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Forecasting Trends in Cryptocurrencies Through the Application of Association Rule Mining Techniques

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Abstract: Information mining in the stock market and cryptocurrencies is the most used. In this paper, we used a data mining approach to execute association rules. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies: Bitcoin, Litecoin, Ethereum, and Monero. Specifically, this paper used data mining techniques like the apriori algorithm to predict and discover association rules between four cryptocurrencies to identify optimal points for selling and buying. Our suggested models utilized the apriori to predict and determine organization rules in our datasets. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies. Specifically, we aim to ascertain the current link between Bitcoin and other items during the next 24 hours. In addition, if there is a current buy or sell of Bitcoin, we can forecast, for instance, the movement of Litecoin over the next three hours. We have already carried out this prediction for the other items. Our objective is to propose a prediction model to generate and discover associations between the cryptocurrencies. In our research, we used apriori to produce the association rules. We assessed the grade of these rules using two metrics: Lift and support. Experiment analysis proves that our method successfully generates a strong association rule. We have already carried out this prediction for the other items. In conclusion, we generated the association rules using an a priori method. One benefit of our analysis is that it helps investors choose which of the four cryptocurrency monies to buy or sell at what time over the next 24 hours.

Keywords: Cryptocurrency, Bitcoin, Apriori, association rules, Ethereum, Litecoin

1. Introduction

Data mining implicates extracting practical insights, habits, and wisdom from vast datasets. Referred to as "knowledge discovery in databases," this approach reveals significant patterns within databases, contributing to informed ruling. Employing data mining confers influential competitive benefits to companies [1].

The exploration of data mining has emerged as a prominent area of research, with the ongoing challenge of extracting valuable knowledge from vast datasets. Effectively processing extensive data poses a difficulty for current computing software and hardware systems [2]. In a study [3], authors suggested a hybrid strategy for predicting future stock values that combines multi-variate deep neural architecture, association rule mining, and linear regression. Features are determined using linear regression models and association rule mining. Listing strongly correlated stocks for the target stock under prediction is the goal of the feature selection step.

This paper used data mining techniques to predict and discover association rules between four cryptocurrencies (Bitcoin, Litecoin, Ethereum, and Monero) to identify optimal points for selling and buying. Our suggested models utilized the apriori to foretell and determine association management in our datasets. Our significant contribution is to ascertain a robust correlation between four cryptocurrencies. Specifically, we aim to ascertain the current link between Bitcoin and other items during the next 24 hours. In addition, if there is a current buy or sell of Bitcoin, we can forecast, for instance, the movement of Litecoin over the next three hours. We have already carried out this prediction for the other items. The specific problem or gap that the research in cryptocurrency data mining is determining rules between the four cryptocurrencies during the next 24 hours helps investors to make the right decision regarding buying and selling between the four cryptocurrencies.

The constraints or difficulties we encountered during the research process, which are crucial for comprehending the

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breadth and relevance of the conclusions, were included in the dataset to extract association rules. The challenging part of forecasting Bitcoin trends is knowing when to sell or purchase. In this research, we employ association rule mining as a potential remedy.

This paper is structured as follows: in the first section, we provide an introduction. In the second section, we present some literature reviews and related works. In the third, we define association rules mining and the apriori algorithm and describe and explain our methodologies. In the fourth section, we discuss the results. In the last section, we provide a conclusion and future works.

2. Literature Review

In this section, we presented some literature reviews and related work.The authors of reference [4] employed forecasting techniques to reduce risk in forex trading decisions. This study uses many dataset divisions to assess the predictions made by the LSTM and GRU techniques for currency trends. A dataset of 4979, divided equally into three sections (ten percent for validation, ten percent for testing), yields the most accurate results.

Machine learning is employed to forecast fluctuations in the price of Bitcoin and has proven to be a helpful tool in this quest, according to [5]. A reusable trading strategy that trained on historical data collected at 4-hour intervals was provided by the authors of reference [6] using candlesticks of six different currency pairings: two minor pairs, like EUR/GBP and GBP/JPY, and four pairs, like GBP/USD, EUR/USD, USD/JPY, and USD/CHF. To predict the prices of nine well-known cryptocurrencies, Chowdhury et al. [7] looked at ensemble methodologies based on machine learning, including K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), gradient-boosted trees, and a mixed ensemble model. According to the results, the ensemble-learning model had the lowest prediction error.

The authors of reference [8] presented a novel paradigm that combines long short-term memory (LSTM) as a nonlinear approach with association rules. The suggested approach uses data from Yahoo Finance from January 2010 to December 2020 for simulation. Features that were pertinent to the gold spot (GS) in the US Dollar Index (DXY) were selected using the association rule. The gold price was predicted by the LSTM using several hyperparameter configurations. The suggested approach LSTM, with GS and DXY, produced low mean absolute percentage error (MAPE) metrics. In reference [9], the authors conducted a study exploring associations within the Warsaw Stock Exchange. They applied an information mining methodology to detect co-movements among various commodities listed on the deal. The Apriori is the method of choice for uncovering these associations.

In reference [10], the authors devised a model COREL (customer purchase prediction model) to anticipate customer buying patterns. This model operates through two stages: firstly, it establishes a roster of conceivable products by analyzing connections among products to forecast customer grounds; subsequently, it selects the most often bought products, taking into account client discretion. The researchers gathered data on customer knowledge and outcome reviews from the ”Jingdong” e-commerce forum. Their findings underscored the substantial impact of customer preferences on purchasing decisions.

Several methods and models are available for time series AR, ARIMA, SARIMA, and LSTM. The authors of [11] studied predicting gold commodities using SVM and ARIMA. In reference [12], the authors utilize Long Short-term Memory (LSTM) and subsequently integrate and contrast it with the ARIMA model. In reference [13], the authors utilize a basic three-layer Long Short-Term Memory (LSTM) model to forecast stock prices based on the LQ45 indices, achieving a mean absolute percentage error of 18.6135.

A recent study [14] examines Bitcoin price forecasting using empirical analysis. The research compares Bayesian neural networks with established linear and non-linear benchmark techniques, providing valuable practical insights. In reference [15], the authors utilized a stochastic neural network model to forecast the prices of Cryptocurrencies. In reference [16], authors explored novel deep learning models for predicting multi-step-ahead time series difficulties.

