INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Minimum, Maximum, and Average Implementation of Patterned Datasets in Mapping Cryptocurrency Fluctuation Patterns

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Abstract*— Cryptocurrency price fluctuations are increasingly interesting and are of concern to researchers around the world. Many ways have been proposed to predict the next price, whether it will go up or down. This research shows how to create a patterned dataset from an API connection shared by Indonesia's leading digital currency market, Indodax. From the data on the movement of all cryptocurrencies, the lowest price variable is taken for 24 hours, the latest price, the highest price for 24 hours, and the time of price movement, which is then programmed into a pattern dataset. This patterned dataset is then mined and stored continuously on the MySQL Server DBMS on the hosting service. The patterned dataset is then separated per month, and the data per day is calculated. The minimum, maximum, and average functions are then applied to form a graph that displays paired lines of the movement of the patterned dataset in Crash and Moon conditions. From the observations, the Patterned Graphical Pair dataset using the Average function provides the best potential for predicting future cryptocurrency price fluctuations with the Bitcoin case study. The novelty of this research is the development of patterned datasets for predicting cryptocurrency fluctuations based on the influence of bitcoin price movements on all currencies in the cryptocurrency trading market. This research also proved the truth of hypotheses a and b related to the start and end of fluctuations.

***Keywords*— patterned datasets, cryptocurrencies, predictions, hypotheses**

Manuscript received 3 Jan. 2023; revised 17 Jul. 2023; accepted 4 Sep. 2023. Date of publication 31 Mar. 2024.

I. INTRODUCTION

Due to the nature of cryptocurrency trading as a way to get the lowest buy/price point and then sell it at a higher price [5], this research builds a patterned data set model based on two initial hypotheses: when is the best time to buy cryptocurrency in the spot market or prepare to take a long position in the futures market, and when is a better time to sell cryptocurrency in the spot market or prepare to take a short position in the futures market? This study offers new insights for crypto investors, traders, and financial analysts [10]. This patterned dataset is expected to help monitor bitcoin price movements and predict future price movements [6]. The novelty of this research lies in the procedure for creating patterned datasets, which are formulated into hypotheses a and b. This patterned dataset model was initially built using cryptocurrency movement data from the Indodax trading market [1]. Still, this model can be easily implemented in many other cryptocurrency trading markets listed on Coinmarketcap [3], [5]. In this study, we will compare a patterned dataset using the minimum, maximum, and average functions to determine which function is best for improving the detection of fluctuations in cryptocurrency price movements with a case study of Bitcoin on the rupiah currency pair (BTC IDR). With the ability to detect the beginning of fluctuations until the end of fluctuations, the risk of loss in cryptocurrency trading can be minimized, and potential profits can be increased.

II. MATERIAL AND METHOD

The rapid growth of the cryptocurrency market, with its high volatility and application in various commercial transactions, has attracted the attention of academics and investors. Bitcoin is increasingly popular and has now attracted the attention of individual and institutional investors. Hence, an accurate forecast of Bitcoin price direction is essential to determine price trends and Bitcoin asset allocation [7]. Among all cryptocurrencies, bitcoin often has the highest trading volume, so investors and companies need to be able to predict its volatility more accurately [9]. Cryptocurrency is now expanding its development as a medium of exchange and a commodity traded 24 hours a day, non-stop, on various global exchanges [5].

Cryptocurrency consists of Bitcoin and Altcoin (an alternative coin). Bitcoin is a peer-to-peer electronic money system that allows online payments and can be sent directly from one party to another without going through a financial institution's intermediary [8]. If there is only 1 type of Bitcoin and it is the cryptocurrency pioneer, then Altcoin has at least thousands of types [2]. On the coinmarketcap page, it is also shown that the bitcoin market capitalization is often more significant than the total altcoin market capitalization recorded; this is what allows Bitcoin to have the power to influence altcoins, either partially or as a whole. Qiu et al. studied whether the spillover effect of volatility among cryptocurrencies is essential for forecasting the volatility of Bitcoin realization, and their results show that the Bitcoin volatility model shows a strong linkage effect between each cryptocurrency. However, using this information in Bitcoin volatility predictions is still not optimal [11].

Previous research proposed a simple algorithm to get a good long position. This is built from API documents shared by each exchange [5]. Then, they tested hundreds of APIs shared by hundreds of cryptocurrency digital markets and extracted the latest bitcoin price data from 20 crypto markets through API access shared by each market [6]. This study proposes a patterned dataset model built using data sources from API access on the Indodax market [1], [4]. The Indodax market is a cryptocurrency market with the most significant marketplace platform in Indonesia for buying and selling digital assets, namely Bitcoin and altcoins. It has been officially registered with Indonesia's Commodity Futures Trading Regulatory Agency [2]. This data is then stored in a MySQL database hosted [6]. In this study, we used data on Bitcoin and Altcoin price movements, where when Bitcoin changes prices and changes its position to the daily lowest and highest prices, it will affect the prices of several other cryptocurrency assets on the Indodax trading market [1]. To help understand this research, a glossary is presented in Table 1.

