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UNVEILING THE HIDDEN PATTERNS IN GREEN CRYPTOCURRENCIES: A TIME-SERIES CLUSTERING APPROACH TOWARDS UNDERSTANDING THE PRICE DYNAMICS

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Abstract

Purpose: The increasing environmental concerns associated with traditional cryptocurrencies led to a growing interest in eco-friendly alternatives and green cryptocurrencies, which utilize energy-efficient consensus mechanisms, offer a sustainable solution to this problem. This research focuses on interconnectedness of price movements of the selected six popular green cryptocurrencies i.e. Cardano (ADA), Algorand (ALG), Solana (SOL), Chia (XCH), Stellar Lumens (XLM), and Nano (XNO). The primary objective is to investigate the non-linear relationships and patterns within the price time series of green cryptocurrencies in order to study which green cryptocurrency performs best under 2 cluster and 3 cluster models by following the time series clustering techniques under Dynamic Time Warping (DTW). **Design/methodology/approach:** Dynamic Time Warping (DTW) is the methodology usedfor flexible alignment of time series. By applying DTW to the price data of the six green cryptocurrencies, we aim to uncover hidden patterns and similarities that may not be apparent through traditional linear analysis. The research methodology involves several steps. Firstly, the historical price data for each cryptocurrency is collected and pre-processed. Secondly, DTW is employed to calculate pairwise distances between the time series, revealing the degree of similarity and dissimilarity among them. Thirdly, clustering of price series of selected cryptocurrencies is done for efficient creation of portfolios with green cryptocurrencies.This study has been carried out on the basis of secondary data. Day-end closing prices of the selected six green cryptocurrencies have been collected from 03rd May 2021 to 10th August 2024 i.e. that longest time window during which prices for all the selected green cryptocurrencies were available at finance.yahoo.com up to 10th August 2024. **Findings:** This study has explored the potential of time series clustering techniques to analyse and categorize green cryptocurrencies based on their historical price and volume data. Out of 2-Clusters and 3-Clusters methodology,3- Clusters Hierarchical methodology is giving the better results where the study reflects Solana (SOL) and Chia (XCH) can be included in a portfolio of cryptocurrencies with Cardano (ADA), Algorand (ALG), Stellar Lumens (XLM), and Nano (XNO) and they are forming the best clusters of green cryptocurrencies. **Originality/value:** Dynamic Data Warping along with the Time Series Clusters methodology is first used in the study of green cryptocurrencies where by studying the non-linear relationships and patterns, investors can make informed decisions and mitigate risks. Additionally, policymakers can leverage these insights to formulate effective regulatory frameworks that promote the sustainable growth of the cryptocurrency industry.

Keywords: Green Cryptocurrencies; Dynamic Time Warping; Historical Prices; Non-Linear Relationships; Time Series Clustering.

INTRODUCTION

Millennials and Gen Z are increasingly drawn to cryptocurrencies, captivated by the promise of blockchain technology. This innovative system offers a secure and transparent way to conduct transactions and store value, resonating with a generation that embraces technological advancements (see Lobao (2022)). Cryptocurrencies like Bitcoin, with their limited supply, are seen as a potential hedge against inflation, appealing to young investors concerned about the erosion of purchasing power. These digital assets also have the potential to revolutionize financial inclusion, providing access to financial services for those traditionally excluded. Additionally, cryptocurrencies offer diversification benefits, helping to reduce overall investment risk (see Wendl *et al*., (2023)).

The allure of significant price appreciation has attracted many young investors, although it's important to acknowledge the inherent risks, including price volatility, regulatory uncertainty, and the environmental impact of cryptocurrency mining (see Wilson (2019)). Cryptocurrencies, like Bitcoin, have become popular but have raised environmental concerns due to their energy-intensive mining process (see Gschossmann*et al*., (2022)). This process, called "proof-of-work," requires a lot of electricity to validate transactions and secure the network, contributing to climate change. Green cryptocurrencies offer a more sustainable solution by using energy-efficient consensus mechanisms like "proof-of-stake."

These mechanisms reduce the need for powerful computers and energy-intensive mining, and some green cryptocurrencies even use renewable energy sources. By adopting these eco-friendly approaches, the cryptocurrency industry can become more sustainable and reduce its carbon footprint (see Monasterolo and Raberto (2018)). This shift is crucial for the long-term success of cryptocurrencies in a world increasingly focused on climate change. Investing in green cryptocurrencies, while promising, comes with challenges similar to traditional cryptocurrencies (as seen from the study made by Dyhrberg (2016) & Corbet *et al*., (2019)). Predicting cryptocurrency prices is notoriously difficult due to their high volatility, rapid price fluctuations, and the impact of global events, regulations, and market sentiment (see Febi*et al*., (2018), Gandal&Hałaburda (2014) & Pham (2016)).

Their relatively short history limits the amount of historical data available for analysis. Additionally, investor psychology and herd mentality (see Lobao (2022)) can drive irrational price movements. Unlike traditional assets, cryptocurrencies often lack tangible assets or earnings to base valuations on, making fundamental analysis challenging. While various technical and statistical models can be used to analyze historical price data (seen from the studies of Monasterolo and Raberto (2018), Selmi *et al*., (2018), Reboredo & Ugolini (2020)), the complex and dynamic nature of cryptocurrency markets makes accurate predictions a significant challenge. While various methods have been used to predict cryptocurrency prices, their accuracy is limited by the market's volatility and complexity. Researchers have employed several techniques, including time series analysis (see Maleki *et al*., (2023)), machine learning (Livieris*et al*., 2020; Gupta & Nain, 2021), and deep learning models (see Livieris*et al.*, (2020) Gupta & Nain (2021)).

Even qualitative methods like sentiment analysis have been explored (Abraham *et al*., (2018), Gurrib, & Kamalov (2022) and Loginova *et al*., (2024)). However, due to the influence of factors like technological advancements, regulations, and investor sentiment, no single method guarantees accurate predictions. This study aims to explore the potential of Dynamic Time Warping (DTW) in analyzing the price movements of six green cryptocurrencies:

Cardano (ADA) (Kiayias*et al.*, (2017)), Algorand (ALGO) (Chen & Micali (2016)), Solana (SOL) (Yakovenko (2018)), Chia (XCH) (Cohen *et al*., (2019)), Stellar Lumens (XLM) (Mazieres (2015)), and Nano (XNO) (LeMahieu (2018)). By clustering their price series, this study aims to contribute to efficient portfolio construction with green cryptocurrencies.

SURVEY OF LITERATURE

This study focused on reviewing past research using Dynamic Time Warping (DTW) to analyze financial time series, particularly daily asset prices. The literature review, conducted on the Scopus database from 2002 to October 2024, used keywords like "Dynamic Time Warping," "Financial Time Series," "Cryptocurrencies," "Predict," and "Trend identification." Out of 63 initial papers, 20 were selected for further analysis.