Using the Apriori algorithm, authors in reference [17] examined association rules between BIST100 stocks. When choosing equities, we employed two strategies. We began with all 87 stocks in the first technique, identified association rules between them, eliminated two stocks based on the best two rules, and then discovered additional association rules. In the second approach, we established association rules on sectoral base sets and divided the stocks according to these sets.

The suggestion in reference [18] involves integrating LSTM networks with machine learning models for forecasting Bitcoin prices. The research outlined in [18] integrates LSTM extracts organized financial data from news and employs this information in a machine learning model. In reference [19], the authors employed a combination of RNN and LSTM techniques, achieving a classification accuracy of 52% and a RMSE of 8%. The claim made by the authors is that the utilization of RNN with LSTM yields superior performance compared to conventional RNN and ARIMA models.

The authors in reference [20] introduced a time series forecasting approach employing Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) specifically, for predicting the electricity load in Turkey. In reference [21], the authors introduced hybrid models combining Principal Component Analysis (PCA) and Support specifically Machine (SVM), while authors [22] put forward an SVM model based on Fisher. In all conducted experiments, hybrid models outperformed individual models.

In [23], this research utilizes machine and deep learning algorithms to forecast stock market directions. The study focused on four stock market sectors: diversified financials, petroleum, non-metallic minerals, and metals, specifically from the Tehran stock exchange. The dataset encompassed ten years of historical data, incorporating ten technical features.

Chang introduced a business analytics approach for assessing stock market performance, enabling investors to monitor and evaluate the market behavior of their selected stocks. He opted for the Heston model and its corresponding API to calculate the anticipated movements in stock indices, providing a significant level of accuracy [24]. Utilizing association rules and the Frequent Pattern-Growth algorithm, the authors of reference [25] were able to create an algorithm that provides clients with personalized recommendations. Our method produced excellent results with a high average likelihood of buying the following product that the recommendation system recommended.

In reference [26], the authors stated that one way to determine marketing strategy is by using transaction data to identify past purchases or transactions. Market Basket Analysis is part of a data mining process that employs the FP-Growth algorithm strategy to figure out connected products. It is found in this study that the minimal confidence level surpasses 0.75, and the minimum support value exceeds 50%. Nine goods exhibit exceptional support values and meet the minimal value. However, in experiments predicting sales values conducted by authors in [27], the ARIMA model effectively projected future sales values.

In reference [28], the authors described a long short-term memory (LSTM) algorithm that can predict the values of four types of cryptocurrencies: AMP, Ethereum, ElectroOptical System, and XRP. The LSTM model uses mean square error, root mean square error, and normalized root mean square error analyses. The results of these models demonstrated that the LSTM algorithm performed better than any other type of cryptocurrency in terms of prediction.

The authors in reference [29] took behavior principles and used them to forecast future return values in Bitcoin, Ethereum, Litecoin, and Ripple closure series. We have proposed a new method of establishing potential future scenarios in which we study the influence of memory on the dynamics of the process using categorical data in the studies and Markov chain models from the first to the tenth order. Our findings suggest that cryptocurrencies have long-range memory. Litecoin showed nine memory stages, while Bitcoin, Ethereum, and Ripple showed seven. Many academics utilize the apriori to extract association rules. For instance, in reference [30], the authors employed apriori to identify consumer purchasing trends using transaction data.

In reference [31], the authors presented a framework that applies deep learning techniques for classification, prediction, and association rules for feature selection. Two datasets for the experiments: InstaCart and actual data from Bits Bakers, a developing business with three locations and 2,233 goods.

In reference [32], the authors employed the Association Rule-Market Basket Analysis technique to ascertain the shopping interests of their clients. The study's findings showed that two regulations, such as 63% (food and beverages) and 58% (cigarettes and drinks), had the greatest confidence values. The minimarket can decide on the necessary actions after these findings, such as arranging the layout and other things.

3. Methodology and Association Rule Mining

This section presented the association rules, the apriori algorithm, the datasets, feature engineering, and our methodology.

A. *Association Rules*

Association rules represent a methodology within machine learning that relies on rules for analysis to discover relationships or associations among a set of variables in large datasets. This approach is often used in data mining and market basket analysis, where the goal is to identify patterns or correlations between different items or attributes. The primary utilization of association rules is typically in analyzing transactional data, such as customer shopping baskets. The rules are: "If A, then B" are expressed. The occurrence of item A aligns with the presence of item B. The strength of the association is measured using metrics like Support and lift. Here are the key concepts related to association rules:

Support: Support measures the frequency or occurrence of a specific item set in the dataset. Equation (1) outlined here delineates the procedure for quantifying Support.

$$Support(A) = \frac{TransactionsContaining(A)}{TotalTransactions} \tag{1}$$

Lift: Lift measures how much more likely item B is purchased when item A is purchased, in contrast to the scenario where item B is bought independently of item A. Equation (2) outlined here delineates the procedure for quantifying Lift.

$$Lift(A->B) = \frac{Confidence(A->B)}{Support(B)} \tag{2}$$

Furthermore, confidence indicates the strength of an association rule and makes it well-known. Confidence (A→B) is the symbol for an association rule's confidence, which is as a ratio by (3):

Datetime	Open	High	Low	Close	Volume
2021-12-16 09:00:00+00:00	48798.386719	48981.316406	48773.707031	48967.699219	0
2021-12-16 10:00:00+00:00	49003.164062	49280.308594	48946.070312	49190.968750	97869824
2021-12-16 11:00:00+00:00	49187.390625	49425.574219	48936.714844	49191.503906	261844992
2021-12-16 12:00:00+00:00	49275.566406	49275.566406	48692.183594	48770.621094	77852672
2021-12-16 13:00:00+00:00	48774.425781	49148.187500	48487.121094	48946.281250	189181952
...	...	...	...	...	...
2023-12-16 04:00:00+00:00	42330.175781	42337.355469	42248.761719	42271.324219	0
2023-12-16 05:00:00+00:00	42274.144531	42290.785156	42197.199219	42235.066406	12761088
2023-12-16 06:00:00+00:00	42236.718750	42291.914062	42134.449219	42183.140625	64708608
2023-12-16 07:00:00+00:00	42181.148438	42239.625000	42157.828125	42196.164062	27404288
2023-12-16 08:00:00+00:00	42195.109375	42228.671875	42107.410156	42151.074219	36182016

Figure 1. Bitcoin Dataset

$$Confidence(A->B) = \frac{Support(AUB)}{Support(B)} \quad (3)$$

Association rule mining algorithms, such as the Apriori algorithm, are commonly used to extract these rules from large datasets. The Apriori algorithm, for example, works by iteratively finding frequent itemsets and generating association rules based on those itemsets. In practical terms, association rules can be applied in various domains, including retail, e-commerce, healthcare, and more, to uncover valuable insights and improve decision-making processes.