TABLE I
GLOSSARY

No	Terms and Brief Description	Additional explanation
1.	*Cryptocurrency* (Blockchain-based digital currency)	Consists of bitcoin and alternative coins. Bitcoin is only one type, but altcoins comprised of thousands of types based on those listed on coinmarketcap.com.
2.	BTC (Bitcoin)	The first cryptocurrency that created an identity was named Satoshi Nakamoto in 2009. Bitcoin is often the Cryptocurrency has the largest capitalization compared to the accumulation of all the combined market capitalization of altcoins.
3.	BTC IDR	Bitcoin is traded in Rupiah, which can be found on the Indodax cryptocurrency trading digital market and determines the price movements of all cryptocurrencies on Indodax.
4.	Crash	The cryptocurrency price decline occurs when the price has decreased until the current price equals the daily lowest price (within 24 hours).
5.	Moon	The cryptocurrency price increase condition occurs when the price increases until the current price is equal to the daily high (within 24 hours).
6.	Patterned Dataset	The dataset was built by programming the low, last, high, and movement time variables in advance and then stored continuously in the MySQL Server database on the hosting.
7.	Low	The lowest price in 24 hours
8.	Last	Current Prices
9.	High	Highest price in 24 hours

Patterned dataset mining begins with translating the Indodax cryptocurrency trading digital market API document. Programming uses the PHP and JavaScript programming languages to form a patterned dataset, as in the first step in Figure 1. Data on cryptocurrency price movements in JSON form (Fig. 2) is then taken for the low, last, high, and data access time variables. These variables are then programmed into patterned datasets. Public API [4] This is data open to the public. No API key is required to call this data. Programmers can make a simple GET request or open it directly from the browser using the BTC/IDR Ticker and ALL Ticker [4].

Fig. 1 Research methods

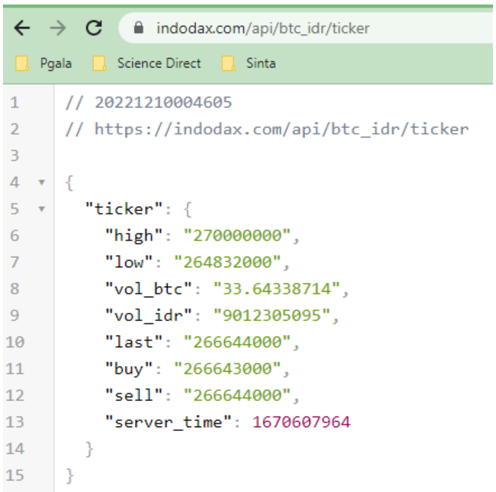

Fig. 2 API access result data in JSON form

In one access, all cryptocurrency data traded on the Indodax cryptocurrency trading digital market will be displayed, where more than 300 cryptocurrency assets each display their data attributes, as shown in Figure 2. Data resulting from API access in JSON is taken first by the low, last, and high variables. Then, several variables are defined as the basis for the patterned dataset formula as follows:

R = Range
H = Highest Price
L = Lowest Price
C = Current Price
TR = Top Range
LR = Lower Range
PTR = Percent of Top Range
PLR = Percent of Lower Range

Then, the basic patterned dataset formula [5] is compiled as follows:

$$R = H - L \quad (1)$$

$$TR = H - C \quad (2)$$

$$LR = C - L \quad (3)$$

$$PTR = \frac{TR}{R} \times 100\% \quad (4)$$

$$PLR = \frac{LR}{R} \times 100\% \quad (5)$$

This 1–5 formula is applied to each cryptocurrency asset in one go. These five formulas filter which cryptocurrency assets have decreasing prices until they reach their lowest prices in 24 hours and which cryptocurrency assets have increasing prices until they reach their highest prices in 24 hours. Bitcoin price movements have an essential influence on the prices of all currencies on the cryptocurrency trading digital market. When Bitcoin moves, there will be several conditions for price changes in each cryptocurrency, including changing to the lowest price, the highest price, and not changing. From the filter formula 1–5, data is only taken for assets that change to the lowest price in 24 hours and assets that change to the highest price in 24 hours. There is a linear relationship between bitcoin prices and the PTR and PLR variables, which are described in Table 2 as follows:

TABLE II
RELATIONSHIP BETWEEN PTR AND PLR VALUE MOVEMENTS AND BITCOIN PRICES

Position of each cryptocurrency asset (Bitcoins and altcoins)		
Crash Condition PLR == 0 PTR == 100 Price = Low (L)	1 ← PLR →99 99← PTR → 1 Current prices To Low ← (C) →To High	Moon Condition PLR == 100 PTR == 0 Price = High (H)