The very first notable study by Chu *et al*. (2002) introduced Iterative Deepening DTW (IDDTW), an advanced technique for measuring similarity in time series data. Another significant study by Jeong *et al*. (2011) presented Weighted DTW (WDTW), a novel distance measure that incorporates adaptive weights to account for phase differences between time series. From the study of *Petitjean et al*., (2011) DTW Barycenter Averaging (DBA) is introduced as a method to average sequences while another measure like Correlation-based Dynamic Time Warping (CBDTW) as proposed by Banco and Abonyi (2012) is used for highly correlated multivariate time series. It is seen from the study of Coelho (2012) that DTW is used to analyze stock index data and identify patterns that could inform investment decisions. For efficiently searching large time series datasets UCR-DTW algorithm is developed by Rakthanmanon*et al*., (2013). Tsinaslanidis*et al*., (2014) explored using DTW to measure similarities between financial time series of varying lengths while to improve the time series classification Kate (2016) used DTW distances by transforming DTW into a feature-based representation, classification accuracy was significantly enhanced compared to traditional methods like one-nearest neighbour. Another research made by Luczak (2016) shows that the combination of Dynamic Time Warping (DTW) and Derivative Dynamic Time Warping (DDTW) improves clustering of time series data. Although the computational complexity of DTW is seen from the study of Mueen & Keogh (2016) but this study outlined optimization strategies to improve its efficiency and effectiveness.

Another kernel-based approach named as Entropic Dynamic Time Warping Kernel is introduced by Bai *et al.*, (2020) is used for analyzing multiple co-evolving financial time series represented as network structures. To capture the business cycle dynamic relationships and temporal alignments Franses and Wiemann (2020) used DTW to analyse similarities in US state GDP time. This study actually leads to another query that can the DTW be used to understand the pattern recognition in financial markets and this query is answered by Li and Hu (2020) where the DTW and its enhanced versions are used to identify close price patterns.

To address the limitations in traditional DTW, Adaptively Constrained DTW (AC-DTW) is introduced by Li *et al*., (2020). For understanding the systematic risk in the European insurance industry Denkowska and Wanat (2021) used DTW by employing Minimum Spanning Trees (MST) and tail dependence coefficients from analyzing 38 major insurance companies stock quotes. Another model Dynamic Type-2 Fuzzy Time Warping (DT2FTW) is postulated by Safari *et al*., (2021) to predict long-term time-series data under uncertainty. More advanced Dynamic Time Warping for Adversarial Robustness (DTW-AR) framework by Belkhouja*et al*., (2022) is used to enhance the robustness of deep neural networks (DNNs) in time-series analysis. Similarly, Grzejszczak*et al*., (2022) applied DTW to analyze stock market data from the Warsaw Stock Exchange, using it alongside statistical tools like Fourier transformation to identify patterns in stock charts. Howard *et al*., (2022) used dynamic time warping (DTW) to study the lead/lag relationships between E-mini-S&P 500 futures and FTSE 100 futures. Similarly, Thirukonda (2023) combined DTW with Long Short-Term Memory (LSTM) networks to better align multivariate financial data, emphasizing the need for precise alignment in robust financial modelling and prediction. The literature review revealed a notable gap in research on using Dynamic Time Warping (DTW) to analyse cryptocurrency price movements and how time-series clustering could be applied to green cryptocurrencies for building portfolios. This particular gaps in literature inspired the study to investigate how DTW could be effectively applied to cryptocurrency prices, aiming to address these unexplored areas.

DATA DESCRIPTION

The cryptocurrency landscape is constantly evolving, and energy consumption and environmental impact is changing rapidly over time. It is essential to refer to up-to-date research and analysis to get the most accurate information on the greenness of specific cryptocurrencies. Hence, this study referred to 34 most visited websites to have the latest information on green cryptocurrencies. The URLs of the websites referred to for this study, are contained in Annexure. To determine the "greenness" of cryptocurrencies, the factors usually considered (Kilic & Altan, 2023) are:

- Consensus Mechanism: Proof-of-Stake (PoS) is generally considered more energy-efficient than Proof-of-Work (PoW).
- Energy Consumption: The specific energy consumption of the network and its validation process.
- Carbon Footprint: The overall environmental impact of the cryptocurrency's operations.

Ali *et al*., (2024) studied green and non-green cryptocurrencies for their comparative efficiencies and singled out Cardano (ADA) to be the greenest cryptocurrency. Based on the findings of Ali *et al*., (2024) and the 34 websites on green cryptocurrencies, six green cryptocurrencies have been selected for the study. The selected cryptocurrencies and their rankings are contained in table 1. The selection and the rankings of the cryptocurrencies have been done on the basis of three criteria as stated above and an additional criteria supporting projects that prioritize sustainability.

Table 1: Cryptocurrencies selected for the study

Rank	Cryptocurrency	Dubbed as	Rationale for selection
1st	Cardano	ADA	Its energy-efficient PoS consensus mechanism and focus on sustainability
2nd	Algorand	ALG	Its energy-efficient PoS consensus mechanism
3rd	Solana	SOL	Its PoS-PoW hybrid consensus mechanism
4th	Chia	XCH	Its unique Proof-of-Space and Time consensus mechanism
5th	Stellar Lumens	XLM	Its hybrid consensus mechanism that combines PoS and Federated Byzantine Agreement, which is generally considered more energy-efficient than traditional PoW
6th	Nano	XNO	Its unique block-lattice structure and feeless transactions which can potentially reduce energy consumption.

A brief description of the selected six cryptocurrencies is given below:

- Cardano (ADA): Cardano (ADA) is a proof-of-stake blockchain platform focused on security, scalability, and sustainability. It aims to be a third-generation blockchain, building upon the successes of Bitcoin and Ethereum. (see, https://www.allcryptowhitepapers.com/ada-whitepaper/)
- Algorand (ALGO): Algorand (ALGO) is a blockchain platform designed for fast, secure, and scalable transactions. It utilizes a unique Pure Proof-of-Stake consensus mechanism, enabling near-instant transaction finality and low fees. (see, https://algorand.co/blog/the-algorand-whitepaper)
- Solana (SOL): Solana (SOL) is a high-performance blockchain platform known for its fast transaction speeds and low fees. It utilizes a unique Proof-of-History (PoH) consensus mechanism, enabling efficient processing of transactions. (see, https://coindcx.com/blog/cryptocurrency/solana-whitepaper-summary/)
- Chia (XCH): Chia (XCH) is a blockchain platform that uses Proof-of-Space-and-Time (PoST) consensus mechanism, which is more energy-efficient than traditional Proof- of-Work (see, https://www.chia.net/white-paper/)
- Stellar Lumens (XLM): Stellar Lumens (XLM) is a decentralized platform designed for fast, low-cost cross-border payments. It aims to connect banks, payment systems, and individuals globally. (see, https://coindcx.com/blog/cryptocurrency/stellar- lumens-whitepaper-summary/)
- Nano (XNO): Nano (XNO) is a cryptocurrency designed for fast and fee-less transactions. It uses a block lattice architecture, aims to be a user-friendly and scalable digital currency, suitable for everyday payments. (see, https://docs.nano.org/living- whitepaper/)