B. Apriori Algorithm

The Apriori algorithm is an algorithm in data mining and machine learning to discover association rules within large datasets. It is for conducting market basket analysis and identifying connections between items bought in tandem. The proposed algorithm dates back to 1994 by Rakesh. agrawal and Ramakrishnan Srikant.

Market basket analysis is a data mining technique that examines product combinations that are purchased together. It provides a detailed analysis of the purchases made by a customer in a supermarket and identifies the items that the customer frequently purchases.

C. Datasets

This research utilized a dataset comprising hourly prices collected without gaps from December 16, 2021, to December 16, 2023. The dataset encompasses Bitcoin, Ethereum, Litecoin, and Monero, spanning 17416 days. The dataset features columns Open, High, Low, Close, and Volume. Python finance package, we gathered the four datasets related to this study. The various datasets used in our study are in Figures 1 through 4.

D. Feature Engineering

The objective of the techniques described in this paper is to detect relationships or associations of cryptocurrencies (BTC_USD, ETC_USD, LTC_USD, and XMR_USD) of variable categories in data files. We have used the apriori algorithm. We collected data on the four cryptocurrencies

Datetime	Open	High	Low	Close	Volume
2021-12-16 09:00:00+00:00	36.354679	36.506054	36.340870	36.471687	0
2021-12-16 10:00:00+00:00	36.510998	36.668381	36.406715	36.509384	0
2021-12-16 11:00:00+00:00	36.522755	36.791813	36.331493	36.610744	1472000
2021-12-16 12:00:00+00:00	36.695660	36.773972	36.066257	36.066257	0
2021-12-16 13:00:00+00:00	36.051460	36.617897	36.040901	36.480553	5784256
...	...	...	...	...	...
2023-12-16 04:00:00+00:00	20.283621	20.286947	20.258204	20.277918	0
2023-12-16 05:00:00+00:00	20.277966	20.298763	20.265141	20.270422	293264
2023-12-16 06:00:00+00:00	20.272310	20.290106	20.202187	20.230736	1494800
2023-12-16 07:00:00+00:00	20.231466	20.244295	20.192734	20.237921	1137088
2023-12-16 08:00:00+00:00	20.237942	20.275040	20.235373	20.253448	280320

Figure 2. Ethereum Dataset

Datetime	Open	High	Low	Close	Volume
2021-12-16 09:00:00+00:00	153.936691	154.715927	153.706619	154.604996	0
2021-12-16 10:00:00+00:00	154.606964	155.712204	154.560532	155.545685	14513152
2021-12-16 11:00:00+00:00	155.415970	156.616104	154.305435	156.126770	15911296
2021-12-16 12:00:00+00:00	156.447144	156.447144	154.052719	154.052719	0
2021-12-16 13:00:00+00:00	154.132690	155.854935	153.253555	155.491882	6569856
...	...	...	...	...	...
2023-12-16 04:00:00+00:00	71.865677	72.006790	71.809021	71.926689	0
2023-12-16 05:00:00+00:00	71.927254	71.987839	71.927254	71.952995	811776
2023-12-16 06:00:00+00:00	71.954689	71.988434	71.873421	71.911713	1403360
2023-12-16 07:00:00+00:00	71.910561	72.058586	71.906540	72.058586	1194336
2023-12-16 08:00:00+00:00	72.060089	72.210381	72.060089	72.202271	1552832

Figure 3. Litecoin Dataset

Datetime	Open	High	Low	Close	Volume
2021-12-16 09:00:00+00:00	188.722672	189.688553	188.574951	189.023697	0
2021-12-16 10:00:00+00:00	189.266235	190.130219	189.126724	189.433624	0
2021-12-16 11:00:00+00:00	189.542908	190.730148	188.454132	190.110519	387472
2021-12-16 12:00:00+00:00	190.563629	191.090652	188.998535	189.831635	33520
2021-12-16 13:00:00+00:00	189.729645	192.602783	189.412598	192.602783	6942912
...	...	...	...	...	...
2023-12-16 04:00:00+00:00	171.171982	171.637405	170.906403	171.622467	0
2023-12-16 05:00:00+00:00	171.624619	171.745667	171.289978	171.289978	616232
2023-12-16 06:00:00+00:00	171.286652	171.533020	170.892929	171.533020	620088
2023-12-16 07:00:00+00:00	171.551804	171.790955	171.047913	171.096207	742784
2023-12-16 08:00:00+00:00	171.073288	171.731613	171.049408	171.275757	812480

Figure 4. Monero Dataset

containing the following features: Open, High, Low, Close, and Volume. Then, we added 24 columns to each database with values: single buying and single selling. Tables that list the characteristics of Bitcoin, Ethereum, Litecoin, and Monero are Tables I through IV. We used these attributes to identify any relationships, such as the movement of Bitcoin today and other products over the next 24 hours. Each attribute has a description for each of the four cryptocurrencies.

The four tables present and describe the attributes of each cryptocurrency. Each table contains two columns, the first column named attribute and the second column named description. The attribute column presents the characteristics used in this article, and the description column presents and shows the significance of each attribute.

