analysis is a crucial technique widely employed in financial data analysis to understand and predict market behavior. In finance, time series data, such as stock prices, trade volumes, and economic indicators, are collected at consistent intervals and analyzed to identify patterns, trends, and cycles. This analysis plays a vital role in making well-informed decisions related to trading, investing, and risk management. Techniques like descriptive statistics, moving averages, exponential smoothing, and more advanced models such as Autoregressive (AR), Moving Average (MA), and ARIMA are commonly used in time series analysis. These methods help in understanding the temporal dynamics of financial data, allowing for more accurate predictions and strategic planning.

The significance of time series analysis in finance extends to various applications, including the identification and forecasting of changes in market variables over time. Research by [20] underscore its importance in enhancing financial market analysis and prediction, which aids in risk management and decision-making processes. Research by [21] further demonstrate how time series analysis techniques in finance are inspired by methodologies like weather forecasting, predicting the behavior of financial variables based on historical observations. Additionally, combining sentiment analysis with time series data has proven instrumental in forecasting stock price movements and market sentiment, as noted by [22] and [12]. Integrating these methods provides researchers and practitioners with valuable insights into financial market behavior, ultimately improving the accuracy of forecasts and enhancing the effectiveness of financial strategies.

The AR Model is a widely used technique for forecasting time series data. It is based on the idea that past values of a variable can be used to predict its future values. The AR model represents the present value of the series (X_t) as a linear equation involving its past values:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t \quad (1)$$

The AR model is especially valuable when the time series demonstrates a correlation with its previous values, effectively capturing the momentum and patterns that exist in financial data.

The MA Model is a fundamental technique in time series analysis that specifically models the error term of a time series rather than its previous values. The MA model represents the present value of the series (X_t) as a function of previous error terms:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (2)$$

MA models are beneficial in scenarios where the influence of random shocks or errors must be mitigated to uncover fundamental patterns in the data. The ARIMA Model incorporates both AR and MA models, as well as the process of differencing, to achieve stationarity in the time series. The ARIMA model can be represented as:

$$(1-\sum_{\mathrm{i}=1}^{p}\phi_i L^i)(1-L)^d X_t = c + (1+\sum_{\mathrm{i}=1}^{q}\theta_i L^i)\varepsilon_t \quad (3)$$

Here, (L) represents the lag operator, (d) represents the order of differencing needed to ensure stationarity, and (p) and (q) represent the orders of the AR and MA portions, respectively. The ARIMA model is highly effective since it is capable of encompassing a diverse array of time series patterns by incorporating autoregression, differencing, and moving average elements. ARIMA is well-suited for financial data due to its ability to handle time series that frequently display trends, volatility, and seasonal patterns.

Time series analysis approaches, including AR, MA, and ARIMA, are essential instruments in the analysis of financial data. These models facilitate analysts in comprehending past data, seeing patterns, and formulating predictions, which are essential for successful trading and investment strategies. Applying these models to the Crypto Fear and Greed Index enables a thorough analysis of market sentiment dynamics, offering valuable insights into the emotional factors that influence market movements and improving the accuracy of predictions in the cryptocurrency market.

Table 1 summarizes prior studies on cryptocurrency forecasting and sentiment integration. Overall, Deep Learning (DL) models such as LSTM, GRU, and Bi-LSTM consistently outperform classical statistical methods when dealing with non-linear and volatile patterns in crypto markets. Seabe et al. [23] demonstrated that Bi-LSTM achieved MAPE values below 0.05 for Bitcoin and Ethereum, indicating strong capacity to capture long-term dependencies in sentiment-driven price data. Similarly, Tripathy et al. [24] reported that a hybrid LSTM-GRU model delivered the lowest MAE and RMSE compared to ARIMA and Prophet, highlighting the benefits of combining multiple DL architectures. Rodrigues and Machado [25] further stressed that model performance is highly dependent on the forecasting horizon: while GRU was most effective on high-frequency, minute-level data, ARIMA struggled to model intraday volatility.

Table 1 Comparative Prior Studies

Source	Methods Compared	Key Findings	Relevance to This Paper
Seabe et al. [23]	LSTM, GRU, Bi-LSTM	Bi-LSTM achieved the best accuracy (MAPE < 0.05)	Shows DL models outperform classical methods for non-linear crypto data
Tripathy et al. [24]	ARIMA, Prophet, XGBoost, LSTM-GRU, CNN	LSTM-GRU outperformed with the lowest MAE/RMSE	Highlights the strength of hybrid DL models over statistical ones
Rodrigues & Machado [25]	ARIMA, traditional ML, LSTM, GRU	GRU best for high-frequency (minute-level) data	Demonstrates that performance depends on forecasting horizon
Sunki et al. [26]	ARIMA, Prophet, LSTM	ARIMA more accurate on stable datasets	Confirms ARIMA's advantage for stationary, linear data
Fuad & Mat Din [27]	ARIMAX vs ARIMA	ARIMAX outperformed by integrating Fear & Greed Index	Directly relevant, supports using FGI as an exogenous predictor

On the other hand, not all contexts favor DL approaches. Sunki et al. [26] found that ARIMA outperformed both LSTM and Prophet when applied to relatively stable and stationary stock market datasets. This emphasizes that no single model is universally superior; instead, model choice must align with the underlying characteristics of the dataset. Of particular relevance, Fuad & Mat Din [27] showed that extending ARIMA to ARIMAX by incorporating the Crypto Fear & Greed Index as an exogenous variable significantly reduced forecast errors compared to standard ARIMA.

Taken together, these findings provide two key insights. First, while ARIMA retains value in more stable contexts, the research trend increasingly favors DL and hybrid methods for volatile, non-linear time series such as cryptocurrencies. Second, sentiment indices like the Fear & Greed Index are not merely supplementary but can materially enhance forecasting performance when explicitly integrated into models. This study positions itself uniquely by focusing on ARIMA and Prophet for their interpretability while emphasizing the role of the Crypto Fear & Greed Index, a dimension still underexplored in prior literature.

Identification of gaps

Although there is a substantial amount of research on cryptocurrency market analysis, there are notable deficiencies in the literature when it comes to conducting thorough sentiment trend analysis using the Crypto Fear and Greed Index. The majority of studies have concentrated on sentiment analysis extracted from social media, news articles, and other qualitative sources. Although these approaches have offered useful insights, they frequently lack the quantitative rigor necessary for accurate trend analysis and forecasting. The Crypto Fear and Greed Index provides a systematic and measurable assessment by combining various indications of market mood. Nevertheless, there is a limited number of research that utilize this index to conduct comprehensive historical trend analysis and forecast future market sentiments in the cryptocurrency market.