From Table 2, insight is obtained that Bitcoin acts as a price determinant, where at every second, Bitcoin may experience price changes that cause changes in the prices of all Cryptocurrencies in a Cryptocurrency trading market.
To clarify the basic patterned dataset model in Table 2, the following six essential points are described:

- Every time the Bitcoin price moves or changes, there are several cryptocurrency assets (bitcoins and altcoins) that experience price increases until they reach a PTR value of 0 and a PLR value of 100. This condition is called the moon condition. Conversely, at the same time, there are also several cryptocurrency assets (bitcoins and altcoins) that experience a price decrease until they reach a PTR value of 100 and a PLR value of 0. This condition is called a crash condition.
- When the PLR value of a cryptocurrency asset equals 100, and the PTR value equals 0, then the altcoin is in a moon condition and provides an additional value of 1 to be accumulated in the total weight of the moon condition.
- Contrary to point 2, when the PTR value of a cryptocurrency asset equals 100 and its PLR value equals 0, then the altcoin is in a crash condition and provides an additional value of 1 to be accumulated in the total weight of the crash condition.
- When a cryptocurrency asset experiences a crash condition (point 3), its value becomes the lowest price in the 24-hour range (L).
- When a cryptocurrency asset experiences a moon condition (point 2), its value increases until the price becomes the highest in the 24-hour range (H).
- Not all cryptocurrency assets will experience crash or moon conditions when Bitcoin moves. Assets that have not reached the maximum PTR or PLR value point will not be counted in the crash or moon weighting.

After knowing the conditions of each cryptocurrency asset when Bitcoin moves, weighting is carried out based on the accumulated crash and moon conditions. The method for forming a primary patterned dataset is then carried out by visualizing the patterned dataset that is already stored in the database. This primary patterned dataset is then visualized as a predictive model by analyzing the pairwise graph between the actual Bitcoin IDR price and the graph containing the total weight data sequentially over time. The results of this step will obtain a patterned dataset model to determine which cryptocurrency price position will tend to be in which position when the weight level is reached in a specific range of values.

Next, the achieved weight level is formulated into a continuous equation. Before building a basic pattern dataset model, an equation is created to define a crash condition variable called Crash_Condt. Total_Crash_Condt is the total number of currencies that experience concurrent conditions PLR = 0 and PTR = 100. The Total_Crash_Condt value is obtained from the following equation: 6a.

$$Total\_Crash\_Condt = Count(\sum_{i=1}^{n} \text{Crash\_Condt}(i)) \quad (6a)$$

n is the total number of cryptocurrencies that experience a crash in a market. Next, an equation defines the Moon Condition Variable, called Moon_Condt. Total_Moon_Condt is the total number of cryptocurrencies that experience concurrent conditions PLR = 100 and PTR = 0. The value of Total_Moon_Condt is obtained from the following equation: 6b.

$$Total\_Moon\_Condt = Count(\sum_{i=1}^{n} \text{Moon\_Condt}(i)) \quad (6b)$$

With, n is the total number of currencies that experience Moon on a cryptocurrency trading market. From equations 6a and 6b, Table 3 results in accumulated weights for crash and moon conditions as follows:

TABLE III
TOTAL_CRASH_CONDT AND TOTALMOON_CONDT WEIGHTS

Total Condition	**Level name in Total_Moon_Condt**	**Level name in Total_Crash_Condt**
>121	Diamond Crash	Diamond Moon
111-121	Golden Crash 2	Golden Moon 2
101-110	Golden Crash 1	Golden Moon 1
91-100	Ultra Crash 2	Ultra Moon 2
81-90	Ultra Crash 1	Ultra Moon 1
71-80	Mega Crash 2	Mega Moon 2
61-70	Mega Crash 1	Mega Moon 1
51-60	Super Crash 2	Super Moon 2
41-50	Super Crash 1	Super Moon 1
31-40	Crash 2	Moon 2
21-30	Crash 1	Moon 1
11-20	Go Crash 2	Go Moon 2
1-10	Go Crash 1	Go Moon 1
0	Equalc	Equalm

The weight table for each condition is made at increasing 10-point intervals. This is so that when collected into a patterned dataset, it can be visualized into the Crash_Condt and Moon_Condt line pairs. This is meant to show what level and in which weight area the process of increasing and decreasing the price of Bitcoin has been at. To get the lowest or best purchase price based on Table 3 above, you must wait for the Diamond Crash condition to be reached. Conversely, to bring the best or highest selling price, you can stay for the Diamond Moon condition to be reached.