After eliminating the absent data points, we consolidated the data of the four cryptocurrencies into a unified database, aligning them based on identical dates. Subsequently, we retained only the columns that depict the subsequent hourly movements of LTC_USD, ETC_USD, and XMR_USD, along with the action of BTC_USD, referred to as the Bitcoin_H00. Each column indicates ”SA” for a simple buying or ”SV” for a simple sale.

Ultimately, we transformed every attribute into binary form, assigning values of 0 or 1 to each attribute within the dataset (We have utilized Bibliotheque get_dummies). 0 means single buying, and 1 means single selling. We performed identical procedures for the remaining three datasets (Litecoin, Ethereum, and Monero). Finally, we have applied the apriori algorithm to generate strong association rules.

E. Proposed Approach

The exploration of relationships and associations between variables within a database has increasingly depended on organization rule mining procedures. These approaches leverage statistical examination and artificial intelligence to uncover prevalent practices. Utilizing established patterns, integrating criteria such as lift and minimum support. In this research, we classified organization rules based on the subsequent measures:
1) The results of the rules: ”single buying” or ”single selling” are categorized.
2) The antecedents of the rules: ”single buying” or ”single selling” are categorized.
3) We established the minimum support threshold at 0.25
4) We established a minimum lift threshold of 1.

We have proposed an algorithm with two main phases: Initially, the extraction of association rules through the Apriori algorithm, followed the evaluation of the obtained relationship rules using a multicriteria study. We suggest a method that employs data mining to pinpoint the most advantageous moments for purchasing and selling cryptocurrency. Our objective is to define optimal ruling for determining purchase and sell cases. Our offered model contains several preliminary stages: datasets, Typical engineering, retrieval of frequent itemsets, generating association rules, and identification of compelling association rules. Figure 5 represents our approach.

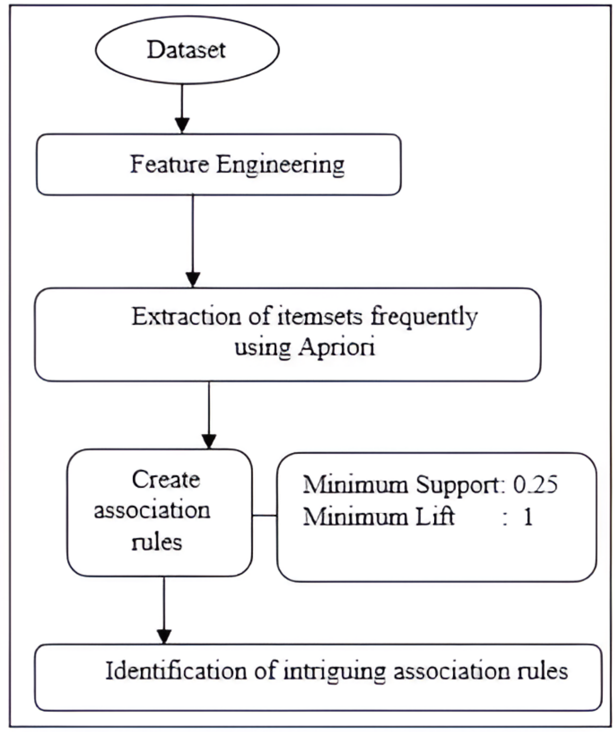

Figure 5. Our approach

Using Association Rule Mining (ARM) approaches to forecast cryptocurrency trends is a revolutionary strategy that combines financial research and data mining to reveal hidden patterns and correlations in cryptocurrency markets. Of their decentralized structure, high volatility, and round-the-clock trading activity. For trend forecasting, these traits offer both opportunities and obstacles. ARM, employed in market basket analysis, can be modified to examine the connections among various market variables in Bitcoin datasets, perhaps aiding in forecasting future trends.

4. Results and Discussion

Following the data trail, we proactively identified a subset of significant forms. Our initial approach involved employing the Apriori algorithm, with a minimum support threshold set at 0.25, to extract frequent itemsets. The frequent sets identified during this phase were crucial in the following step, which involved creating association rules.

In addressing the problem of monotonous and uninspiring regulations, we implemented our technique in the succeeding stage, the preferences of those making decisions. We assessed the previously derived rules as options using specific quality metrics. Out of the numerous metrics suggested in existing literature, we honed in on two criteria:

TABLE I. Attributes for Bitcoin

Attribute	Description
Bitcoin_H00	Bitcoin hour action
Bitcoin_H01	The subsequent move of the Bitcoin hour
Bitcoin_H02	The forthcoming movement of Bitcoin within the next two hours
Bitcoin_H03	The forthcoming movement of Bitcoin within the next 3 hours
Bitcoin_H04	The forthcoming movement of Bitcoin within the next 4 hours
Bitcoin_H05	The forthcoming movement of Bitcoin within the next 5 hours
Bitcoin_H06	The forthcoming movement of Bitcoin within the next 6 hours
Bitcoin_H07	The forthcoming movement of Bitcoin within the next 7 hours
Bitcoin_H08	The forthcoming movement of Bitcoin within the next 8 hours
Bitcoin_H09	The forthcoming movement of Bitcoin within the next 9 hours
Bitcoin_H10	The forthcoming movement of Bitcoin within the next 10 hours
Bitcoin_H11	The forthcoming movement of Bitcoin within the next 11 hours
Bitcoin_H12	The forthcoming movement of Bitcoin within the next 12 hours
Bitcoin_H13	The forthcoming movement of Bitcoin within the next 13 hours
Bitcoin_H14	The forthcoming movement of Bitcoin within the next 14 hours
Bitcoin_H15	The forthcoming movement of Bitcoin within the next 15 hours
Bitcoin_H16	The forthcoming movement of Bitcoin within the next 16 hours
Bitcoin_H17	The forthcoming movement of Bitcoin within the next 17 hours
Bitcoin_H18	The forthcoming movement of Bitcoin within the next 18 hours
Bitcoin_H19	The forthcoming movement of Bitcoin within the next 19 hours
Bitcoin_H20	The forthcoming movement of Bitcoin within the next 20 hours
Bitcoin_H21	The forthcoming movement of Bitcoin within the next 21 hours
Bitcoin_H22	The forthcoming movement of Bitcoin within the next 22 hours
Bitcoin_H23	The forthcoming movement of Bitcoin within the next 23 hours
Bitcoin_H24	The forthcoming movement of Bitcoin within the next 24 hours