The cryptocurrencies Cardano, Algorand, Solana, Chia, Stellar Lumens and Nano has been dubbed as ADA, ALG, SOL, XCH, XLM and XNO respectively. This study has been carried out on the basis of secondary data. Day-end closing prices of the selected green cryptocurrencies have been collected from 03rd May 2021 to 10th August 2024 i.e. that longest time window during which prices for all the selected green cryptocurrencies were available at finance.yahoo.com up to 10th August 2024 which was fixed as the cut-off date for collection of data for the study. The collected data set had 1196 data points. The descriptive statistics of the data are contained in Table 2

Table 2: Descriptive Statistics of the Closing Prices of the six selected Cryptocurrencies

Particulars	ADA	ALG	SOL	XCH	XLM	XNO
Mean	0.761	0.524	76	94.2	0.167	2.01
Std. error mean	0.018	0.015	1.77	4.91	0.003	0.059
95% CI mean lower bound	0.727	0.494	72.6	84.6	0.161	1.89
95% CI mean upper bound	0.796	0.554	79.5	104	0.173	2.12
Median	0.47	0.259	42.4	37.8	0.119	1.03
Standard deviation	0.605	0.529	61.4	170	0.104	2.03
Variance	0.366	0.28	3766	28801	0.0109	4.12
Inter-Quartile Range	0.684	0.652	106	44	0.0992	1.5
Range	2.73	2.29	249	1581	0.659	11.8
Minimum	0.242	0.089	9.65	14.8	0.0711	0.569
Maximum	2.97	2.38	259	1595	0.73	12.4
Skewness	1.57	1.46	0.815	4.85	1.97	1.88

Std. error skewness	0.071	0.071	0.071	0.071	0.0707	0.071
Kurtosis	1.64	1.03	-0.605	28.1	4.58	3.12
Std. error kurtosis	0.141	0.141	0.141	0.141	0.141	0.141
Shapiro-Wilk W	0.768	0.757	0.855	0.421	0.747	0.694
Shapiro-Wilk p	< .001	< .001	< .001	< .001	< .001	< .001
25th percentile	0.367	0.169	24.1	31.2	0.104	0.766
50th percentile	0.47	0.259	42.4	37.8	0.119	1.03
75th percentile	1.05	0.821	130	75.2	0.204	2.26

Source: https://finance.yahoo.com and authors' own calculations

Note: The Confidence Interval of the mean has been computed on the assumption that sample means follow a t- distribution withN-1 degrees of freedom.

The null hypotheses for Shapiro-Wilk Test for normality is rejected for all the six cryptocurrencies indicating that the distribution of daily closing prices of all the selected six cryptocurrencies come from a non-normal distribution.

This fact is corroborated by the measures of skewness and kurtosis of all the six selected cryptocurrencies. Daily closing prices of the cryptocurrencies reflect that they all are right skewed. Though skewness of SOL is slightly less than 1, the score of 0.815 exhibits tendency towards right skewedness.

The kurtosis measures of XCH, XLM and XNO are above 2 indicating presence of leptokurtic distribution. The kurtosis of the other three cryptocurrencies i.e. ADA, ALG and SOL are in the range of -3 to +3 indicating mesokurtic distribution.

The Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for the selected cryptocurrencies are shown below.