After the accumulation of Crash_Condt and Moon_Condt data is obtained, implementing the Minimum, Maximum, and Average functions is applied. Implementing these three functions will be related to Hypotheses A and B, which aim to predict monthly fluctuations by applying descriptive statistics such as MIN, MAX, and AVG. For this reason, it is described in equations 7 to 9 below. AVG on Total Crash and Moon Conditions :

$AVG\ on\ Total\ Crash\ Conditions$:

$$\text{AVGTCC} = \frac{\text{Total\_Crash\_Condt}}{\text{n}} \quad (7a)$$

$AVG\ on\ Total\ Moon\ Conditions$:

$$\text{AVGTMC} = \frac{\text{Total\_Moon\_Condt}}{\text{n}} \quad (7b)$$

$MIN\ on\ Accumulated\ Crash\ Conditions$:

$$= MIN \begin{pmatrix} Crash_{Condt(1)}, Crash_{Condt(2)}, \\ Crash_{Condt(3)} \dots Crash_{Condt(n)} \end{pmatrix} \quad (8a)$$

$MIN\ on\ Accumulated\ Moon\ Conditions$:

$$= MIN \begin{pmatrix} Moon_{Condt(1)}, Moon_{Condt(2)}, \\ Moon_{Condt(3)} \dots Moon_{Condt(n)} \end{pmatrix} \quad (8b)$$

$MAX\ on\ Accumulated\ Crash\ Conditions$

$$= MAX \begin{pmatrix} Crash_{Condt(1)}, Crash_{Condt(2)}, \\ Crash_{Condt(3)} \dots Crash_{Condt(n)} \end{pmatrix} \quad (9a)$$

$MAX\ on\ Accumulated\ Moon\ Conditions$ =

$$MAX \begin{pmatrix} Moon_{Condt(1)}, Moon_{Condt(2)}, \\ Moon_{Condt(3)} \dots Moon_{Condt(n)} \end{pmatrix} \quad (9b)$$

With n as the number of data points in one selected day and i as the sequence of data points in one day,

III. RESULTS AND DISCUSSION

Using Equations from 7 to 9, Crash_Condt and Moon_Condt data are grouped using the Max, Min, and AVG functions. Next, a line chart is made to see the relationship between the Crash_Condt data group and the Moon_Condt data group with the BTC/IDR price chart. An example of the results of the 5-month 2022 Crash_Condt Data Grouping can be seen in Table 4, and an example of the 5-month 2022 Moon_Condt Data Grouping results can be seen in Table 5.

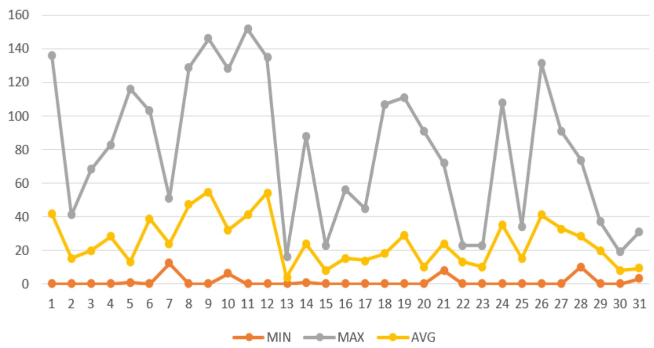

Fig. 3 Weight of Crash Conditions in Month 5 of 2022 with MIN (bottom line), AVG (middle line), and MAX (top line)

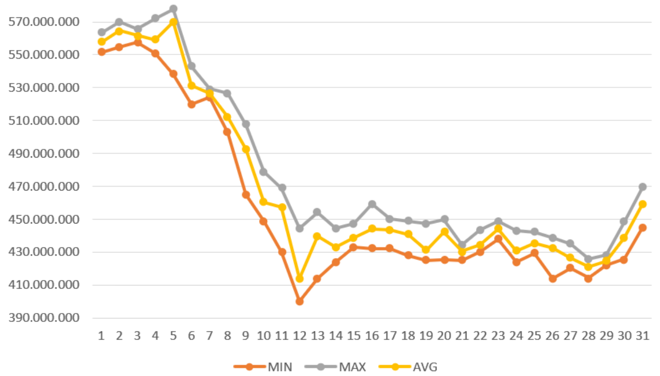

Fig. 4 The price of Bitcoin IDR in Crash Condition in Month 5 2022 with MIN, MAX, and AVG

To clarify the data profile in Table 5, a line chart graph is made as shown in Figures 5 and 6.

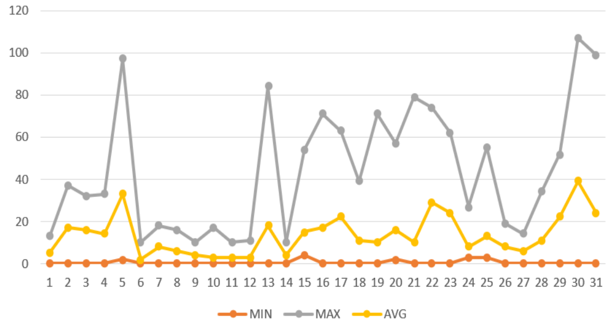

Fig. 5 The weight of the moon conditions in Month 5 of 2022 with MIN, MAX, and AVG