TABLE II. Attributes for Litecoin

Attribute	Description
LTC_H00	Litecoin hour action
LTC_H01	The subsequent move of the Litecoin hour
LTC_H02	The forthcoming movement of Litecoin within the next two hours
LTC_H03	The forthcoming movement of Litecoin within the next 3 hours
LTC_H04	The forthcoming movement of Litecoin within the next 4 hours
LTC_H05	The forthcoming movement of Litecoin within the next 5 hours
LTC_H06	The forthcoming movement of Litecoin within the next 6 hours
LTC_H07	The forthcoming movement of Litecoin within the next 7 hours
LTC_H08	The forthcoming movement of Litecoin within the next 8 hours
LTC_H09	The forthcoming movement of Litecoin within the next 9 hours
LTC_H10	The forthcoming movement of Litecoin within the next 10 hours
LTC_H11	The forthcoming movement of Litecoin within the next 11 hours
LTC_H12	The forthcoming movement of Litecoin within the next 12 hours
LTC_H13	The forthcoming movement of Litecoin within the next 13 hours
LTC_H14	The forthcoming movement of Litecoin within the next 14 hours
LTC_H15	The forthcoming movement of Litecoin within the next 15 hours
LTC_H16	The forthcoming movement of Litecoin within the next 16 hours
LTC_H17	The forthcoming movement of Litecoin within the next 17 hours
LTC_H18	The forthcoming movement of Litecoin within the next 18 hours
LTC_H19	The forthcoming movement of Litecoin within the next 19 hours
LTC_H20	The forthcoming movement of Litecoin within the next 20 hours
LTC_H21	The forthcoming movement of Litecoin within the next 21 hours
LTC_H22	The forthcoming movement of Litecoin within the next 22 hours
LTC_H23	The forthcoming movement of Litecoin within the next 23 hours
LTC_H24	The forthcoming movement of Litecoin within the next 24 hours

TABLE III. Attributes for Ethereum

Attribute	Description
ETC_H00	Ethereum hour action
ETC_H01	The subsequent move of the Ethereum hour
ETC_H02	The forthcoming movement of Ethereum within the next two hours
ETC_H03	The forthcoming movement of Ethereum within the next 3 hours
ETC_H04	The forthcoming movement of Ethereum within the next 4 hours
ETC_H05	The forthcoming movement of Ethereum within the next 5 hours
ETC_H06	The forthcoming movement of Ethereum within the next 6 hours
ETC_H07	The forthcoming movement of Ethereum within the next 7 hours
ETC_H08	The forthcoming movement of Ethereum within the next 8 hours
ETC_H09	The forthcoming movement of Ethereum within the next 9 hours
ETC_H10	The forthcoming movement of Ethereum within the next 10 hours
ETC_H11	The forthcoming movement of Ethereum within the next 11 hours
ETC_H12	The forthcoming movement of Ethereum within the next 12 hours
ETC_H13	The forthcoming movement of Ethereum within the next 13 hours
ETC_H14	The forthcoming movement of Ethereum within the next 14 hours
ETC_H15	The forthcoming movement of Ethereum within the next 15 hours
ETC_H16	The forthcoming movement of Ethereum within the next 16 hours
ETC_H17	The forthcoming movement of Ethereum within the next 17 hours
ETC_H18	The forthcoming movement of Ethereum within the next 18 hours
ETC_H19	The forthcoming movement of Ethereum within the next 19 hours
ETC_H20	The forthcoming movement of Ethereum within the next 20 hours
ETC_H21	The forthcoming movement of Ethereum within the next 21 hours
ETC_H22	The forthcoming movement of Ethereum within the next 22 hours
ETC_H23	The forthcoming movement of Ethereum within the next 23 hours
ETC_H24	The forthcoming movement of Ethereum within the next 24 hours

TABLE IV. Attributes for Monero

Attribute	Description
monero_H00	Monero hour action
monero_H01	The subsequent move of the Monero hour
monero_H02	The forthcoming movement of Monero within the next two hours
monero_H03	The forthcoming movement of Monero within the next 3 hours
monero_H04	The forthcoming movement of Monero within the next 4 hours
monero_H05	The forthcoming movement of Monero within the next 5 hours
monero_H06	The forthcoming movement of Monero within the next 6 hours
monero_H07	The forthcoming movement of Monero within the next 7 hours
monero_H08	The forthcoming movement of Monero within the next 8 hours
monero_H09	The forthcoming movement of Monero within the next 9 hours
monero_H10	The forthcoming movement of Monero within the next 10 hours
monero_H11	The forthcoming movement of Monero within the next 11 hours
monero_H12	The forthcoming movement of Monero within the next 12 hours
monero_H13	The forthcoming movement of Monero within the next 13 hours
monero_H14	The forthcoming movement of Monero within the next 14 hours
monero_H15	The forthcoming movement of Monero within the next 15 hours
monero_H16	The forthcoming movement of Monero within the next 16 hours
monero_H17	The forthcoming movement of Monero within the next 17 hours
monero_H18	The forthcoming movement of Monero within the next 18 hours
monero_H19	The forthcoming movement of Monero within the next 19 hours
monero_H20	The forthcoming movement of Monero within the next 20 hours
monero_H21	The forthcoming movement of Monero within the next 21 hours
monero_H22	The forthcoming movement of Monero within the next 22 hours
monero_H23	The forthcoming movement of Monero within the next 23 hours
monero_H24	The forthcoming movement of Monero within the next 24 hours

Support and lift.

This research highlighted the robust correlation patterns for Bitcoin, Litecoin, Monero, and Ethereum. We created association rules that link the behavior of BTC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (ETC_USD, LTC_USD, and XMR_USD). Table V displays the foremost association rules for Bitcoin. We displayed the guidelines for linking Bitcoin with other commodities within the subsequent 24 hours.

Rule 1 in the transaction "Bitcoin_H00_SA → ETC_H11_SV", the antecedent represents a simple buying now of Bitcoin, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a lift level surpassing 1, and a support level of 0.27.