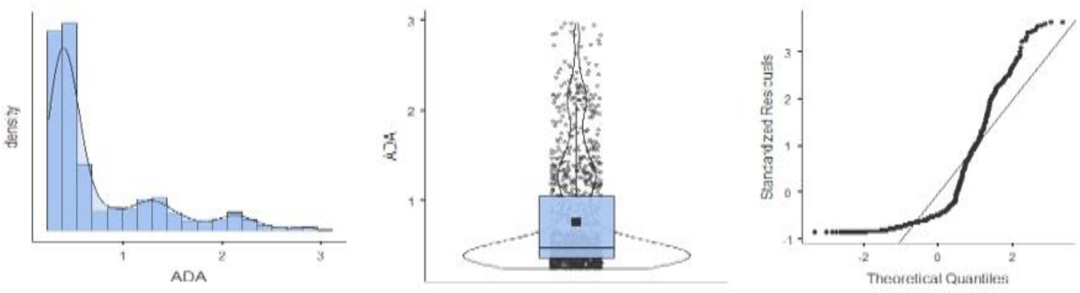

Figure 1: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for ADA

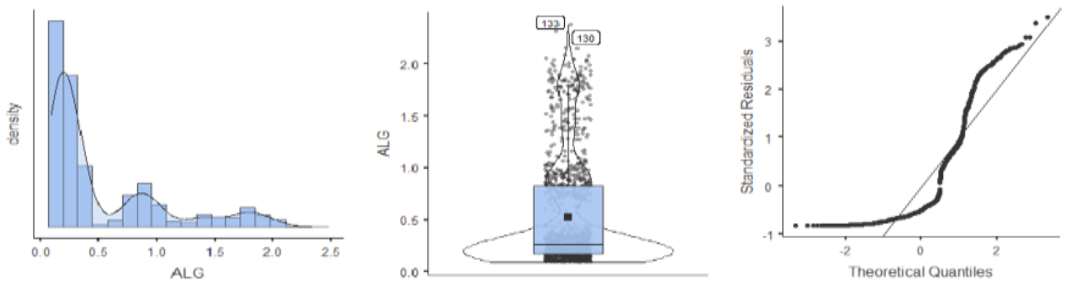

Figure 2: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for ALG

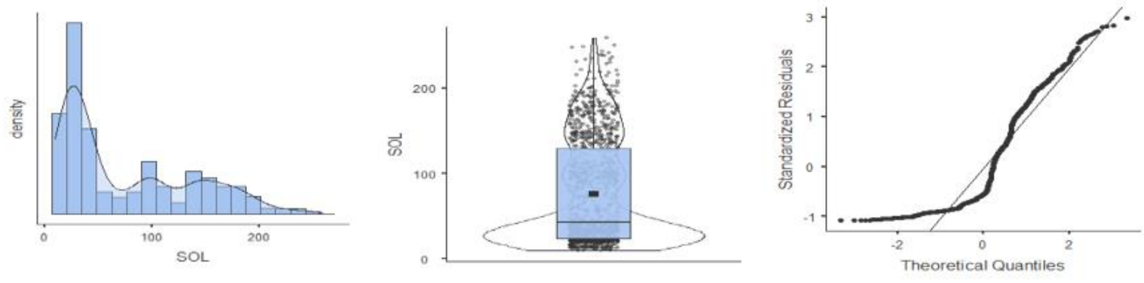

Figure 3: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for SOL

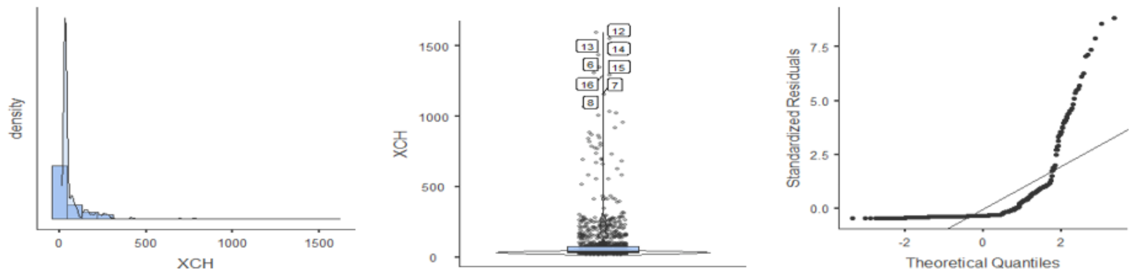

Figure 4: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for XCH

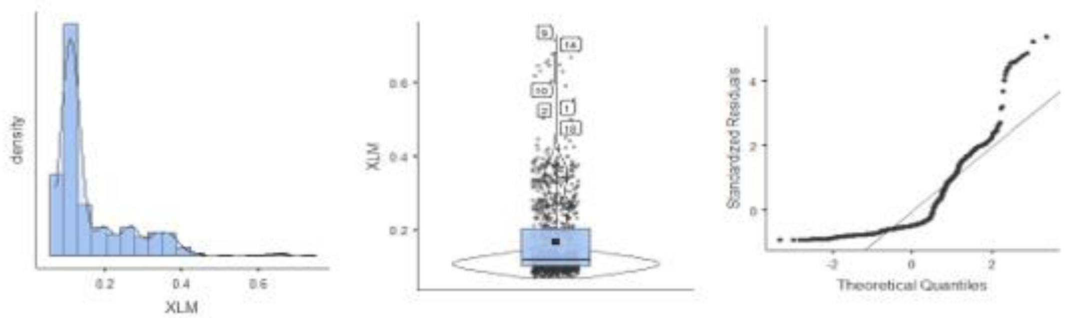

Figure 5: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for XLM

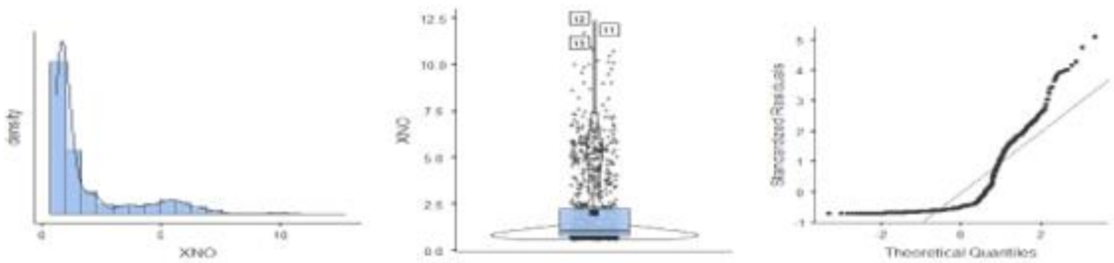

Figure 6: Density Plots, Box and Whiskers Plots and Quantile-Quantile Plots for XNO

The density plots, box plots, and Quantile-Quantile (Q-Q) reveal that the price series of all selected cryptocurrencies exhibit right skewness, where most data points are concentrated on the lower end, and a few extreme values pull the distribution's tail to the right. This is evidenced by means being greater than medians, as means are more sensitive to outliers. Box plots further confirm this by showing outliers on the upper end. Quantile-Quantile (Q-Q) plots comparing the data to a normal distribution reveal significant deviations from the theoretical quantiles, confirming that the price series do not follow a normal distribution and indicating non-normality in the data.

METHODOLOGY ADOPTED IN THIS STUDY

As has been found out in the survey of literature done for this study, Dynamic Time Warping (DTW) is a powerful technique for measuring similarity between two time series, even when they differ in length or speed. It works by finding an optimal alignment between the two sequences, minimizing the cumulative distance between corresponding points.

If two time series, P and Q are considered with lengths m and n, respectively, DTW constructs a cost matrix C, where C(i,j) represents the local distance between points P(i) and

Q(j). The common distance metrics covers the Euclidean distance or Manhattan distance.

The goal of DTW is to find a warping path W, which is a sequence of pairs (i,j) connecting the start (1,1) to the end (m,n) of the cost matrix. The warping path must satisfy certain constraints:

1. Monotonicity**:** The indices in the warping path must be monotonically increasing.
2. Continuity**:** The warping path can only move one step up, down, or diagonally.

The optimal warping path minimizes the accumulated cost along the path: D(P,Q) = min(Σ C(i,j)) for all (i,j) in W

The DTW algorithm uses dynamic programming to efficiently compute the optimal warping path. It starts from the top-left corner of the cost matrix and iteratively fills the matrix using a recurrence relation:

C(i,j) = d(P(i), Q(j)) + min(C(i-1,j-1), C(i-1,j), C(i,j-1))

where d(P(i), Q(j)) is the local distance between the two points. The final distance D(P,Q) is stored in the bottom-right corner of the matrix.

By finding the optimal alignment between two different time series, DTW can identify similarities that may not be apparent from a simple point-wise comparison. This makes it a valuable tool for various applications, including speech recognition, gesture recognition, and financial time series analysis.

Daily closing prices (in USD) of the selected six cryptocurrencies have been collected for 1196 days i.e. from 03 May 2021 to 10 August 2024. Thus, for each of the six cryptocurrencies, there were 1196 data points. The dates were so chosen subject to two constraints. Firstly the closing prices had to be available for all the six cryptocurrencies chosen. Secondly, the data had to be available in https://yahoo.finance.com wherefrom the data have been collected.

With the six cryptocurrencies, 15 pairwise comparisons can be done to assess dissimilarities through DTW. However, as ADA has been found to be the greenest among the six selected cryptocurrencies, pairwise DTW has been done for all the other five cryptocurrencies with ADA. While doing the pairwise analysis, Line-Curves, Distances, 3-way Alignments and Rabiner- Juang Step patterns have been visualized as follows. The blue line represents Cardano (ADA) is all the visualizations and the magenta line represents the other

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cryptocurrency in the pair. The figures 7-11 contain the pair-wise plots of the Time Series Alignments, Query Indices and Query Plots.