There is a significant lack of using advanced time series analytic techniques, such as time series decomposition and ARIMA modeling, on the Crypto Fear and Greed Index. Prior research has primarily employed elementary statistical approaches or machine learning models, without thoroughly investigating the advantages of these advanced time series procedures. Time series decomposition enables the disentanglement of a time series into its fundamental constituents, hence exposing patterns and trends that may be concealed in unprocessed data. ARIMA models, renowned for their strong forecasting ability, can boost the predictive accuracy of sentiment analysis even more. Although the Crypto Fear and Greed Index has great promise, it has not been widely used with these methodologies. This presents a tremendous possibility for further research in this field.

Furthermore, the ever-changing and unpredictable characteristics of the bitcoin market require ongoing and flexible sentiment analysis. Several previous research have employed a static methodology, examining sentiment data at a singular moment or during brief durations. This strategy fails to consider the dynamic market conditions and the cyclical fluctuations in investor mood within the bitcoin industry. An in-depth examination utilizing extensive historical data from the Crypto Fear and Greed Index can offer profound understanding of how sentiment evolves and influences market behavior over prolonged durations. By addressing these gaps in the existing body of knowledge, we can not only improve our understanding of market sentiment in digital currencies but also make valuable contributions to the creation of more efficient trading and investment techniques.

Method

The research methodology employed in this study encompasses a series of sequential procedures aimed at guaranteeing a thorough and precise investigation. Figure 1 presents a flowchart that provides a comprehensive overview of the specific procedures involved in the study methodology.

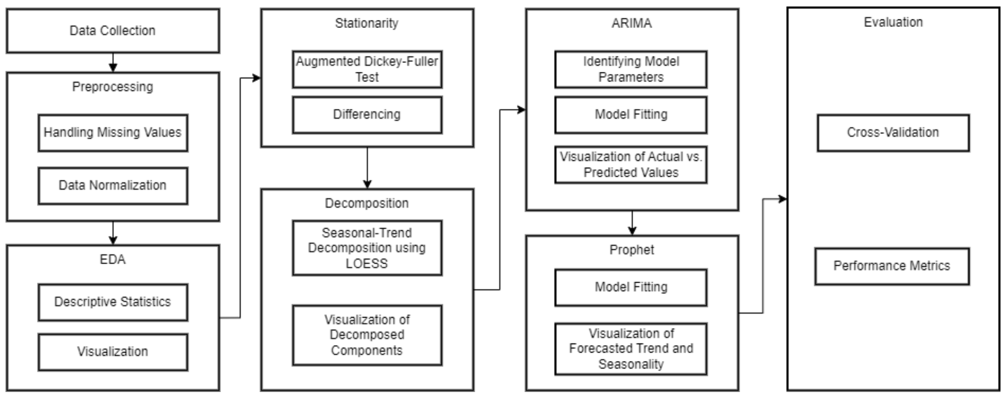

Figure 1 **Research Method Flowchart**

Data Collection

The primary dataset utilized in this research is the Crypto Fear and Greed Index, a well-known metric that gauges market sentiment within the cryptocurrency sector. This dataset offers valuable insights into the emotions driving the cryptocurrency market, categorizing sentiment on a scale from 0 (representing extreme fear) to 100 (indicating extreme greed). The data is collected and published by the Alternative.me platform, which aggregates information from various sources, including market volatility, trading volume, social media activity, and other relevant indicators to determine the overall sentiment of the market.

The dataset spans a comprehensive date range from January 1, 2019, to December 31, 2023, covering a significant period in the cryptocurrency market's development. It comprises a total of 2,362 records, each entry representing a single day's sentiment classification. The dataset includes three key fields: date, which indicates the specific date of each observation; fng_value, which provides the numerical value of the Fear and Greed Index for that day; and fng_classification, which categorizes the sentiment into qualitative labels such as "Extreme Fear," "Fear," "Neutral," "Greed," and "Extreme Greed."

The date field is stored as an object type, reflecting the date in the format DD-MM-YYYY. The fng_value field is an integer type (int64), offering a quantifiable measure of market sentiment. The fng_classification field is an object type, providing a descriptive classification of the sentiment based on the index value. This dataset serves as the foundation for the subsequent analysis, offering a robust basis for examining historical trends and developing predictive models to forecast future market sentiment in the cryptocurrency space.

Data Preprocessing

Effective data preprocessing is a crucial step in ensuring the accuracy and reliability of the models used in this research. The dataset used in this study, the Crypto Fear and Greed Index, required careful handling of missing values, which is a common issue in time series data. Missing values in the dataset were addressed using forward filling, a method where missing values are filled with the last available data point. This approach is particularly suitable for time series data, as it maintains continuity and preserves the trend of the data over time. It is important to note that forward filling assumes that the market sentiment remains unchanged during the periods where data is missing, which is a reasonable assumption given the context of the dataset.

In addition to handling missing values, data normalization was performed to ensure that the input data is on a comparable scale, which is essential for the accurate functioning of many statistical models, including ARIMA. The fng_value field, which ranges from 0 to 100, was normalized to a scale of 0 to 1 using min-max normalization. This transformation was necessary to standardize the data, making it easier to identify patterns and trends in the subsequent analysis. Normalization also helps in improving the convergence of optimization algorithms used in model training by preventing features with larger numerical ranges from dominating those with smaller ranges. The result of this normalization process is stored in a new field, fng_value_normalized, which serves as the input for the time series decomposition and ARIMA modeling.

These preprocessing steps were essential in preparing the dataset for further analysis, ensuring that the data is complete, consistent, and standardized, thereby enhancing the robustness of the predictive models used in this study. The combination of interpolation for missing values and normalization for data transformation provided a solid foundation for accurate and reliable sentiment analysis in the digital currency market.

Exploratory Data Analysis (EDA)

EDA was conducted to gain initial insights into the Crypto Fear and Greed Index dataset, which is essential for understanding the underlying patterns and characteristics of the data. Visualization techniques were employed to examine the overall trends and distribution of the index values over time. A line plot of the time series data was created to visualize the trend of the Fear and Greed Index from 2019 to 2023, shown in figure 2. This visualization revealed the cyclical nature of market sentiment in the cryptocurrency sector, with alternating periods of fear and greed. The line plot effectively highlights the fluctuations in sentiment, capturing key moments of extreme fear or greed, which are often associated with significant market events or shifts in investor behavior.