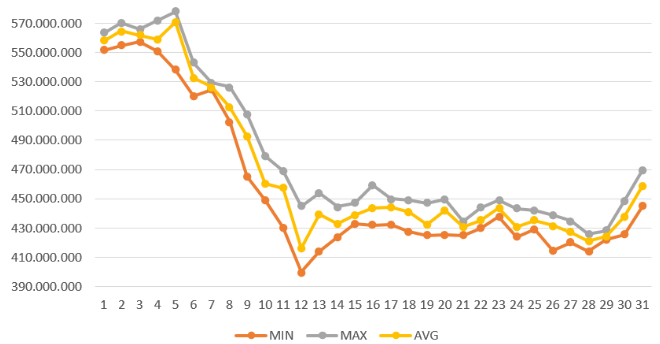

Fig. 6 Price of Bitcoin IDR Moon Conditions in Month 5 2022 with MIN, MAX, and AVG

Figures 3 and 4 show that the Bitcoin IDR price decreases when the Max and AVG values are higher in crash conditions. Figures 5 and 6 show that the Bitcoin IDR price decreases when the Max and AVG values are lower under moon conditions. There is a small difference if we pay attention to the appearance of the Bitcoin IDR chart in crash conditions (Figure 4) and moon conditions (Figure 6). To further clarify the appearance of the BTC IDR price line in Crash and Moon conditions, it can be seen in Figure 7 on the right. From Figure 7, when the BTC IDR data line in crash conditions and moon conditions is put together, it turns out that they can merge because they have almost no price difference.

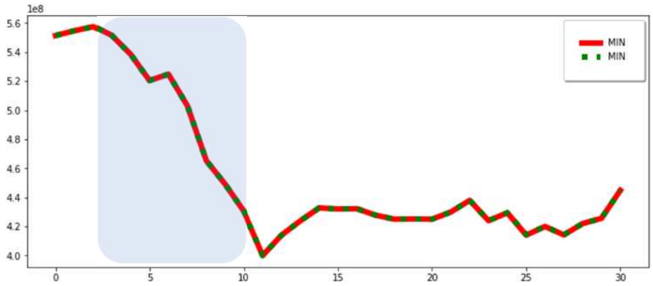

Fig. 7 Bitcoin IDR daily crash and moon conditions

If in Figure 7, the BTC IDR price variable is compared in crash and moon conditions, then in Figure 8, it is compared between the patterned dataset in crash conditions and the patterned dataset in moon conditions in month 5 of 2022 with minimum function implementation. Figure 9 compares the patterned dataset in crash conditions to the patterned dataset in moon conditions in month 5 of 2022 with maximum function.

TABLE IV

MIN, MAX, AVG VALUES FOR CRASH_CONDT AND BTC/IDR MONTH 5 2022

MIN CC	MAX CC	AVG CC	MIN (BTC IDR)	MAX (BTC IDR)	AVG (BTC IDR)
0	136	42	551.425.000	563.472.000	557.741.467
0	41	15	554.725.000	569.999.000	564.762.072
0	68	20	557.512.000	565.879.000	561.859.570
0	83	28	551.000.000	571.969.000	559.161.677
1	116	13	537.999.000	577.811.000	570.150.559
0	103	39	519.970.000	543.017.000	531.295.539
12	51	24	524.321.000	529.303.000	526.506.293
0	129	47	502.705.000	526.366.000	512.169.890
0	146	55	465.096.000	507.611.000	492.621.812
6	128	32	448.825.000	479.039.000	460.415.894
0	152	41	430.100.000	468.762.000	457.172.425
0	135	54	400.000.000	444.604.000	413.886.424
0	16	4	414.000.000	454.098.000	439.524.000
1	88	24	423.841.000	444.534.000	432.885.645
0	23	8	432.769.000	447.100.000	438.917.064
0	56	15	432.047.000	459.142.000	444.193.160
0	45	14	432.250.000	450.000.000	443.640.212
0	107	18	427.761.000	448.999.000	440.757.655
0	111	29	425.001.000	447.163.000	431.298.115
0	91	10	425.162.000	449.842.000	442.112.250
8	72	24	425.000.000	434.546.000	430.463.496
0	23	13	429.952.000	443.499.000	434.417.953
0	23	10	437.951.000	448.817.000	443.995.691
0	108	35	424.000.000	443.162.000	430.706.873
0	34	15	429.413.000	442.140.000	435.168.688
0	131	41	414.000.000	438.758.000	432.336.579
0	91	33	420.000.000	434.910.000	426.361.491
10	74	28	414.200.000	425.900.000	420.837.963
0	37	20	422.000.000	428.000.000	424.521.461
0	19	8	425.604.000	448.326.000	438.801.903
3	31	9	444.857.000	469.421.000	459.046.429

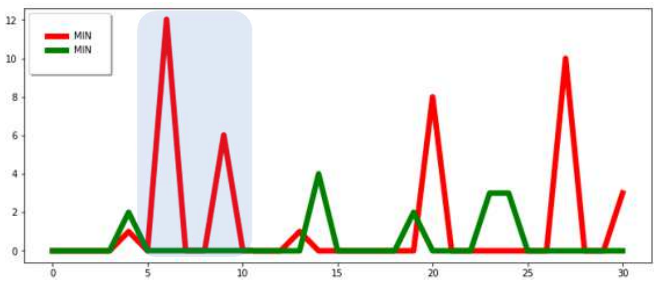

Fig. 8 Daily Minimum Weight of Crash and Moon Conditions in Month 5, 2022

In Figure 10 it is compared between the patterned dataset in crash conditions compared to the patterned dataset in moon conditions in month 5 of 2022 with average function.