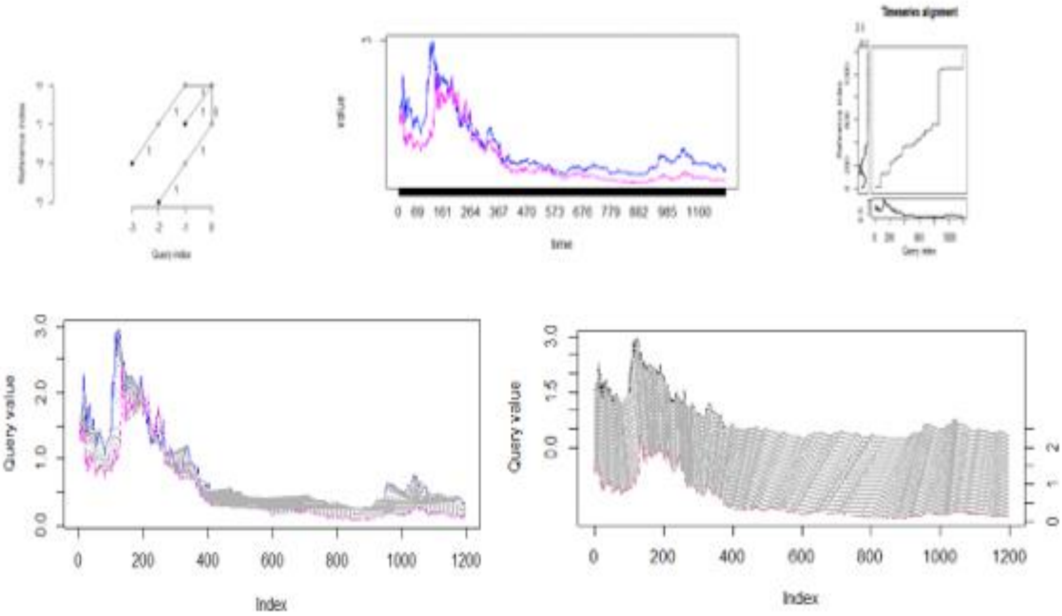


Figure 7: Visualization of patterns between Cardano (ADA) and Algorand (ALG)

The plots in Figure 7 depict a synchronized movement between ADA and ALG indicating that they can be members of a cluster.

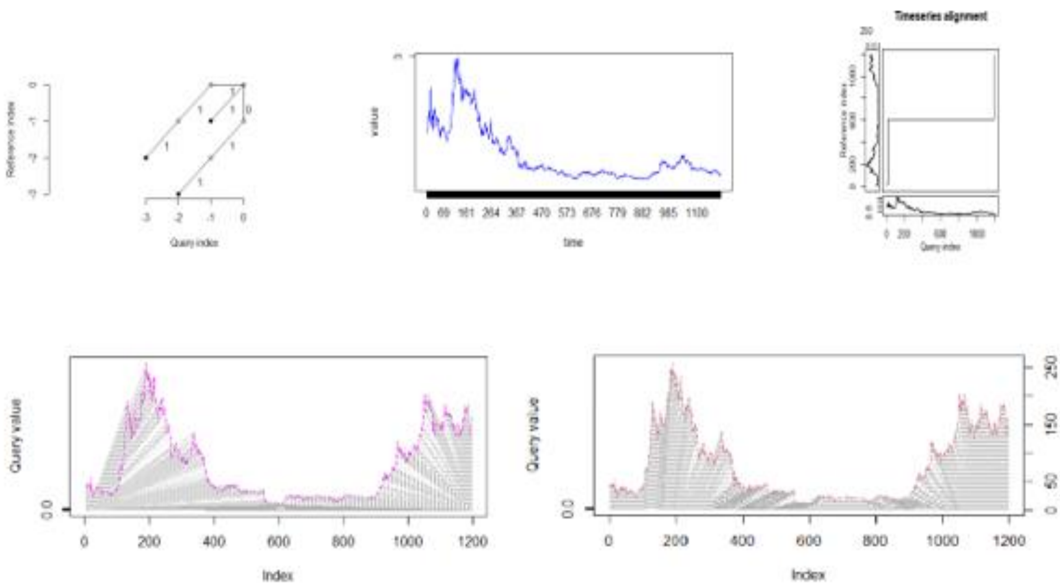


Figure 8: Visualization of patterns between Cardano (ADA) and Solana (SOL)

The plots in Figure 8depict a non-synchronized movement between ADA and SOL indicating that the possibility of them being included in the same cluster is low.

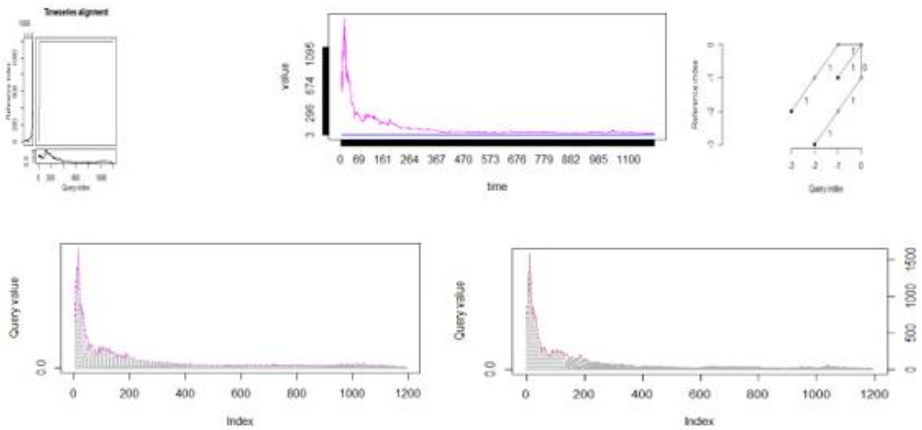


Figure 9: Visualization of patterns between Cardano (ADA) and Chia (XCH)

The plots in Figure 9depict a non-synchronized movement between ADA and XCH indicating that the possibility of them being included in the same cluster is not very high.