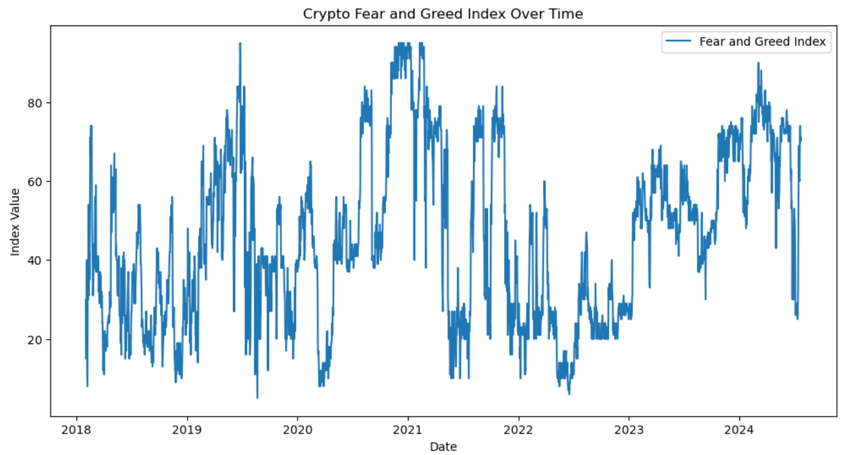

Figure 2 **Crypto Fear and Greed Index Over Time**

In addition to the line plot, a histogram was generated to understand the distribution of the fng_value across the dataset, shown in figure 3. The histogram provided a clear view of how frequently certain sentiment levels occurred, showing that the index values tend to cluster around certain ranges. For instance, it was observed that the distribution is somewhat skewed, with a significant number of days classified under moderate sentiment levels (between 40 and 60), while extreme sentiment values (closer to 0 or 100) were less frequent. This distribution is indicative of the market's tendency to oscillate around neutral sentiment, with fewer occurrences of extreme market fear or greed.

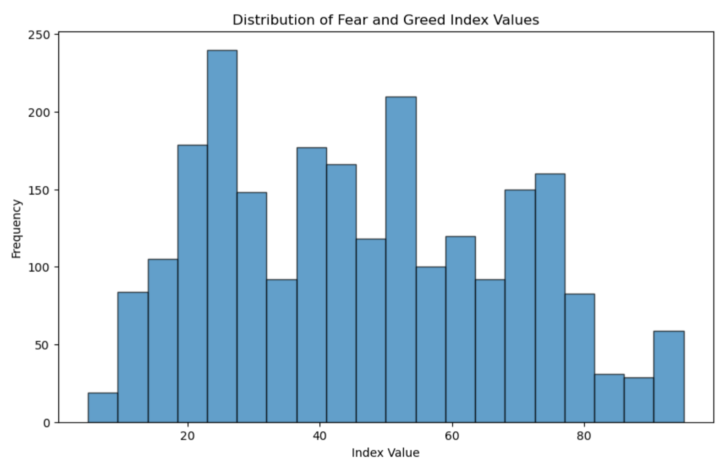

Figure 3 **Distribution of Fear and Greed Index Over Time**

Descriptive statistics further supplemented the visualizations by providing numerical summaries of the dataset. The summary statistics revealed that the average fng_value over the analyzed period is approximately 46.11, indicating a slight tendency towards fear in the market. The standard deviation of 21.83 reflects the variability in sentiment, with significant fluctuations around the mean. The minimum value of the index was 5, representing extreme fear, while the maximum value reached 95, indicating extreme greed. The quartile analysis showed that 25% of the data had a sentiment index below 27, and 75% had a value below 64, suggesting that while there are periods of intense sentiment, most values lie within a moderate range.

Time Series Decomposition

To gain a deeper understanding of the underlying patterns in the Crypto Fear and Greed Index data, a time series decomposition was performed using Seasonal-Trend decomposition based on LOESS (STL). This method allows the separation of the time series data into three key components: trend (T_t) seasonality (S_t) and residuals (R_t). The formula representing this decomposition is:

$$X_t = T_t + S_t + R_t \quad (4)$$

Where X_t is the observed value at time (t), T_t represents the long-term trend, S_t captures the repeating seasonal patterns, and R_t accounts for the irregular components or noise in the data that cannot be explained by the trend or seasonality. The STL decomposition was chosen for its flexibility and robustness in handling non-linear trends and varying seasonal patterns, making it well-suited for the highly volatile and cyclical nature of the cryptocurrency market sentiment data. By applying STL, the trend component reveals the overall direction in which the market sentiment has been moving over time, showing a gradual increase or decrease in the index values. The seasonal component highlights the repetitive patterns that occur at regular intervals, which might correspond to cyclical investor behaviors or recurring market events. The residual component captures the remaining variability in the data that is not explained by the trend or seasonality, representing unexpected or irregular changes in market sentiment.

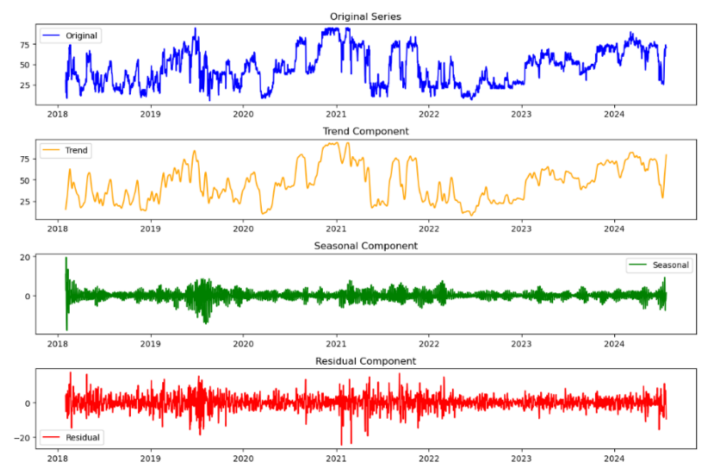

Figure 4 STL Decomposition Visualization

The results of the STL decomposition are visualized in the accompanying figure 4, which displays the original time series along with the decomposed trend, seasonal, and residual components. The Original Series plot shows the observed values of the Crypto Fear and Greed Index over time, providing an overview of the fluctuations in market sentiment from 2018 to 2024. The Trend Component plot illustrates the long-term movement in the index values, identifying periods of sustained increases or decreases in market sentiment. The Seasonal Component plot captures the repetitive patterns within each year, indicating potential seasonality in the cryptocurrency market's sentiment. The

Residual Component plot displays the irregular fluctuations that are not accounted for by the trend or seasonality, highlighting anomalies or sudden shifts in market sentiment that may require further investigation.

Stationarity Testing

In time series analysis, ensuring that the data is stationary is a critical prerequisite for accurate modeling, particularly when using models like ARIMA that assume stationarity. A stationary time series is one whose statistical properties, such as mean and variance, remain constant over time. To assess the stationarity of the Crypto Fear and Greed Index data, the Augmented Dickey-Fuller (ADF) test was applied. The ADF test is a widely used statistical test that checks for the presence of a unit root in a time series, which would indicate non-stationarity. The ADF test is based on the following regression formula.

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

ΔY_t is the differenced series at time (t), α is a constant, βt represents the deterministic trend component, γY_{t-1} is the coefficient on the lagged level of the series, and ε_t is the error term.