TABLE V
MIN, MAX, AVG VALUES FOR MOON_CONDT AND BTC/IDR MONTH 5 2022

MIN CC	MAX CC	AVG CC	MIN (BTC IDR)	MAX (BTC IDR)	AVG (BTC IDR)
0	13	5	551.425.000	563.472.000	557.747.507
0	37	17	554.725.000	569.999.000	564.765.162
0	32	16	557.512.000	565.879.000	561.817.141
0	33	14	551.000.000	571.969.000	559.148.938
2	97	33	537.999.000	577.811.000	570.808.724
0	10	2	519.970.000	543.017.000	532.449.233
0	18	8	524.321.000	529.303.000	526.440.579
0	16	6	502.705.000	526.366.000	512.350.078
0	10	4	465.096.000	507.611.000	492.875.165
0	17	3	448.825.000	479.039.000	460.503.850
0	10	3	430.100.000	468.762.000	457.397.707
0	11	3	400.000.000	444.604.000	416.125.366
0	84	18	414.000.000	454.098.000	439.647.835
0	10	4	423.841.000	444.534.000	432.843.146
4	54	15	432.769.000	447.100.000	438.658.526
0	71	17	432.048.000	459.142.000	443.803.756
0	63	22	432.250.000	449.999.000	444.305.151
0	39	11	427.761.000	448.999.000	440.767.456
0	71	10	425.001.000	447.163.000	432.262.769
2	57	16	425.162.000	449.842.000	441.979.690
0	79	10	425.000.000	434.546.000	430.543.035
0	74	29	429.952.000	443.820.000	435.089.249
0	62	24	437.951.000	448.817.000	443.761.095
3	27	8	424.000.000	443.162.000	430.988.636
3	55	13	429.413.000	442.140.000	435.174.206
0	19	8	414.460.000	438.758.000	431.819.040
0	14	6	420.000.000	434.910.000	427.151.125
0	34	11	414.200.000	425.900.000	420.976.041
0	52	22	422.000.000	428.000.000	424.370.311
0	107	39	425.604.000	448.326.000	437.834.447
0	99	24	444.857.000	469.421.000	458.859.890

In Figure 7, some areas mark fluctuations in the decline in the BTC IDR price as an example of cryptocurrency, which will be compared with the fluctuation areas that mark a decline in the pattern dataset graph, namely in Figures 8, 9, and 10. Figure 8 shows that the Minimum function implementation on the Patterned Dataset shows a pattern of two sharp ends on the Crash condition line, indicating a decrease in fluctuations. It is difficult to mark the beginning and end of a decrease or increase in fluctuations using the minimum function because it does not show any intersection between the patterned dataset line in the red crash condition and the green moon condition line.

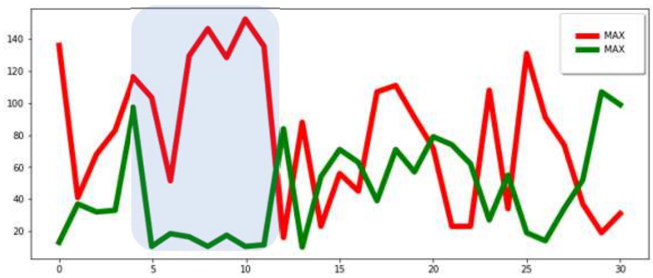

Fig. 9 Daily Maximum Weight of Crash and Moon Conditions in Month 5, 2022

In Figure 9, the implementation of the Maximum function in the Patterned Dataset shows the line pattern of the crash condition and the moon condition line getting closer as an initial sign of a decline fluctuation, while at the end of the decline fluctuation, it is marked by the intersection between the red crash condition line, which cuts the colored moon condition line green down. The end of the fluctuation can be easily recognized because of the intersection between the two lines. Whereas at the beginning of the fluctuation, it is more difficult to recognize because there is no intersection between the patterned dataset lines in crash conditions and the patterned dataset lines in moon conditions.

