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K-Medoids: Inflation Clustering of 90 Cities in Indonesia (January-October 2020)

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Abstract

Inflation affects society and the economy of a country. For the general public, inflation is a concern because inflation directly affects the welfare of life, and for the business world, the inflation rate is a very important factor in making various decisions. Therefore, the aim of this study is to cluster the inflation rate that occurs in 90 cities in Indonesia, so that it is known which cities have high, medium, or low inflation levels. The grouping algorithm used is K-Medoids data mining. The research data is quantitative data, namely inflation data that occurred in 90 major cities in Indonesia from January to October 2020. The data was obtained from the Indonesian Central Statistics Agency. The clustering in this study is divided into 5, among others: cities with very high inflation rates, cities with high inflation rates, cities with moderate inflation rates, cities with low inflation rates, and cities with very low inflation rates. Based on the results of clustering analysis using rapidminer, for cities with a very high inflation rate category consists of 1 city (available on Cluster_4), high category consists of 4 cities (Cluster_0), medium category consists of 4 cities (Cluster_3), low category consists of 79 cities (Cluster_2) and very low category consisted of 2 cities (Cluster 1). This can provide information for the Indonesian government to keep the inflation rate stable.

Keywords: *Data Mining, K-Medoids, Clusters, Inflation, Indonesia*

1. Introduction

Indonesia is the largest archipelagic country globally, with many cities in each province; of course, each city has a different inflation rate from time to time [1]. Inflation is a process of increasing prices in general and continuously, related to market mechanisms that can be caused by various factors, including increased public consumption, excess liquidity in the market that triggers consumption, or even speculation, including the consequences of the non-smooth distribution of goods [2]. Inflation is an indicator to see the rate of change and is considered to occur if the process of price increases takes place continuously and influences each other [3]. The high level of inflation indicates that the risk of investing is quite large because high inflation will reduce the returns from investors [4][5]. Inflation stability is a prerequisite for sustainable economic growth, which provides benefits for improving the welfare of the community. The importance of controlling inflation is based on the consideration that high and unstable inflation harms the people's socio-economic conditions in an area. Also, inflation directly affects people's welfare.

Based on data from the Indonesian Central Statistics Agency, in October 2020, there was an inflation of 0.07% with a Consumer Price Index (CPI) of 104.92. Of the 90 CPI cities, 66 cities experienced inflation. The highest inflation occurred in Sibolga with 1.04 percent with CPI of 104.43, and the lowest occurred in DKI Jakarta, Cirebon, Bekasi, and Jember with 0.01 percent each with CPI of 105.40; 102.50; 106.95; and 104.65. Inflation occurred due to price increases as indicated by increases in the index for most expenditure groups, namely: the food, beverage, and tobacco group by 0.29%; clothing and footwear group by 0.09%; health group of 0.15%; recreation, sports, and culture group at 0.02%;

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education group of 0.04%; and the food and beverage/restaurant supply group by 0.19%. Meanwhile, the expenditure group that experienced a decrease in the index were the housing, water, electricity and household fuels group by 0.04%; equipment, tools, and household routine maintenance group of 0.03%; transportation group of 0.14%; the information, communication, and financial services group of 0.02%; and personal care and other services group of 0.11%. The calendar year (January – October) 2020 is 0.95%, and the year-on-year inflation rate (October 2020 to October 2019) is 1.4%. The core component in October 2020 experienced inflation of 0.04%. The inflation rate for the core component for the calendar year (January - October) 2020 was 1.50%, and the inflation rate for the core component year on year (October 2020 against October 2019) was 1.74% [6].

This research aims to cluster the inflation rate in 90 cities in Indonesia so that it is known which cities have high, medium, or low inflation rates. These clustering results are expected to provide input and information for the Indonesian government to act quickly and always be vigilant so that the inflation rate remains stable. The clustering method in this study uses the K-Medoids Algorithm, one of the data mining algorithms. Another clustering data mining algorithm that is often used for clustering is K-Means [7]–[14]. Apart from clustering, data mining is also often used for data classification problems [15]–[19], predictions and Association.