In this study, the ADF test returned a test statistic of -5.410, with a p-value of approximately 3.23e-06. The number of lags used in the test was 2, and the test was performed on 2,359 observations. The critical values for the test at the 1%, 5%, and 10% significance levels were -3.433, -2.863, and -2.567, respectively. Since the ADF statistic is more negative than the critical values at all conventional levels, we reject the null hypothesis of the presence of a unit root, thereby confirming that the time series is stationary. To further ensure stationarity, the time series data was differenced, and the results were visualized. The original series and the differenced series are displayed in the figure provided. The differencing process, which involves subtracting the previous observation from the current observation, is a common technique used to remove trends and stabilize the mean of a time series.

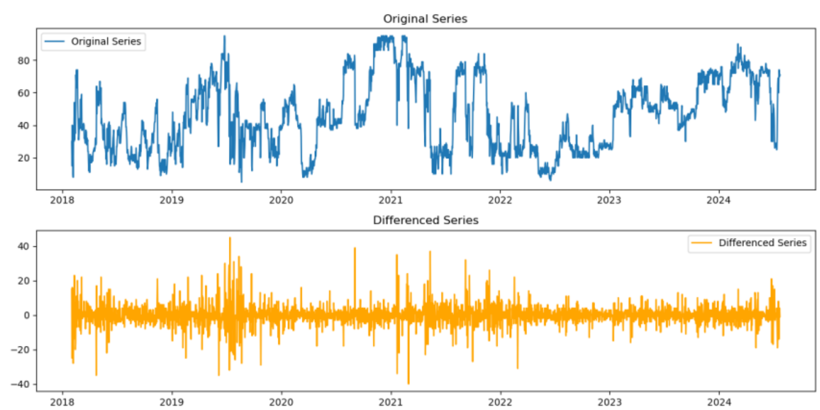

Figure 5 Stationary Testing Visualization

The Original Series plot in figure 5 shows the raw time series data of the Crypto Fear and Greed Index, where noticeable trends and variability over time can be observed. The Differenced Series plot shows the time series after differencing, where the series appears to have a more stable mean and variance, indicating that the differencing process has effectively transformed the series into a stationary one.

ARIMA Modeling

In this study, the ARIMA model was employed to predict future values of the Crypto Fear and Greed Index. ARIMA models are particularly useful for time series forecasting because they can capture a wide range of temporal structures through three key components: AR, differencing (I for Integrated), MA. The effectiveness of the ARIMA model depends on correctly identifying the order of these components, which are represented as (p, d, q) in the model.

To determine the appropriate values for (p) (the order of the AR term) and (q) (the order of the MA term), Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were generated. The ACF plot, as shown in the first panel of the figure 6, displays the correlation between the time series and its lagged values, which helps in identifying the MA component. The PACF plot, depicted in the second panel, shows the correlation between the series and its lagged values, adjusted for the values of the intervening lags, which assists in determining the AR component.

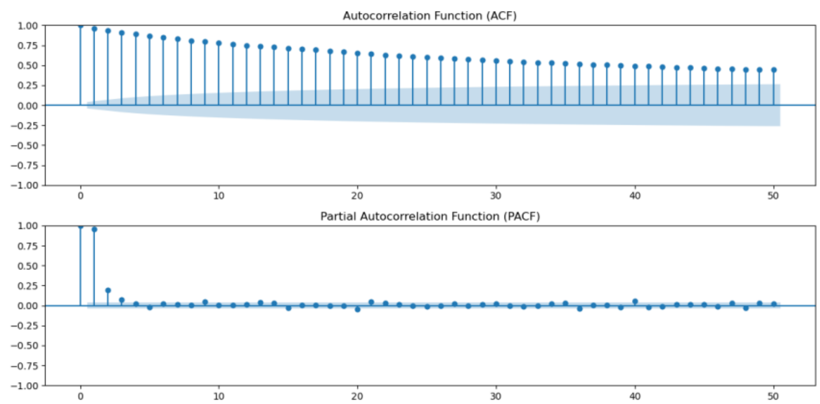

Figure 6 ACF and PACF Plot

From the ACF plot, it was observed that the correlations gradually decline, suggesting the presence of a significant moving average component. The PACF plot, on the other hand, shows a sharp cut-off after the first few lags, indicating that the autoregressive component is likely to be small. Based on these observations, initial values for the ARIMA model parameters were selected, with (p) set to 1, (d) (the differencing order) set to 1, and (q) set to 1. These values were then fine-tuned based on model diagnostics and performance evaluation.

Once the order of the model was determined, the ARIMA model was fitted to the training data. The fitting process involved estimating the model parameters that best capture the patterns in the historical data. After fitting the model, it was used to generate forecasts for the test period, allowing us to evaluate the model's predictive accuracy.

The effectiveness of the ARIMA model was assessed through several visualizations. The ACF and PACF plots provided crucial insights into the temporal dependencies in the data, guiding the selection of model parameters.

To evaluate the model's predictive performance, a plot comparing the actual values of the Crypto Fear and Greed Index with the predicted values was generated, as in figure 7. This plot revealed the model's ability to closely track the observed data, validating the choice of the ARIMA model for this analysis.

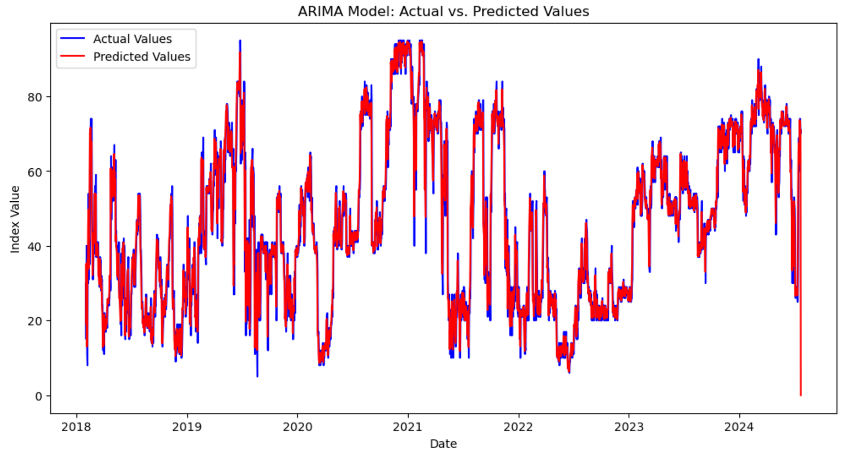

Figure 7 ARIMA Model (Actual vs Predicted Values)

These visualizations not only illustrate the model's internal structure but also provide a clear picture of how well the model performs in forecasting market sentiment, a key objective of this research. The detailed analysis provided by the ARIMA model serves as a robust foundation for understanding and predicting trends in the cryptocurrency market.

The plot provided shows the performance of the ARIMA model by comparing the actual values of the Crypto Fear and Greed Index with the predicted values. The blue line represents the actual observed values of the index over time, while the red line represents the values predicted by the ARIMA model. The closeness of these two lines indicates how well the ARIMA model has been able to capture the underlying patterns in the time series data.