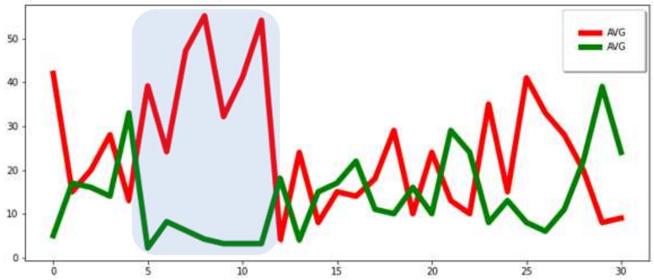

Fig. 10 Daily Average Weight of Crash and Moon Conditions in Month 5, 2022

Figure 10 clearly shows that the patterned dataset, with the implementation of the averaging function, can clearly show the beginning of the decline fluctuation marked by the intersection between the red crash condition line and the green moon condition line. At the beginning of the downward fluctuation, the red line of crash conditions crosses and moves upwards, indicating that the crash condition is getting deeper to the highest point before experiencing a reversal. In this downward fluctuation area, the downward fluctuation will end when the red crash condition line crosses the green moon condition line downward again. So, with the pattern shown by applying the Min, MAX, and AVG functions to the Patterned Dataset to detect fluctuations, it appears that the Average function shows the potential for more precise readings and markings. This is in line with Hypothesis A, as follows: **Hypothesis A** is "The upward fluctuations begin to occur when the moon line (green) crosses the crash line (red) in an upward direction, and the longer the vertical distance between the two lines. The rise's peak occurs at the highest point reached by the moon line (green). Fluctuations end when the vertical distance gets smaller".

Hypothesis B is the opposite of Hypothesis A. If Hypothesis A provides a theory of start-to-finish increase fluctuations, then Hypothesis B delivers a theory of start-to-finish decline fluctuations. Hypothesis B is explained as follows: "Descent fluctuations begin to occur when the moon line (green) crosses the crash line (red) downwards, and the longer the vertical distance between the two lines. The decline peak occurs at the lowest point of the moon line (green). Fluctuations end when the vertical distance gets smaller".

Figure 11 successfully shows that hypotheses A and B are well-proven. For clarity, Hypothesis B explains that when the green moon line crosses below the red crash line, and the distance between the two gets farther apart, then this is where the sign of downward fluctuation begins. Hypothesis A explains that when the red crash line crosses under the green moon line and the distance between the two increases, then this is where the rising sign of fluctuation begins. When the two lines have reached their sharp ends, they reverse and cross again. Figure 10 before and Figure 12 below are exemplary forms of proof of hypothesis B.

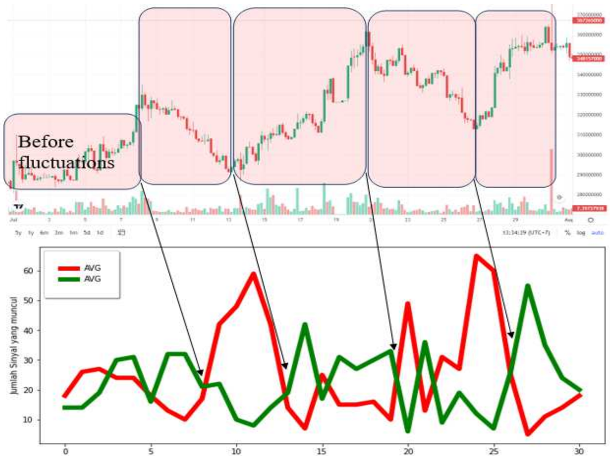

Fig. 11 Detect fluctuations with the daily average of crash conditions and month conditions in July 2022

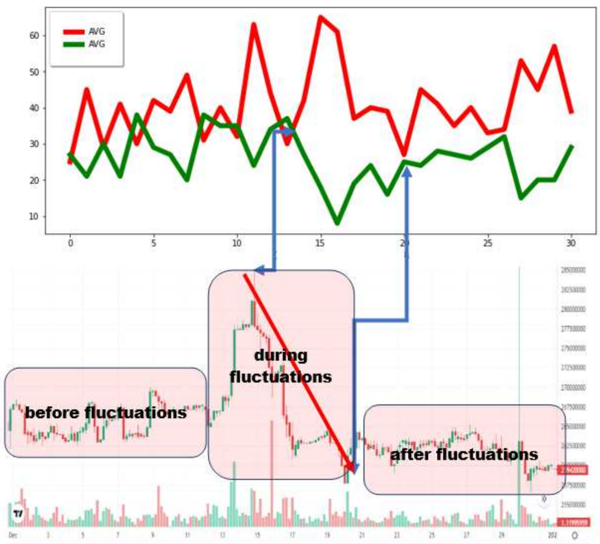

Fig. 12 Detection of fluctuations with the daily average of crash and moon conditions

The following job is to set thresholds. Hypotheses A2 and B2 enrich Hypotheses A and B. Hypothesis B2: "Decreased fluctuations will occur when the average crash condition crosses the maximum line on the average moon condition." Hypothesis A2: "Increased fluctuations will occur when the average moon conditions cross the maximum line in the average crash conditions."