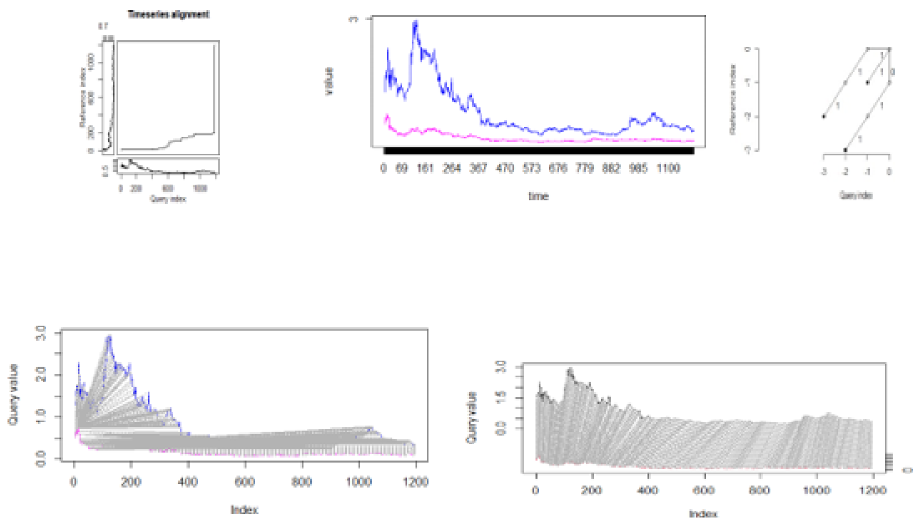


Figure 10: Visualization of patterns between Cardano (ADA) and Stellar Lumens (XLM)

The plots in Figure 10 depict a non-synchronized movement between ADA and XLM indicating that the possibility of them being included in the same cluster is low.

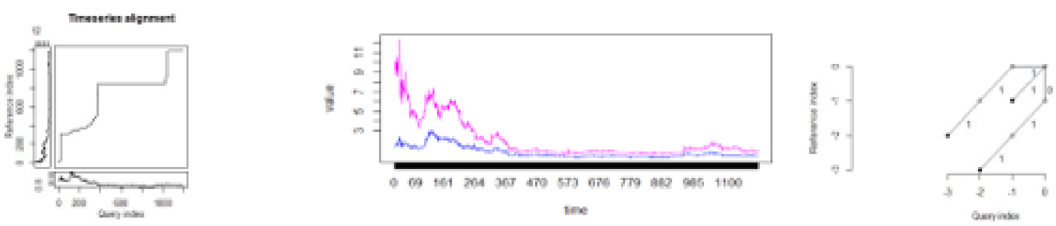


Figure 11: Visualization of patterns between Cardano (ADA) and Nano (XNO)

The plots in Figure 11depict a non-synchronized movement between ADA and SOL indicating that the possibility of them being included in the same cluster is low.

For clustering of the prices of the six selected cryptocurrencies, only two possibilities have been explored. As the number of selected cryptocurrencies is only six and a cluster needs a minimum of two different time series, only two possible numbers of clusters have been explored i.e. 2 clusters and 3 clusters.

The figures 7-11 portrays that SOL and XCH form poor clusters with other cryptocurrencies. On the other hand, ADA and ALG form a distinct cluster just like XLM and XNO also forms a distinct cluster.

Clustering of the six selected cryptocurrency price series has been done using two methods

i.e. k-Medoid method and hierarchical method.

K-Medoids is a clustering algorithm that, unlike K-Means, selects actual data points as cluster centers, making it more robust to outliers and noise because it uses actual data points as medoids. In this method each time series is represented as a sequence of data points:

$$X\_i = \{x\_i(1), x\_i(2), ..., x\_i(T)\}$$

where:

- X_i: the i-th time series
- x_i(t): the value of the i-th time series at time step t
- T: the length of the time series

A distance metric is used to measure the dissimilarity between any two-time series. This study has used DTW as the metric instead of Euclidean Distance i.e.

d(X_i, X_j) = √[sum((x_i(t) - x_j(t))^2 for t in 1...T)]

DTW has been chosen over Euclidean Distance is a powerful distance metric for time series, as it allows for flexibility in aligning time series with different temporal patterns.

The process is initialized by a random selection of K data points as initial medoids i.e. M = {M_1, M_2, ..., M_K}

Each data point is assigned to the nearest medoid based on the chosen distance metric

i.e. C_j = {X_i | d(X_i, M_j) <= d(X_i, M_k) for all k != j}

Where C_j: the j-th cluster and d(X_i, M_j) = the distance between data point X_i and medoid M_j

The steps are updated for each medoid M_j by calculating the total cost of assigning each data point in C_j to a different data point as a potential new medoid and subsequent selection of the data point with the minimum total cost as the new medoid.

The steps are repeated until the assignment of data points to clusters no longer changes and the process converges.

Agglomerative Hierarchical Clustering (AHC) is a bottom-up approach to clustering time series data. It starts by treating each time series as an individual cluster and then iteratively merges the two closest clusters until all data points are in a single cluster.

In this method also, pairwise distance between all time series using DTW. Each time series is initially considered as a separate cluster. At each iteration, the two closest clusters are identified based on a chosen linkage criterion. In this study, Ward's linkage method is used over Single Linkage, Complete Linkage and Average Linkage methods. The two closest clusters are then merged into a single cluster. The Distance Matrix is updated to reflect the new cluster structure. The distance between the newly formed cluster and other clusters has been calculated using the ward's linkage criterion. This process will repeat further until all data points are in a single cluster. The advantages of this method are threefold i.e. it does not require specifying the number of clusters beforehand, it provides a hierarchical structure of clusters and it can handle non-spherical clusters. However, this method has three drawbacks. The computational complexity can be high for large datasets; this method is sensitive to noise and outliers and choice of the distance metric and the linkage criterion can impact results.

Divisive Hierarchical Clustering (DHC) is a top-down approach to time series clustering. This method starts with a single cluster containing all data points and then iteratively splits clusters into smaller ones. All-time series are initially assigned to a single cluster. At each iteration, a cluster is selected for division. Then the cluster is split into two sub-clusters based on a chosen criterion e.g. maximizing the distance between the two sub-clusters and minimizing the within-cluster variance of the two sub-clusters. This process is repeated until a desired number of clusters (2 and 3 in this study) is reached or a stopping criterion is met. In this study, DHC has not been done as it is less commonly used than AHC due to its computational complexity, the choice of splitting criterion significantly impacts the clustering results and most importantly DHC can be sensitive to noise and outliers. The significant number of outliers, as reported in the data description above, makes DHC unsuitable for this study.

FINDINGS OF THE STUDY AND DISCUSSIONS

This research leverages Dynamic Time Warping (DTW) to uncover hidden temporal patterns within cryptocurrency price movements. By employing DTW, this study aims to identify similarities and dissimilarities among the selected cryptocurrencies, providing valuable insights into their market behaviour. To delve deeper into these patterns, this study explores two distinct cluster configurations: a two-cluster model and a three-cluster model. For each configuration, this paper examines the following aspects:

- *Inter-Cluster Centroid Distance Measurement*: The distance between the centroids of different clusters is quantified to assess their similarity and divergence. This metric provides a quantitative measure of the separation between clusters, enabling understanding the degree of distinction among the identified groups;
- *Cluster Size*: The number of cryptocurrencies assigned to each cluster is analyzed which offers insights into the relative importance and influence of different clusters within the market. By examining cluster sizes, dominant groups are identified and their impacts are assessed for overall market dynamics.
- *Cluster Membership Determination*: Specific cryptocurrencies belonging to each cluster are identified. This analysis facilitates understanding of the underlying factors that drive the clustering behavior of different cryptocurrencies. By examining the characteristics of cryptocurrencies within each cluster, insights can be gained into their commonalities and potential correlations.