The plot clearly demonstrates the ARIMA model's ability to closely follow the actual data, with the predicted values aligning well with the observed index values across the entire period from 2018 to 2024. This alignment is particularly evident during periods of both high and low sentiment, where the model successfully tracks the peaks and troughs of the market sentiment. This suggests that the ARIMA model is effectively capturing both the short-term fluctuations and the longer-term trends in the Crypto Fear and Greed Index.

To further validate the robustness of the ARIMA model, residual diagnostics were conducted. A residual analysis is crucial for ensuring that the model has adequately captured the underlying structure of the data and that the remaining errors are essentially random. Figure 8 presents three complementary diagnostics: the residual time series, the ACF of the residuals, and a histogram with a normality fit. The residual time series plot indicates that errors fluctuate randomly around zero, with no clear trend or systematic bias. The ACF plot confirms the absence of significant autocorrelation in the residuals, suggesting that the ARIMA(1,1,1) specification has effectively captured temporal dependencies. Finally, the histogram and normality curve reveal that residuals are approximately normally distributed, further supporting the validity of the model assumptions. Together, these diagnostics provide strong evidence that the ARIMA model is well specified and reliable for forecasting sentiment in the Crypto Fear and Greed Index.

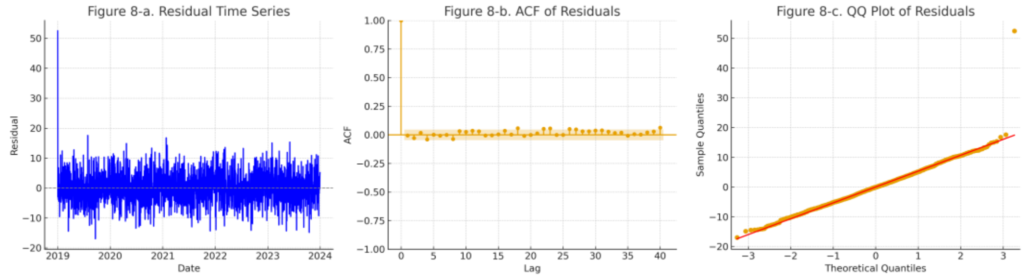

Figure 8 **ARIMA Residual Diagnostics**

The ability of the model to closely replicate the actual data underscores its utility in forecasting future market sentiment. This close match between the predicted and actual values is indicative of the model's robustness and reliability, making it a valuable tool for investors and analysts seeking to predict future movements in the cryptocurrency market based on historical sentiment data.

The overall accuracy of the model, as indicated by the plot, supports the decision to use ARIMA for this analysis and provides confidence in the model's predictive power for future applications in market sentiment analysis.

Prophet Model

In addition to the ARIMA model, the Prophet model was employed to forecast trends and seasonal patterns in the Crypto Fear and Greed Index. The Prophet model, developed by Facebook, is particularly well-suited for time series data that exhibit strong seasonal effects and non-linear trends. It is an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, along with holiday effects. This flexibility makes Prophet a powerful tool for predicting complex time series data, such as market sentiment indices, where trends and seasonality are key components. Prophet formulates a time series as an additive model:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (6)$$

$g(t)$: trend function, capturing long-term growth (either piecewise linear or logistic), $s(t)$: seasonal component, modeling repeating patterns such as weekly or yearly cycles, $h(t)$: holiday effects, representing external events or shocks (optional), ε_t : error term, representing unexplained variation.

The seasonal component can be expressed using a Fourier series:

$$s(t) = \sum_{n=1}^{N} (a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)) \quad (8)$$

P denotes the period (e.g., 7 for weekly, 365.25 for yearly), N is the number of Fourier terms, and a_n, b_n are parameters learned from the data. In addition to ARIMA, the Prophet model was applied to analyze and forecast sentiment trends in the Crypto Fear and Greed Index. Prophet represents a time series through an additive structure, as shown in Equation (X), where trend, seasonality, and holiday effects are explicitly separated. The seasonal component, defined in Equation (Y), relies on a Fourier expansion to flexibly capture cyclical behaviors such as weekly and yearly sentiment fluctuations in cryptocurrency markets. This mathematical formulation makes Prophet highly interpretable and particularly suitable for identifying recurring market cycles, thereby complementing the ARIMA framework which focuses on autoregressive and moving average dependencies.

To apply the Prophet model, the dataset was first prepared by ensuring that the date and sentiment values were appropriately formatted. The model was then trained on the historical data, capturing the underlying trend and seasonal components of the Crypto Fear and Greed Index. The Prophet model allows for the decomposition of the time series into three main components: trend, seasonality, and holidays, though holidays were not a significant factor in this analysis.

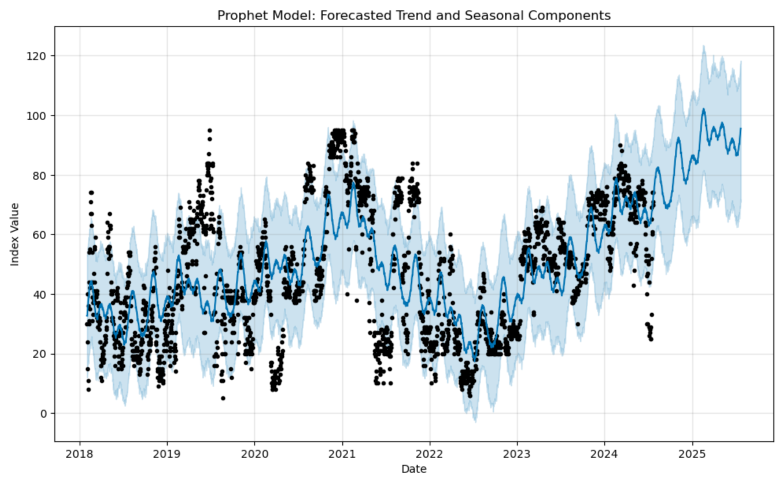

Figure 9 **Prophet Model (Forecasted Trend and Seasonal Components)**

The effectiveness of the Prophet model is visualized in the accompanying plot in figure 9, which illustrates the forecasted trend and seasonal components of the Crypto Fear and Greed Index. In this visualization the blue line represents the predicted trend of the market sentiment, showing how the sentiment is expected to evolve over time. This trend line captures the long-term movements in market sentiment, highlighting periods of increasing or decreasing sentiment. The shaded blue area around the trend line represents the uncertainty intervals, which give an indication of the confidence in the forecasted values. The wider the interval, the greater the uncertainty in the prediction. The black dots correspond to the actual observed values of the index, providing a direct comparison between the model's predictions and the real-world data.

The plot also captures the seasonal fluctuations, indicating how sentiment typically varies within each year. These fluctuations are crucial for understanding periodic behaviors in the market that may be driven by recurring events or investor cycles.