Some of the previous studies that became the reference for this paper include research that discusses landslide vulnerability mapping using the Hausdorff distance (OA-HD) algorithm and the K-medoids clustering algorithm. The OA-HD algorithm distributes the mapping unit into many subclasses with similar topographic and geological value characteristics. To get a more optimal subclass, HD was adopted to measure rainfall. The K-Medoids algorithm classifies these subclasses into five levels of vulnerability according to the landslide density values in each subclass [20]. The next research introduces the Convex Fuzzy k-Medoids (CFKM) model, which not only relaxes the assumption that objects should be assigned entirely to one and only one medoid but also that the medoids should all be assigned to one and only one cluster. The resulting model is convex, so the resolution is powerful for initialization [21]. The next reference research is to Improve the K-Medoids Clustering Algorithm Based on Fixed Point Iterations. The authors used fixed-point iterations to find the optimal clustering center and construct the medoid-FPK (K-medoids). By constructing a fixed point equation for each cluster, the optimal center finding problem is converted into solving the set equation in parallel. The experiments were carried out on six standard data sets, and the results show that the proposed algorithm's clustering efficiency is significantly increased compared to the conventional algorithm [22]. These related studies are the background for conducting research to cluster inflation in 90 major cities in Indonesia. The results of the cluster are expected to be useful information for the Indonesian government to further maximize efforts in maintaining the inflation rate to remain stable.

2. ResearchMethodology

2.1. Research data

The research data is quantitative data, namely inflation data in 90 major cities in Indonesia from January to October 2020 which is presented in table 1.

Table 1. Inflation Data for 90 Cities in Indonesia (January-October 2020)

No	City	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
1	Ambon	0,65	0,21	-0,71	-0,11	0,21	0,43	0,06	0,43	-0,21	-0,59
2	Balikpapan	0,27	0,44	-0,15	0,02	0,31	0,28	-0,30	-0,21	-0,46	-0,17
3	Banda Aceh	0,77	0,54	0,61	-0,08	0,31	-0,18	-0,34	0,44	-0,32	0,62
4	Bandar Lampung	0,86	0,44	-0,44	-0,16	-0,29	0,03	0,33	0,41	-0,26	0,23
5	Bandung	0,38	0,35	0,25	0,16	-0,25	0,41	-0,14	-0,10	-0,05	0,08