Rule 2 in the transaction "Bitcoin_H00_SA → LTC_H11_SV", the antecedent represents a simple buying now of Bitcoin, they demonstrate a simple selling next eleven hours of LTC_USD (Litecoin) with a support level of 0.27 and lift level surpassing 1.

Rule 3 in the transaction "Bitcoin_H00_SV → Bitcoin_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of Bitcoin support proportion of 0.28, and a lift degree surpassing 1.

Rule 4 in the transaction "Bitcoin_H00_SV → Bitcoin_H05_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next five hours of Bitcoin support proportion of 0.28, and a lift degree surpassing 1.

Rule 5 in the transaction "Bitcoin_H00_SV → ETC_H01_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next hour of ETC_USD (Ethereum) support proportion of 0.29, and a lift degree surpassing 1.

Rule 6 in the transaction "Bitcoin_H00_SV → ETC_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) support proportion of 0.30, and a lift degree surpassing 1.

Rule 7 in the transaction "Bitcoin_H00_SV → ETC_H04_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) support proportion of 0.28, and a lift degree surpassing 1.

Rule 8 in the transaction "Bitcoin_H00_SV → ETC_H05_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next five hours of ETC_USD (Ethereum) support proportion of 0.29, and a lift degree surpassing 1.

Rule 9 in the transaction "Bitcoin_H00_SV → LTC_H01_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next hour of LTC_USD (Litecoin) support proportion of 0.30, and a lift degree surpassing 1.

Rule 10 in the transaction "Bitcoin_H00_SV → LTC_H02_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) support proportion of 0.29, and a lift degree surpassing 1.

Rule 11 in the transaction "Bitcoin_H00_SV → LTC_H04_SA", the antecedent represents a simple selling now of Bitcoin, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) support proportion of 0.29, and a lift degree surpassing 1.

After that, we created association rules that link the behavior of ETC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, LTC_USD, and XMR_USD). Table VI displays the foremost association rules for Ethereum. We displayed the guidelines for linking Ethereum with other commodities within the subsequent 24 hours.

Rule 1 in the transaction "ETC_H00_SA → ETC_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a lift level surpassing 1, and a support level of 0.29.

Rule 2 in the transaction "ETC_H00_SA → Bitcoin_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next eleven hours of BTC_USD (Bitcoin) with a support level of 0.28 and lift level surpassing 1.

Rule 3 in the transaction "ETC_H00_SA → LTC_H11_SV", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple selling next eleven hours of LTC_USD (Litecoin) support proportion of 0.29, and a lift degree surpassing 1.

In Rule 4 of the transaction "ETC_H00_SA → monero_H19_SA", the condition signifies the immediate purchase of Ethereum. It indicates a subsequent purchase of Monero against USD occurring in the next 19 hours, with a support level set at 0.27 and a lift level exceeding 1.

Rule 5 in the transaction "ETC_H00_SA → monero_H21_SA", the antecedent represents a simple buying now of Ethereum, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) support proportion of 0.29, and a lift degree surpassing 1.

Rule 6 in the transaction "ETC_H00_SV → ETC_H01_SA", the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next hour of ETC_USD (Ethereum) support proportion of

TABLE V. Top association rules for Bitcoin

N°	Antecedents	Consequents	Support	Lift
R1	Bitcoin_H00_SA	ETC_H11_SV	0.279614	1.014665
R2	Bitcoin_H00_SA	LTC_H11_SV	0.278237	1.017145
R3	Bitcoin_H00_SV	Bitcoin_H02_SA	0.287879	1.070736
R4	Bitcoin_H00_SV	Bitcoin_H05_SA	0.289256	1.037920
R5	Bitcoin_H00_SV	ETC_H01_SA	0.290634	1.058865
R6	Bitcoin_H00_SV	ETC_H02_SA	0.305785	1.070270
R7	Bitcoin_H00_SV	ETC_H04_SA	0.286501	1.033240
R8	Bitcoin_H00_SV	ETC_H05_SA	0.293388	1.079950
R9	Bitcoin_H00_SV	LTC_H01_SA	0.304408	1.070711
R10	Bitcoin_H00_SV	LTC_H02_SA	0.298898	1.091767
R11	Bitcoin_H00_SV	LTC_H04_SA	0.290634	1.029891

TABLE VI. Top association rules for Ethereum

N°	Antecedents	Consequents	Support	Lift
R1	ETC_H00_SA	ETC_H11_SV	0.297521	1.085743
R2	ETC_H00_SA	Bitcoin_H11_SV	0.283747	1.080498
R3	ETC_H00_SA	LTC_H11_SV	0.296143	1.088721
R4	ETC_H00_SA	monero_H19_SA	0.278237	1.048788
R5	ETC_H00_SA	monero_H21_SA	0.290634	1.112413
R6	ETC_H00_SV	ETC_H01_SA	0.289256	1.048181
R7	ETC_H00_SV	ETC_H02_SA	0.297521	1.035745
R8	ETC_H00_SV	ETC_H04_SA	0.289256	1.037566
R9	ETC_H00_SV	ETC_H15_SV	0.289256	1.072876
R10	ETC_H00_SV	Bitcoin_H05_SA	0.290634	1.037255
R11	ETC_H00_SV	LTC_H01_SA	0.300275	1.050498
R12	ETC_H00_SV	LTC_H02_SA	0.297521	1.080893
R13	ETC_H00_SV	LTC_H04_SA	0.289256	1.019499
R14	ETC_H00_SV	monero_H20_SA	0.289256	1.019499

0.28, and a lift degree surpassing 1.

Rule 7 in the transaction ”ETC_H00_SV → ETC_H02_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) support proportion of 0.29, and a lift degree surpassing 1.

Rule 8 in the transaction ”ETC_H00_SV → ETC_H04_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) support proportion of 0.28, and a lift degree surpassing 1.

Rule 9 in the transaction ”ETC_H00_SV → ETC_H15_SV”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple selling next 15 hours of ETC_USD (Ethereum) support proportion of 0.28, and a lift degree surpassing 1.

Rule 10 in the transaction ”ETC_H00_SV → Bitcoin_H05_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next five hours of BTC_USD (Bitcoin) support proportion of 0.29, and a lift degree surpassing 1.