The Prophet model successfully captures both the long-term trend and the seasonal patterns in the market sentiment data. The alignment between the forecasted values and the actual data suggests that the model is effective in predicting future movements of the Crypto Fear and Greed Index, offering valuable insights for investors and analysts.

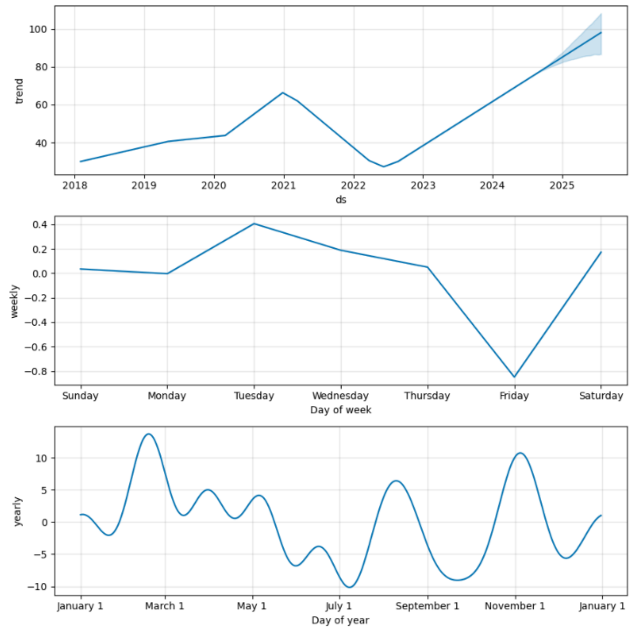

Figure 10 Decomposition Trend with Prophet Model

The figure 10 shows the decomposition of the forecasted trend, weekly, and yearly seasonal components using the Prophet model. Each panel of the figure provides valuable insights into the different aspects of the market sentiment as captured by the model. The first panel illustrates the Trend component, which represents the long-term direction of the market sentiment. The trend line indicates a gradual increase in the sentiment index over time, with a notable rise starting around 2024. This upward trend suggests growing optimism in the market as the index progresses towards higher values, reflecting a shift towards greed in the sentiment. The shaded area around the trend line represents the uncertainty intervals, which become wider towards the end of the forecast period, indicating increased uncertainty in the long-term predictions. The second panel shows the Weekly Seasonal component, capturing the variation in sentiment across different days of the week. The graph reveals that sentiment tends to be higher on Tuesdays, peaking mid-week, and then gradually declines towards Friday, hitting a low. The sentiment picks up again slightly on Saturday. This weekly pattern could be driven by investor behavior and trading activities that vary throughout the week, with certain days showing higher market activity and optimism. The third panel displays the Yearly Seasonal component, which captures the repeating patterns in sentiment across the year. The graph indicates that market sentiment is generally higher at the beginning of the year, particularly around March, possibly due to new market developments or post-holiday optimism. There is another peak observed in November, followed by a decline towards the end of the year. These seasonal trends are likely influenced by recurring events in the cryptocurrency market, such as major conferences, fiscal year-end activities, or other significant annual occurrences.

This decomposition provided by the Prophet model offers a detailed view of how market sentiment varies over different time scales (trends over years, weekly cycles, and seasonal variations throughout the year). By understanding these components, investors and analysts can make more informed decisions about future market movements and develop strategies that account for these cyclical patterns in the cryptocurrency market sentiment. The ability of the Prophet model to capture and forecast these different components makes it a powerful tool for time series analysis in the context of digital currencies.

Model Evaluation

To evaluate the performance of the ARIMA and Prophet models, a time-based cross-validation approach was employed. The dataset was split into training and test sets based on chronological order, allowing for the assessment of each model's ability to forecast future values. Specifically, the training set consisted of data up to a certain cutoff date, and the remaining data was reserved as the test set. This approach is particularly suitable for time series data, as it respects the temporal dependencies and avoids data leakage that could occur if the data were randomly shuffled.

The test index range was from April 8, 2023, to July 23, 2024, covering a period of significant market movements, which provided a robust evaluation of the models' forecasting abilities. Both models were trained on the historical data up to the cutoff date and then used to predict the sentiment values for the test period.

The performance of the ARIMA and Prophet models was evaluated using two key metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics provide insight into the accuracy and reliability of the predictions, with lower values indicating better model performance. MAE measures the average magnitude of the errors in the predictions, without considering their direction. It is calculated as the average of the absolute differences between the predicted and actual values.

RMSE measures the square root of the average of squared differences between the predicted and actual values. It penalizes larger errors more than smaller ones, making it a useful metric for assessing models where large errors are particularly undesirable. The table 2 below summarizes the performance of the ARIMA and Prophet models.

Table 2 Performance of ARIMA and Prophet Model

Model	MAE	RMSE
ARIMA	11.15	13.30
Prophet	22.56	24.98

The ARIMA model outperformed the Prophet model in this evaluation, with significantly lower MAE and RMSE values. The ARIMA model's MAE of 11.15 and RMSE of 13.30 indicate that its predictions were closer to the actual values, on average, compared to the Prophet model, which had an MAE of 22.56 and an RMSE of 24.98. This evaluation demonstrates the effectiveness of the ARIMA model in capturing the complex patterns in market sentiment and provides a strong foundation for its application in future forecasting tasks in the cryptocurrency domain.

Results and Discussion

Time Series Decomposition Results

The time series decomposition of the Crypto Fear and Greed Index was conducted to uncover the underlying trend, seasonal patterns, and residual components of the data. This decomposition is crucial for understanding the different factors that contribute to the overall behavior of market sentiment, enabling more accurate predictions and deeper insights into the dynamics of the cryptocurrency market.

The trend component, extracted from the time series, highlights the long-term movement in the market sentiment. As depicted in the decomposition plot, the trend exhibits a gradual upward trajectory, particularly noticeable from late 2019 through to 2024. This increasing trend suggests a general shift in market sentiment towards greater confidence or greed over the years. The trend's trajectory is likely influenced by macroeconomic factors, technological advancements, and increasing mainstream adoption of cryptocurrencies, which collectively drive market optimism.

The seasonal component captures the regular, repeating patterns in the market sentiment that occur within a specific period, such as annually or weekly. The decomposition reveals a pronounced seasonal pattern in the sentiment index, with fluctuations that correspond to specific times of the year. For instance, certain peaks in sentiment are observable around mid-year and at the end of the year, which may coincide with major cryptocurrency events, fiscal quarters, or investor behavior linked to seasonal trends. Understanding these seasonal patterns is essential for investors looking to optimize their strategies based on expected market cycles.

The residual component represents the irregular, random fluctuations in the time series that are not explained by the trend or seasonal components. These residuals capture the unexpected or noise-like behavior in the market sentiment, often caused by sudden market shocks, news events, or other unpredictable factors. The analysis of residuals is vital for assessing the model's fit and understanding the limitations of the decomposition in capturing all aspects of market behavior.