No	City	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
6	Banjarmasin	0,25	-0,02	-0,30	-0,28	0,11	0,39	-0,28	0,31	-0,32	0,22
7	Banyuwangi	0,51	0,10	0,27	0,24	0,02	0,06	0,01	-0,01	-0,17	0,07
8	Baru	0,68	0,30	-0,14	-0,49	0,28	0,12	-0,37	0,23	-0,12	0,22
9	Batam	0,16	-0,15	-0,39	0,07	0,16	0,06	-0,17	0,02	-0,12	0,13
10	Bekasi	0,38	0,38	0,39	0,25	-0,08	0,48	-0,01	-0,01	-0,03	0,01
11	Bengkulu	0,14	0,09	-0,02	-0,35	0,41	0,04	-0,23	0,22	0,08	0,02
12	Bima	0,49	-0,08	0,09	-0,08	-0,34	-0,22	0,43	-0,12	-0,02	0,14
13	Bogor	0,78	0,25	0,04	-0,02	0,01	0,27	-0,01	-0,16	0,11	0,13
14	Bau-Bau	-1,39	0,11	0,06	0,88	0,09	-0,06	0,73	0,39	-0,40	-0,68
15	Bukittinggi	0,25	0,46	0,07	0,06	0,39	-0,13	-0,39	-0,17	-0,01	0,75
16	Bulukumba	0,22	0,61	0,15	0,37	0,28	0,03	-0,01	-0,04	0,05	0,08
17	Bungo	0,74	0,36	-0,56	-0,29	0,49	0,24	-0,34	0,06	0,02	0,59
18	Cilacap	-0,03	0,49	0,06	0,05	0,29	0,28	-0,17	-0,09	-0,03	0,12
19	Cilegon	0,59	0,46	0,11	0,20	0,26	0,22	-0,18	-0,02	0,10	0,24
20	Cirebon	0,10	0,17	0,29	0,02	-0,09	0,45	-0,12	-0,23	-0,25	0,01
21	Denpasar	0,55	0,39	0,11	-0,32	-0,10	0,08	-0,46	-0,12	-0,16	-0,25
22	Depok	0,61	0,25	0,36	0,02	-0,17	0,10	-0,16	-0,08	0,02	0,14
23	DKI Jakarta	0,25	0,27	0,33	0,29	-0,02	0,06	-0,05	-0,10	0,02	0,01
24	Dumai	0,54	0,21	-0,05	-0,19	0,95	0,11	-0,26	-0,05	-0,02	0,44
25	Gorontalo	0,03	0,32	-0,13	-0,08	-0,33	0,37	0,08	0,03	-0,06	0,13
26	Gunungsitoli	1,31	-0,73	0,43	-0,71	0,37	0,22	-0,01	0,61	1,00	0,71
27	Jambi	0,81	0,75	-0,65	-0,66	0,29	0,35	-0,05	0,03	0,13	0,77
28	Jayapura	0,17	0,40	-0,29	0,30	-0,07	0,15	0,62	-0,32	-0,09	-1,30
29	Jember	0,38	0,51	0,34	-0,13	-0,03	0,30	0,01	-0,11	-0,01	0,01
30	Kediri	0,52	0,38	0,11	0,08	-0,19	0,25	-0,06	0,02	0,15	-0,05
31	Kendari	-0,27	-0,47	0,06	-0,05	0,31	1,33	0,25	0,21	0,26	-0,48
32	Kudus	-0,01	0,39	0,04	-0,08	0,10	0,09	-0,09	0,05	-0,08	0,16
33	Kupang	0,47	0,49	-0,66	0,19	0,15	-0,07	-0,36	-0,92	-0,18	0,19
34	Lhokseumawe	0,08	0,49	0,64	-0,29	0,05	-0,07	-0,35	0,30	0,24	0,86
35	Lubuklinggau	0,36	0,39	0,07	-0,43	0,40	0,31	-0,18	-0,11	0,04	0,38
36	Luwuk	0,19	0,06	-0,59	0,54	-0,39	0,77	-0,01	0,35	0,18	-0,32
37	Madiun	0,35	0,38	0,19	-0,19	0,01	0,20	-0,04	-0,02	-0,02	0,11
38	Makassar	0,66	0,50	-0,11	0,48	0,55	0,01	-0,54	-0,09	0,05	-0,13
39	Malang	0,41	0,28	-0,41	-0,12	0,27	0,44	0,06	-0,06	-0,05	-0,06
40	Mamuju	-0,04	0,81	0,62	0,25	0,07	0,56	-0,16	-0,06	-0,34	-0,33
41	Manado	-0,09	-0,04	-0,90	-0,21	-0,01	0,19	-0,30	0,71	-0,36	0,10
42	Manokwari	-0,77	1,07	-1,30	0,15	0,16	0,48	-1,09	0,49	-0,63	-1,81
43	Mataram	0,57	-0,05	-0,30	-0,33	-0,15	0,15	0,09	-0,03	-0,04	0,19
44	Maumere	0,64	-0,25	-0,89	-0,06	-0,05	0,55	0,08	0,71	-0,35	0,87
45	Medan	0,58	0,14	-0,19	-0,28	0,42	-0,09	-0,21	0,04	-0,05	0,45
46	Merauke	0,42	0,93	-1,53	0,56	0,70	0,20	-0,48	-0,64	0,21	-0,61
47	Metro	1,15	0,19	0,27	-0,23	-0,35	0,26	0,11	0,06	0,10	0,05
48	Meulaboh	1,44	-0,10	0,52	-0,22	0,45	-0,19	-0,09	0,88	0,15	0,32
49	Mobagu	0,75	0,37	0,25	0,51	-0,27	1,23	-0,09	0,02	-0,33	-0,18
50	Padang	0,65	-0,29	-0,02	-0,47	0,66	-0,16	-0,11	0,09	-0,05	0,59
51	Padangsidimpuan	0,32	-0,01	0,53	0,04	0,76	-0,02	-0,25	0,07	-0,12	0,52
52	Palangka Raya	-0,06	0,63	-0,20	-0,10	0,23	0,33	-0,22	-0,55	-0,36	0,02
53	Palembang	0,62	0,26	0,04	-0,12	0,13	0,19	-0,28	-0,35	-0,05	0,16
54	Palopo	0,13	0,04	-0,09	0,34	0,49	0,07	0,15	-0,11	-0,17	0,10
55	Palu	-0,25	0,54	-0,35	0,17	0,15	0,34	0,16	0,07	-0,10	0,41
56	Pangkal Pnang	1,09	-0,68	-0,07	-0,92	0,51	0,20	0,06	-0,61	0,05	-0,32
57	Parepare	0,96	0,02	-0,10	-0,14	0,15	0,65	0,18	-0,24	0,18	-0,11
58	Pekanbaru	0,40	0,37	0,01	-0,34	0,44	0,06	-0,20	0,08	0,01	0,59
59	Pematang Siantar	0,62	0,12	-0,12	-0,40	0,37	-0,13	-0,76	0,20	0,29	0,46
60	Pontianak	0,73	0,63	-0,13	-0,08	0,48	0,33	-0,37	-0,15	0,01	-0,04