Rule 11 in the transaction ”ETC_H00_SV → LTC_H01_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) support proportion of 0.30, and a lift degree surpassing 1.

Rule 12 in the transaction ”ETC_H00_SV → LTC_H02_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) support proportion of 0.29, and a lift degree surpassing 1.

Rule 13 in the transaction ”ETC_H00_SV → LTC_H04_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) support proportion of 0.28, and a lift degree surpassing 1.

Rule 14 in the transaction ”ETC_H00_SV → monero_H20_SA”, the antecedent represents a simple selling now of Ethereum, they demonstrate a simple buying next 20 hours of XMR_USD (Monero) with a support level of

0.28, and a lift level surpassing 1.

After that, we created association rules that link the behavior of XMR_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, LTC_USD, and ETC_USD). Table VII displays the foremost association rules for Monero. We displayed the guidelines for linking Monero with other commodities within the subsequent 24 hours.

Rule 1 in the transaction ”monero_H00_SA → monero_H21_SA”, the antecedent represents a simple buying now of Monero, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) with a lift level surpassing 1, and a support level of 0.31.

Rule 2 in the transaction ”monero_H00_SA → LTC_H11_SV”, the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next 11 hours of LTC_USD (Litecoin) with a support level of 0.31, and lift level surpassing 1.

Rule 3 in the transaction ”monero_H00_SA → Bitcoin_H08_SV”, the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next 8 hours of Bitcoin support proportion of 0.30, and a lift degree surpassing 1.

Rule 4 in the transaction ”monero_H00_SA → Bitcoin_H11_SV”, the antecedent represents a simple buying now of Monero, they demonstrate a simple selling next eleven hours of BTC_USD (Bitcoin) support proportion of 0.30, and a lift degree surpassing 1.

Rule 5 in the transaction ”monero_H00_SA → Bitcoin_H21_SA”, the antecedent represents a simple buying now of Monero, they demonstrate a simple buying next 21 hours of BTC_USD (Bitcoin) support proportion of 0.30, and a lift degree surpassing 1.

Rule 6 in the transaction ”monero_H00_SV → monero_H24_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 24 hours of XMR_USD (Monero) support proportion of 0.25, and a lift degree surpassing 1.

Rule 7 in the transaction ”monero_H00_SV → LTC_H04_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) support proportion of 0.25, and a lift degree surpassing 1.

Rule 8 in the transaction ”monero_H00_SV → LTC_H17_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 17 hours of LTC_USD (Litecoin) support proportion of 0.26, and a lift degree surpassing 1.

Rule 9 in the transaction ”monero_H00_SV → LTC_H24_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 24 hours of LTC_USD (Litecoin) support proportion of 0.25, and a lift degree surpassing 1.

Rule 10 in the transaction ”monero_H00_SV → Bitcoin_H17_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next 17 hours of BTC_USD (Bitcoin) support proportion of 0.25, and a lift degree surpassing 1.

Rule 11 in the transaction ”monero_H00_SV → ETC_H01_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next hour of ETC_USD (Ethereum) support proportion of 0.25, and a lift degree surpassing 1.

Rule 12 in the transaction ”monero_H00_SV → ETC_H02_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) support proportion of 0.26, and a lift degree surpassing 1.

Rule 13 in the transaction ”monero_H00_SV → ETC_H04_SA”, the antecedent represents a simple selling now of Monero, they demonstrate a simple buying next four hours of ETC_USD (Ethereum) support proportion of 0.25, and a lift degree surpassing 1.

Rule 14 in the transaction ”monero_H00_SV → ETC_H11_SV”, the antecedent represents a simple selling now of Monero, they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) support proportion of 0.25, and a lift degree surpassing 1.

After that, we created association rules that link the behavior of LTC_USD at a given moment to the behavior of the next hour for three other cryptocurrencies (BTC_USD, ETC_USD, and XMR_USD). Table VIII displays the foremost association rules for Litecoin. We provided the guidelines for linking Litecoin with other commodities within the subsequent 24 hours.

Rule 1 in the transaction ”LTC_H00_SA → LTC_H11_SV”, the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 11 hours of LTC_USD (Litecoin) with a lift level surpassing 1, and a support level of 0.29.

Rule 2 in the transaction ”LTC_H00_SA → monero_H21_SA ”, the antecedent represents a simple buying now of Litecoin, they demonstrate a simple buying next 21 hours of XMR_USD (Monero) with a support level of 0.28, and lift level surpassing 1.

Rule 3 in the transaction ”LTC_H00_SA → Bitcoin_H08_SV”, the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 8 hours of Bitcoin support proportion of 0.29, and a lift degree surpassing 1.

TABLE VII. Top association rules for Monero

N°	Antecedents	Consequents	Support	Lift
R1	monero_H00_SA	monero_H21_SA	0.316298	1.076248
R2	monero_H00_SA	LTC_H11_SV	0.310773	1.025883
R3	monero_H00_SA	Bitcoin_H08_SV	0.306630	1.017266
R4	monero_H00_SA	Bitcoin_H11_SV	0.309392	1.058176
R5	monero_H00_SA	Bitcoin_H21_SA	0.308011	1.064425
R6	monero_H00_SV	monero_H24_SA	0.258287	1.044451
R7	monero_H00_SV	LTC_H04_SA	0.258287	1.033954
R8	monero_H00_SV	LTC_H17_SA	0.265193	1.114820
R9	monero_H00_SV	LTC_H24_SA	0.255525	1.097338
R10	monero_H00_SV	Bitcoin_H17_SA	0.255525	1.085633
R11	monero_H00_SV	ETC_H01_SA	0.255525	1.043878
R12	monero_H00_SV	ETC_H02_SA	0.261050	1.016997
R13	monero_H00_SV	ETC_H04_SA	0.259669	1.058093
R14	monero_H00_SV	ETC_H11_SV	0.255525	1.012718