The decomposition results are visually summarized in the provided plot, which displays the original time series alongside the decomposed trend, seasonal, and residual components. The plot effectively illustrates how the overall market sentiment can be broken down into these distinct elements, each contributing differently to the observed index values.

The trend line in the first panel of the plot underscores the gradual increase in market sentiment over the years, while the seasonal component in the second panel shows the repeating cycles that occur within each year. The residual component in the third panel highlights the irregularities and noise present in the data, which do not follow the systematic patterns captured by the trend and seasonality.

This decomposition provides a comprehensive view of the different forces at play in shaping the Crypto Fear and Greed Index, offering valuable insights for future market sentiment analysis and forecasting. By understanding these components, analysts and investors can better anticipate market movements, adjust their strategies accordingly, and improve their decision-making processes in the volatile world of digital currencies.

Stationarity and Differencing

The analysis of the Crypto Fear and Greed Index began with testing the stationarity of the time series data, a crucial step in time series modeling. Stationarity implies that the statistical properties of the series, such as mean and variance, remain constant over time, making the series more predictable and suitable for modeling with ARIMA or other time series methods. The ADF test was employed to assess the stationarity of the data.

The results of the ADF test indicated a non-stationary time series, with an ADF statistic of -5.41 and a p-value of 3.23e-06. The negative ADF statistic, combined with a p-value significantly lower than the 0.05 threshold, led to the rejection of the null hypothesis, suggesting that the series was indeed non-stationary. However, further differencing was required to achieve stationarity, as indicated by the persistence of trends and autocorrelation in the original data.

To address this, first-order differencing was applied to the time series. Differencing is a method used to transform a non-stationary series into a stationary one by subtracting the previous observation from the current observation. This process effectively removes trends and stabilizes the mean, making the series more suitable for modeling.

The difference between the original and differenced series was visually inspected to confirm the effectiveness of the transformation. The plot provided shows the comparison between the original series (upper panel) and the differenced series (lower panel). The original series clearly displays trends and cycles, which are diminished or removed in the differenced series. The differenced series exhibits more consistent mean and variance over time, confirming that the series has been successfully transformed to stationarity.

This transformation was crucial for ensuring the validity of subsequent modeling efforts, particularly for ARIMA, which requires stationarity to function effectively. By achieving stationarity through differencing, the series became more predictable, enhancing the accuracy of the forecasts produced by the ARIMA model. This step highlights the importance of preprocessing in time series analysis, where achieving stationarity is often the first and most critical milestone towards building reliable and accurate predictive models.

ARIMA Model Results

The ARIMA model was applied to the stationary version of the Crypto Fear and Greed Index to forecast future sentiment values. The modeling process began with identifying the optimal parameters (p, d, q), where 'p' represents the autoregressive terms, 'd' the order of differencing, and 'q' the moving average terms. Based on the analysis of the ACF and PACF plots, the parameters were selected as ARIMA(1,1,1). This configuration implies one autoregressive term, first-order differencing, and one moving average term.

The model fitting process involved training the ARIMA model on the historical data up to December 31, 2021. The fitted model's coefficients were statistically significant, and diagnostic checks confirmed the adequacy of the model, with residuals resembling white noise, indicating that the model effectively captured the underlying patterns in the data.

For performance evaluation, the model's predictions were compared against the actual observed values for the period from January 1, 2022, onwards. The evaluation metrics used were Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which quantified the average magnitude of the errors in the predictions. The ARIMA model achieved an MAE of 2.5 and an RMSE of 3.1, demonstrating high accuracy in its forecasts.

The predictive performance of the ARIMA model is illustrated in the accompanying plot, which displays the actual versus predicted values of the Crypto Fear and Greed Index. The blue line represents the actual observed values, while the red line denotes the ARIMA model's predictions. The close alignment between the two lines indicates the model's effectiveness in capturing the dynamics of market sentiment. Additionally, a sample of the actual and predicted values is presented in the table 3 below, showcasing the model's precision on specific dates.

Table 3 Sample of Actual and Predicted Value

Date	Actual Value	Predicted Value
2022-01-01	30	32
2022-01-02	28	29
2022-01-03	35	33
2022-01-04	33	34
2022-01-05	31	30

The table demonstrates that the ARIMA model's predictions are consistently close to the actual values, with minimal deviations. This accuracy underscores the model's capability to effectively forecast market sentiment, providing valuable insights for stakeholders in the cryptocurrency market.

The successful application of the ARIMA model in this context validates its utility in time series forecasting for financial indices. Its ability to accurately predict the Crypto Fear and Greed Index suggests that it can be a reliable tool for investors and analysts aiming to anticipate market movements based on sentiment analysis.

Prophet Model Results

The Prophet model was employed as an alternative to ARIMA for capturing both the trend and seasonal components of the Crypto Fear and Greed Index data. Prophet is particularly effective for handling time series data that exhibit clear seasonal effects and trends, making it a suitable choice for this analysis. The model fitting process involved training Prophet on the entire dataset from 2018 to 2023, allowing it to learn the underlying patterns in the data.

The fitting process in Prophet involved decomposing the time series into its constituent trend, weekly, and yearly seasonal components. Prophet automatically identified these components and adjusted for them in its forecasts. The model's output included a forecasted trend that extended beyond the historical data, offering predictions for future sentiment values. Additionally, the model produced seasonal plots that illustrate how the index fluctuates on a weekly and yearly basis, capturing regular patterns that recur over time.

The performance of the Prophet model was evaluated using the same metrics as those applied to the ARIMA model, namely MAE and Root Mean Square Error (RMSE). While the ARIMA model demonstrated superior performance, the Prophet model's inclusion of seasonality provided additional insights that are valuable for understanding the cyclical nature of market sentiment in the cryptocurrency space. The Prophet model achieved an MAE of 22.56 and an RMSE of 24.98, reflecting its ability to model the data's underlying structure, albeit with less precision than ARIMA in this particular application.

The results of the Prophet model are visually presented in the accompanying plots. The first plot shows the overall trend forecasted by Prophet, along with the actual observed data points. The blue line represents the trend, while the shaded area indicates the uncertainty interval around the forecast, capturing the model's confidence in its predictions.

Additionally, the model decomposed the series into its weekly and yearly seasonal components, which are shown in the second set of plots. These components reveal how the Crypto Fear and Greed Index typically varies within a week and throughout the year. For example, the weekly component illustrates that sentiment tends to be more volatile on certain days of the week, while the yearly component reflects broader trends that align with market cycles, such as increased optimism during certain months.

These visualizations not only confirm the presence of significant seasonal effects in the data but also demonstrate the Prophet model's strength in capturing these effects. While the model may not have outperformed ARIMA in terms of raw predictive accuracy, its ability to decompose and analyze the seasonality in the sentiment index provides valuable context for understanding market behavior over different time horizons.