- *Visualization of Cluster-Wise Price Movements*: The price movements of the selected cryptocurrencies within each cluster are visualized to provide a visual representation of their temporal patterns. This visualization technique helps in identifying distinct trends, cycles, and anomalies within each cluster, which facilitates gaining of a deeper understanding of the underlying dynamics.

By combining these analyses, this study aims to provide a comprehensive understanding of the complex relationships between cryptocurrency prices and to identify potential investment opportunities and risk mitigation strategies.

Considering 2 clusters

The inter-cluster centroid distances, cluster size & cluster memberships are contained in Table 3

Table 3: Inter-cluster centroid distance, cluster size and cluster memberships

Cluster No.	Cluster Size	Cluster Memberships	Average Distance
1	1	SOL	0
2	5	ADA, ALG, XCH, XLM, XNO	134.2584

The clusters are visualized in Figure 12.

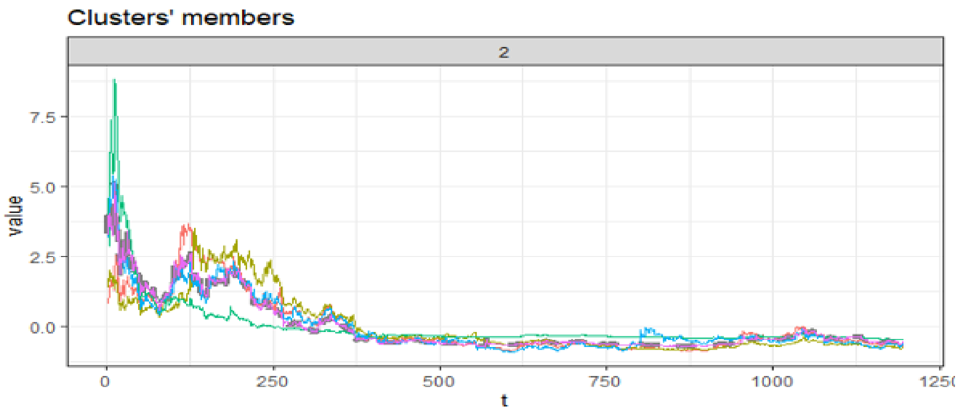
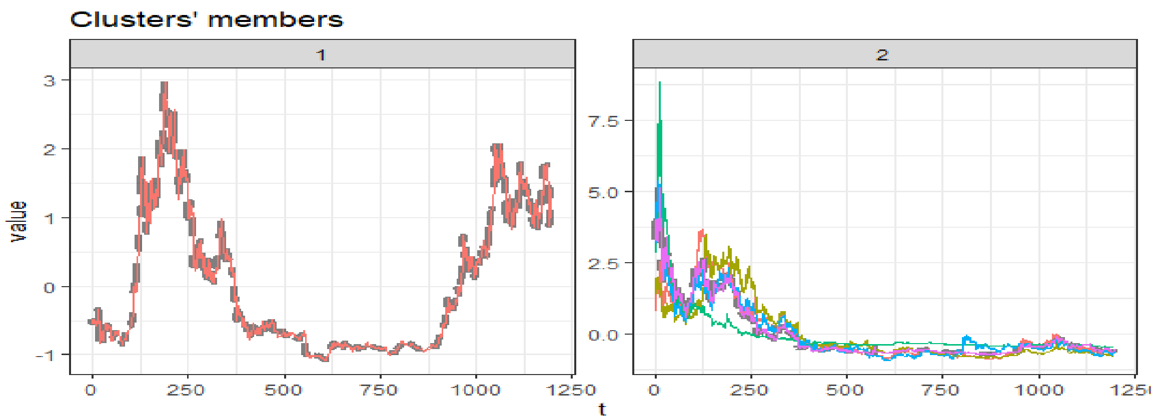


Figure 12: Clustering of the six-time series into 2 clusters

Looking at the plot above, it is evident that two clusters are prominent. The green curve (SOL) is clearly separate from the other five curves.



The same results were obtained when Hierarchical Method was applied considering 2 clusters. Here also the two clusters are visibly distinct.

Considering 3 clusters

The inter-cluster centroid distances, cluster size & cluster memberships are contained in Table 4

Table 4: Inter-cluster centroid distance, cluster size and cluster memberships

Cluster No.	Cluster Size	Cluster Memberships	Average Distance
1	2	ADA, ALG	52.57803
2	1	SOL	0
3	3	XCH, XLM, XNO	117.11443

The clusters are visualized in Figure 13. It is evident that the clusters are well separated from each other.

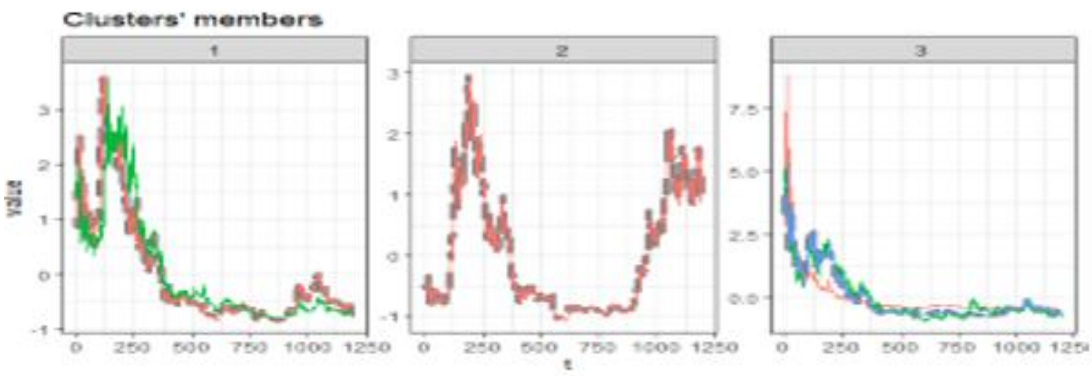


Figure 13: Cluster Membership under K-Medoids Method (Considering 3 clusters)

However, the cluster compositions change if the Hierarchical Method is used.

The inter-cluster centroid distances, cluster size & cluster memberships are displayed in Table 5 if Hierarchical Clustering method is used.