In the Fluctuation Detection Model, an upper and lower threshold are required. The upper threshold formula is used.

between $$\text{MAXAVGC} = \text{MAX}\left(\frac{\text{Total\_Crash\_Condt}}{n}\right) \quad (10a)$$

and $$\text{MAXAVGM} = \text{MAX}\left(\frac{\text{Total\_Moon\_Condt}}{n}\right) \quad (10b)$$

The lower Threshold Formula is used

between $$\text{MINAVGC} = \text{MIN}\left(\frac{\text{Total\_Crash\_Condt}}{n}\right) \quad (11a)$$

and $$\text{MINAVGM} = \text{MIN}\left(\frac{\text{Total\_Moon\_Condt}}{n}\right) \quad (11b)$$

As an example, when the condition of Hypothesis B2 is reached, an early warning notification will appear for decreasing fluctuations.

IF (AVGTCC ≥ MAXAVGM) Then notify info = "Potential Fluctuation Decrease,"

with predictions of when the peak will occur AVGTCC = MAXAVGM or AVGTCC = MAXAVGC (12a)

And when the condition of Hypothesis A2 is reached, an early warning notification of an increase in fluctuation will appear.

IF (AVGTCM ≥ MAXAVGM) Then notification info = "Potential Fluctuation Increase",

with predictions of when the peak will occur AVGTCM = MAXAVGM or AVGTCM = MAXAVGC (12b)

In subsequent studies, an in-depth discussion of the upper and lower thresholds will be studied.

Apart from the upper and lower thresholds, there are several potential developments for further research using patterned dataset models. The Patterned Dataset Model, which then produces a patterned dataset, can be used as comparative or complementary test data in various studies. For example, comparative analysis research uses random forest models to predict Bitcoin [21], [7]. Patterned datasets can also be used as additional features in research predicting the next bitcoin price using machine learning techniques [13], combining machine learning models, SARIMA, and Facebook Prophet [16], forecasting cryptocurrency returns [29], Rao's algorithm-based artificial neural network [27], and other similar forms of research. Fuzzy prediction models, such as those used in computational intelligence engineering research using hybrid neuro-fuzzy controllers [14], QFTS models and QFTS-ANN hybrids [26], and dataset-based fuzzy modeling [18], can also use patterned datasets as data components to predict the direction of changes in cryptocurrency prices.

The Patterned Dataset Model has the potential to be combined with other models, such as in stochastic neural network research, to predict the next cryptocurrency price [24]. Cryptocurrency trading volatility prediction can also combine patterned dataset models using deep learning [28]. Patterned datasets can also be used as material for estimating cryptocurrency returns or subsequent prices using autoregressive integrated moving average (ARIMA) and neural network autoregression (NNAR) models [30], LSTM models and wavelet decomposition [22], LSTM and GRU models [19], as well as cryptocurrency price estimation using a comparison of hyperparameters and forecasting model architecture between machine learning, deep learning, or a combination of both [17].

Combining sentiment analysis, such as using a collection of Twitter posts with a patterned dataset, has the potential to show the relationship between sentiment and the fluctuations displayed by the patterned dataset graph [23], as well as the predictive power of investor sentiment on bitcoin returns [12], the relationship of tweets to sentiment analysis, and emotion prediction. using the LSTM-GRU Model Ensemble on Cryptocurrency Trading [20], as well as using Google search volume data to predict the profit and volatility of various cryptocurrencies [15]. Patterned datasets can also be validated using various technical indicators such as moving average convergence or divergence (MACD), the Relative Strength Index (RSI), stochastic, Bollinger bands, moving average (MA) or exponential moving average (EMA) cross indicators, and others [25].

IV. CONCLUSIONS

In research, it is proven that patterned datasets use the implementation of the average function in the accumulation of data under daily crash and moon conditions, which show more precise results compared to the use of the minimum and maximum functions. Using the AVG function, the beginning and end of fluctuations can be seen more clearly with the pattern of intersection of the Patterned Dataset line for crash conditions, which is red, with the Patterned Dataset line for the moon condition, which is green. If the first intersection of the red crash condition line cuts up and is farther away from the green moon condition line, this indicates that downward fluctuations have begun. Conversely, if the green moon condition line crosses upwards, it shows that price increase fluctuations have begun. In the downward fluctuation, when the red crash condition line cuts downward as a closing of the downward fluctuation process, the downward fluctuation has ended. Conversely, if the fluctuation cover shows the green moon condition line cutting downward, the price increase has been completed. Further research can be developed by making the upper and lower threshold the fluctuation area reversal points. By marking fluctuation patterns, the risk of losing cryptocurrency trading can be minimized, and the profit potential can be enlarged. As a form of broader development, the Patterned Dataset Model can be collaborated with various research results that use various variants of machine learning models, deep learning or their combinations to predict the next price direction, the sentiment that influences it, as well as estimates of returns from cryptocurrency trading. Patterned Datasets can also be improved in accuracy by using them as training data and testing data for machine learning models, deep learning models, statistical models, and various technical trading indicators.

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