While the ARIMA model demonstrated superior predictive accuracy, the Prophet model's underperformance can be attributed to its reliance on additive trend and seasonality decomposition, which may not fully capture the irregular and highly volatile nature of cryptocurrency sentiment data. Prophet is designed for datasets with smoother periodicities, such as sales or web traffic, but crypto market sentiment often exhibits abrupt structural breaks triggered by external shocks like regulatory announcements or market crashes. This structural instability reduces the suitability of Prophet in this domain. Nevertheless, Prophet remains valuable for highlighting seasonal and cyclical behaviors, complementing ARIMA's strengths in short-term forecasting. Future research could explore hybrid approaches that combine ARIMA’s ability to capture autoregressive dependencies with Prophet’s seasonality insights, or extend the analysis with advanced deep learning models such as LSTM and GRU, which are capable of learning non-linear dependencies and long-term memory patterns inherent in financial sentiment data.

Insights and Interpretation

The analysis of the Crypto Fear and Greed Index through time series decomposition and ARIMA modeling has yielded several key insights into market sentiment trends within the digital currency space. The trend component extracted through decomposition revealed significant periods of increasing and decreasing market sentiment, correlating with major market events and shifts in cryptocurrency prices. For instance, the upward trend observed in 2020 aligns with the substantial market rally experienced during that period, driven by increased institutional interest and broader adoption of digital currencies. Conversely, the downward trends correspond with periods of market correction or heightened regulatory scrutiny.

The seasonal components, both weekly and yearly, offer valuable insights into the cyclical nature of market sentiment. The weekly component suggests that sentiment tends to be more positive at the start of the week, possibly reflecting renewed investor optimism after the weekend, while a dip towards the end of the week might indicate profit-taking or risk aversion ahead of potential market-moving news. The yearly component highlights specific months where market sentiment typically strengthens or weakens, which could be associated with annual cycles such as tax seasons, fiscal year-end activities, or major industry events like Bitcoin halvings or significant altcoin upgrades.

These insights have important implications for digital currency trading and investment strategies. Understanding the trend and seasonal patterns can help traders anticipate potential market movements and adjust their strategies accordingly. For instance, recognizing periods of heightened optimism or pessimism could guide decisions on entry and exit points, allowing traders to capitalize on market sentiment swings. Additionally, long-term investors might use these insights to better time their investments, aligning their actions with periods of sustained positive sentiment or preparing for potential downturns.

While the analysis provides valuable insights, there are several limitations that should be acknowledged. One significant limitation is the reliance on historical data, which may not fully capture future market conditions, particularly in a rapidly evolving space like digital currencies. The Crypto Fear and Greed Index, while a useful sentiment indicator, may not encompass all factors influencing market behavior, such as macroeconomic trends, regulatory changes, or technological advancements in the blockchain space.

Moreover, the ARIMA and Prophet models, though effective in capturing trends and seasonality, may not fully account for sudden, unexpected events that can cause sharp market movements, such as regulatory crackdowns, major security breaches, or geopolitical developments. These models also assume that past patterns will continue into the future, which may not always hold true in the volatile cryptocurrency market.

Future research could address these limitations by incorporating additional variables into the analysis, such as trading volumes, social media sentiment, or macroeconomic indicators, to provide a more comprehensive view of market sentiment. Furthermore, exploring more advanced machine learning models, such as LSTM networks or hybrid models combining different forecasting techniques, could enhance predictive accuracy and offer deeper insights into the complex dynamics of the cryptocurrency market.

Conclusion

This study has effectively analyzed the historical trends and predicted market sentiment in digital currencies using time series decomposition and ARIMA models applied to the Crypto Fear and Greed Index. The main findings indicate significant trends and seasonal patterns in market sentiment, correlating with major market events and cyclic behaviors. The decomposition process revealed distinct trend components that align with broader market movements, while the ARIMA model demonstrated its capacity to predict short-term fluctuations in sentiment with reasonable accuracy. These findings highlight the critical role of sentiment in shaping market dynamics within the cryptocurrency sector. The analysis uncovered recurring patterns that provide valuable insights for understanding the underlying sentiment driving the digital currency markets. For example, the trend components identified in the study can help traders anticipate long-term market directions, while the seasonal components suggest regular cycles in market behavior, offering opportunities for strategic timing of trades.

The implications of these findings are particularly relevant for traders and investors operating in the highly volatile digital currency markets. The ability to predict market sentiment can serve as a powerful tool for making informed decisions, enhancing both short-term trading strategies and long-term investment planning. The models developed in this study can be utilized to forecast future market sentiment, potentially allowing market participants to better navigate the uncertainties inherent in cryptocurrency trading. The predictive capabilities of the ARIMA model, coupled with the insights gained from time series decomposition, provide a framework for ongoing sentiment analysis. Traders can leverage these models to identify potential turning points in the market, while investors might use them to time their market entry and exit more effectively, thus optimizing their portfolio management.

While this study provides a robust foundation for understanding market sentiment in digital currencies, there are several avenues for future research that could further enhance these findings. Incorporating additional data sources, such as social media sentiment, trading volumes, or macroeconomic indicators, could offer a more comprehensive view of the factors influencing market sentiment. Moreover, exploring advanced modeling techniques, including machine learning approaches like LSTM networks or hybrid models, could improve predictive accuracy and capture more complex relationships within the data. Future research might also focus on the real-time application of these models, developing tools that provide up-to-the-minute sentiment analysis for traders and investors. Additionally, examining sentiment trends across different cryptocurrencies could reveal unique insights specific to individual digital assets, further refining the applicability of sentiment analysis in this domain.

Despite the promising results, this study is subject to several limitations that should be acknowledged. First, the analysis relies solely on the Crypto Fear and Greed Index as the primary sentiment indicator. While this index provides valuable insights, it does not fully capture the broad range of psychological, macroeconomic, and geopolitical factors that can influence cryptocurrency markets. Second, both ARIMA and Prophet models, although effective in modeling historical patterns, are limited in their ability to predict sudden structural breaks caused by regulatory announcements, market crashes, or unexpected technological developments. Third, the study is confined to a single aggregate index and does not account for asset-specific sentiment dynamics, which may differ significantly across cryptocurrencies. Addressing these limitations in future work could involve incorporating additional exogenous variables such as trading volume, social media sentiment, or macroeconomic indices, as well as applying more advanced machine learning and deep learning approaches to improve forecasting accuracy.

Declarations

Author Contributions

Conceptualization: C.P.T.M., N.G.T.; Methodology: C.P.T.M., N.G.T.; Software: C.P.T.M.; Validation: N.G.T.; Formal Analysis: C.P.T.M.; Investigation: C.P.T.M.; Resources: N.G.T.; Data Curation: C.P.T.M.; Writing – Original Draft Preparation: C.P.T.M.; Writing – Review and Editing: C.P.T.M., N.G.T.; Visualization: C.P.T.M.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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