Table 5: Cluster size and cluster memberships

Cluster No.	Cluster Size	Cluster Memberships
1	ADA, ALG, XLM, XNO	ADA, ALG
2	SOL	SOL
3	XCH	XCH, XLM, XNO

The three clusters under Hierarchical Method are visualized in Figure 13A.

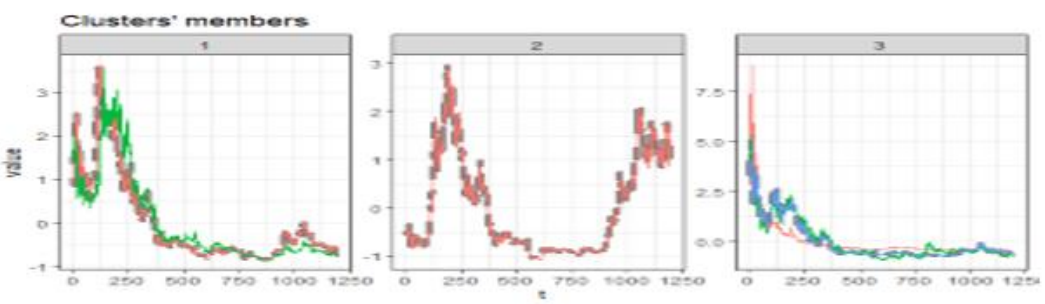


Figure 13A: Cluster Membership under Hierarchical Method (3 Clusters)

Figures 12, 13 and 13A depict the visualizations of the price-series cluster memberships. The clusters as depicted in the Tables 4 and 5 are corroborated through the time-warped movement of the price movements of cryptocurrencies of a single cluster. The curves are clearly well-separated from each other indicating presence of distinct clusters of time series. To decide which of the clustering is better, 2-clusters or 3-clusters, seven indices have been calculated for both the two clustering alternatives. The results are contained in Table 6.

Table 6: Time Series Clustering Indices

Indices	Score for 2 Clusters	Score for 3 Clusters	Criteria	Decision
Silhouette Index	$6.171598e^{-01}$	0.22611061	Higher is better	3 Clusters are better
Score Function	$1.876961e^{-05}$	0	Higher is better	2 Clusters are better
Calinski-Harabasz Index	$8.821804e^{-01}$	3.82750641	Higher is better	3 Clusters are better
Davies–Bouldin Index	$1.515881e^{-01}$	0.76083695	Lower is better	2 Clusters are better
Modified Davies– Bouldin index	$1.515881e^{-01}$	0.77322745	Lower is better	2 Clusters are better
Dunn Index	$1.672840e^{-01}$	0.61530240	Higher is better	3 Clusters are better
COP Index	$1.618342e^{-01}$	0.09542997	Lower is better	3 Clusters are better

3-Cluster has been found to be better in four indices while 2-cluster has been found to be better in three indices. Though the 3-Cluster system seems to be marginally better, from a prudent viewpoint, the cluster memberships need to be looked into. The synopsis of the cluster memberships is contained in Table 7.

Table 7: Comparative Cluster Memberships

Cryptocurrencies	2 Clusters	3 Clusters	
	K-Medoids & Hierarchical	K-Medoids	Hierarchical
ADA	2	1	1
ALG	2	1	1
SOL	1	2	2
XCH	2	3	3
XLM	2	3	1
XNO	2	3	1

It is evident from the table that SOL is not clustered with any other cryptocurrency irrespective of the number of clusters and methodology of clustering. XCH cannot be clustered with any other cryptocurrency but only in 3-Cluster system under Hierarchical method of clustering. It is further observed that ADA and ALG form a distinct cluster irrespective of number of clusters and method of clustering. XLM and XNO also forms a distinct cluster under 3-Cluster Hierarchical method but includes XCH under 2-Clusters and 3-Cluster Hierarchical methods.

This highlights that SOL and XCH can be included in a portfolio of cryptocurrencies with ADA, ALG, XLM and XNO. ADA and ALG should not be included in the same portfolio but can be used in pair trading after suitable tests for cointegration. Similarly, XLM and XNO should ideally not be there in the same portfolio but may be considered for pair trading subject to fulfilment of conditions for cointegrated time series.

The major findings are outlined as:

i) Out of the above three discussed methodology, 3- Clusters Hierarchical methodology is giving the better results since all the six green cryptocurrencies are visually performing the best clusters.

ii) Under 2- Clusters methodology, ADA, ALG, XCH, XLM and XNO are forming the clusters of green cryptocurrencies.

iii) Under 3- Clusters K-Medoids methodology, ADA and ALG forming their own distinct cluster and the others green cryptocurrencies like XCH, XLM and XNO are acting as the best clusters of portfolios.

iv) Under 3- Clusters Hierarchical methodology SOL and XCH can be included in a portfolio of cryptocurrencies with ADA, ALG, XLM and XNO.

The clustering technique is different in this paper and better cluster results has been achieved in contrast to the study made by Haraty*et al*., (2024). Clusters arising out of green cryptocurrencies is much better rather than non-green cluster of cryptocurrencies (See Kilic *et al*., (2023), Pham *et al*., (2022)

CONCLUSION

The confluence of environmental consciousness, technological innovation, and financial investment has given rise to a new class of assets i.e. green cryptocurrencies. As the world grapples with climate change and seeks sustainable solutions, these digital assets offer a unique opportunity to align financial goals with environmental responsibility. This study has explored the potential of time series clustering techniques to analyse and categorize green cryptocurrencies based on their historical price and volume data. In this study it is clear that time clustering technique through hierarchical methodology is giving better results and all the green cryptocurrencies are taken into consideration while forming clusters. By leveraging the power of time series clustering, investors can optimize their portfolios, mitigate risks, and capitalize on emerging opportunities. Furthermore, this study contributes to the growing body of literature on green cryptocurrencies. Time series clustering offers a valuable tool for investors seeking to navigate the complex and dynamic world of green cryptocurrencies. By embracing sustainability and innovation, green cryptocurrencies have the potential to shape the future of finance.

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ANNEXURE - I

URL of websites visited from 11th June 2024 to 10th August 2024
https://blockgeeks.com/guides/top-5-eco-friendly-cryptocurrencies-to-invest-in-2022/
https://blog.nebeus.com/7-greener-eco-friendly-cryptocurrencies-you-should-know-about/
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https://coinswitch.co/switch/crypto/which-are-the-top-5-most-sustainable-cryptos/
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https://www.analyticsinsight.net/the-9-most-eco-friendly-crypto-on-the-market-right-now-and-where-to-invest/

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https://www.allcryptowhitepapers.com/ada-whitepaper/ https://algorand.co/blog/the-algorand-whitepaper https://coindcx.com/blog/cryptocurrency/solana-whitepaper-summary/
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