TABLE VIII. Top association rules for Litecoin

N°	Antecedents	Consequents	Support	Lift
R1	LTC_H00_SA	LTC_H11_SV	0.294766	1.025708
R2	LTC_H00_SA	monero_H21_SA	0.289256	1.025883
R3	LTC_H00_SA	Bitcoin_H08_SV	0.294766	1.046377
R4	LTC_H00_SA	ETC_H11_SV	0.292011	1.008651
R5	LTC_H00_SA	ETC_H22_SV	0.290634	1.047540
R6	LTC_H00_SV	LTC_H01_SA	0.290634	1.074537
R7	LTC_H00_SV	LTC_H02_SA	0.279614	1.073558
R8	LTC_H00_SV	LTC_H04_SA	0.274105	1.020989
R9	LTC_H00_SV	monero_H20_SA	0.274105	1.020989
R10	LTC_H00_SV	Bitcoin_H02_SA	0.272727	1.066253
R11	LTC_H00_SV	ETC_H01_SA	0.280992	1.076087
R12	LTC_H00_SV	ETC_H02_SA	0.278237	1.023649

Rule 4 in the transaction ”LTC_H00_SA → ETC_H11_SV”, the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next eleven hours of ETC_USD (Ethereum) support proportion of 0.29, and a lift degree surpassing 1.

Rule 5 in the transaction ”LTC_H00_SA → ETC_H22_SV”, the antecedent represents a simple buying now of Litecoin, they demonstrate a simple selling next 22 hours of ETC_USD (Ethereum) support proportion of 0.29, and a lift degree surpassing 1.

Rule 6 in the transaction ”LTC_H00_SV → LTC_H01_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next hour of LTC_USD (Litecoin) support proportion of 0.29, and a lift degree surpassing 1.

Rule 7 in the transaction ”LTC_H00_SV → LTC_H02_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of LTC_USD (Litecoin) support proportion of 0.27, and a lift degree surpassing 1.

Rule 8 in the transaction ”LTC_H00_SV → LTC_H04_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next four hours of LTC_USD (Litecoin) support proportion of 0.27, and a lift degree surpassing 1.

Rule 9 in the transaction ”LTC_H00_SV → monero_H20_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next 20 hours of XMR_USD (Monero) support proportion of 0.27, and a lift degree surpassing 1.

Rule 10 in the transaction ”LTC_H00_SV → Bitcoin_H02_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of BTC_USD (Bitcoin) support proportion of 0.27, and a lift degree surpassing 1.

Rule 11 in the transaction ”LTC_H00_SV → ETC_H01_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next hour of ETC_USD (Ethereum) support proportion of 0.28, and a lift degree surpassing 1.

Rule 12 in the transaction ”LTC_H00_SV → ETC_H02_SA”, the antecedent represents a simple selling now of Litecoin, they demonstrate a simple buying next two hours of ETC_USD (Ethereum) support proportion of 0.27, and a lift degree surpassing 1.

This article utilized the apriori algorithm to produce robust association rules. The association rules presented in the four tables assist investors in making informed decisions regarding optimal buying and selling times for the next 24 hours across four cryptocurrencies: Bitcoin, Monero, Litecoin, and Ethereum.

We have determined a strong link between Ethereum, Monero, Litecoin, and Bitcoin. More specifically, during the following day, we hope to determine the present connection between Bitcoin and other goods. Furthermore, if there is a buy or sell of Bitcoin, we can predict, for example, how Litecoin will move over the next three or four hours. For the other goods, we have already executed this prediction.

The association rules displayed in the four tables are robust and produced by the apriori algorithm. We discovered the associations between the various attributes in the ”feature engineering” step. With a support proportion of 0,29 and a lift degree greater than 1, the antecedent in the transaction ”LTC_H00_SA → Bitcoin_H08_SV” shows a straightforward immediate purchase of Litecoin. They also show a straightforward selling of Bitcoin during the following eight hours, as per Table VIII, Rule 3.

In line with the other regulations about strong ties, Litecoin’s current purchase of Bitcoin will result in a straightforward sale within the next eight hours.

One benefit of our analysis is that it helps investors decide which of the four cryptocurrencies to buy or sell at what time during the next 24 hours. Nevertheless, the study’s authors [25] created an algorithm that uses association rules to make personalized customer suggestions. This FrequentPattern-Growth algorithm helps buyers buy the future product that the recommendation system suggests.

Using Association Rule Mining (ARM) algorithms to predict cryptocurrency trends may have several drawbacks. Because of their extreme volatility, cryptocurrencies are challenging for ARM methods. While ARM usually works with categorical data, bitcoin data contains continuous numerical features like market caps, prices, and volumes. Call for adjustments that lessen the data’s richness and restrict the understanding drawn from the rules.

In conclusion, there are advantages and disadvantages to using Association Rule Mining algorithms for predicting Bitcoin trends. ARM implementation inherent volatility and complexity of cryptocurrency. Nonetheless, the possibility of hybrid models, real-time data integration, and enhanced scalability offer encouraging directions for further study. This work’s practical significance stems from its ability to guide more open, understandable trading methods and aid in the creation of more advanced, flexible forecasting tools for the financial industry.

5. Conclusions and Future Work

Several researchers in this domain use the association rules to forecast and discover association rules and explore frequent item sets. In our paper, we used apriori algorithm to generate the association rules. We have made a substantial contribution by establishing a strong correlation between four cryptocurrencies: Ethereum, Monero, Litecoin, and Bitcoin. In particular, we want to find out what connection is between Bitcoin and other things during the next day. We estimated the grade of these rules operating two metrics: Lift and support. We extracted the strong association rules with a support level of 0,25 and a lift level surpassing 1. For instance, from Table V Rule 1 in the transaction ”Bitcoin_H00_SA → ETC_H11_SV”, the antecedent represents a simple buying now of Bitcoin they demonstrate a simple selling next 11 hours of ETC_USD (Ethereum) with a lift level surpassing one and a support level of 0,27. In forthcoming research, we intend to utilize our suggested model across various cryptocurrencies, commodities, and other stocks, and EUR_USD. Future studies on using Association Rule Mining (ARM) methods to predict cryptocurrency movements’ predictive accuracy increased by combining ARM with cutting-edge machine learning methods like neural networks, decision trees, or time series forecasting models (such as LSTM or Autoregressive Integrated Moving Average).

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