No	City	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
61	Probolinggo	0,40	0,39	0,04	0,05	0,05	0,15	0,16	-0,07	-0,35	0,15
62	Purwokerto	0,32	0,58	0,05	-0,08	0,19	0,40	-0,20	-0,12	-0,04	0,07
63	Samarinda	0,36	0,37	-0,15	-0,28	0,14	0,17	0,36	-0,16	-0,34	-0,21
64	Sampit	0,27	0,55	-0,26	-0,33	0,37	0,64	0,28	-0,43	-0,20	0,04
65	Semarang	0,06	0,43	0,02	-0,02	0,10	0,16	-0,10	-0,06	0,07	0,20
66	Serang	0,63	0,17	0,22	0,23	0,05	0,18	0,07	-0,05	-0,05	0,03
67	Sibolga	0,20	0,69	-0,79	-0,66	0,17	0,13	-0,31	-0,01	0,29	1,04
68	Singaraja	0,67	0,70	0,15	-0,36	-0,22	0,32	0,11	-0,42	0,27	-0,21
69	Singkawang	0,68	0,60	-0,18	-0,15	0,36	0,55	-0,45	-0,28	-0,01	0,35
70	Sintang	1,10	1,21	-0,15	-0,21	0,62	0,65	-0,43	-0,58	0,20	0,26
71	Sorong	-0,35	0,10	-0,09	0,26	-0,06	0,46	0,60	-0,33	-0,42	-0,61
72	Sukabumi	0,42	0,26	0,30	0,07	0,03	0,16	-0,06	-0,22	-0,08	0,02
73	Sumenep	0,84	0,16	0,09	0,15	0,02	-0,15	-0,12	0,03	-0,12	-0,07
74	Surabaya	0,52	0,32	0,01	-0,16	0,21	0,28	-0,41	0,07	-0,18	-0,02
75	Surakarta	0,14	0,41	0,01	-0,03	-0,20	0,29	-0,03	0,12	0,09	0,10
76	Tangerang	0,36	0,21	-0,01	0,26	0,04	0,14	-0,06	-0,10	-0,07	0,10
77	Tanjung	0,43	0,91	-0,11	-0,28	0,10	0,42	-0,08	-0,43	-0,30	0,27
78	Tanjung Pandan	0,46	-1,20	-0,13	-0,19	1,20	0,27	0,26	-0,67	0,20	0,45
79	Tanjung Pinang	0,36	-0,19	-0,40	-0,23	0,01	0,09	0,34	0,12	-0,32	0,37
80	Tanjung Selor	0,35	1,04	-0,45	-0,17	0,56	0,45	-0,28	-0,53	0,19	0,07
81	Tarakan	-0,07	-0,25	-0,46	0,20	-0,27	0,99	0,24	0,35	0,63	-0,28
82	Tasikmalaya	0,17	0,32	0,31	0,13	0,03	0,15	0,13	-0,27	-0,03	0,14
83	Tegal	0,34	0,38	-0,02	0,26	-0,10	0,42	-0,05	0,09	-0,06	0,22
84	Tembilahan	0,41	0,31	-0,04	0,43	0,62	1,13	-0,75	-0,01	-0,22	0,52
85	Ternate	0,34	1,00	-0,48	0,12	0,89	-0,34	-0,95	0,53	-0,74	0,28
86	Timika	1,00	0,81	-1,91	0,72	0,90	0,92	1,45	0,41	-0,83	0,24
87	Tual	0,68	-0,29	-0,55	0,31	0,65	1,07	-0,34	-0,57	0,21	-0,09
88	Waingapu	0,98	-0,04	0,39	-0,80	0,06	-0,30	-0,49	-0,48	0,22	0,18
89	Watampone	0,45	0,23	0,02	0,21	0,21	0,14	0,35	-0,19	-0,31	0,40
90	Yogyakarta	0,27	0,40	0,07	-0,24	0,22	0,08	-0,08	-0,04	0,03	0,08

Source: Indonesian Central Bureau of Statistics [23]

2.2. Flowcharts and Research Stages

The following will present a research flowchart of the K-Medoids clustering algorithm.

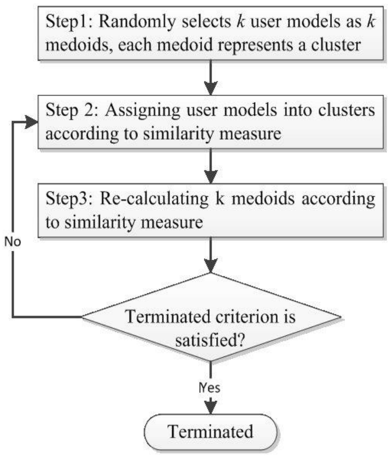

Figure 1. Research Flowchart [24]

The steps of the K-Medoids algorithm can be explained as follows [25]:

a) Initialize k cluster centers (number of clusters).
b) Allocate each data (object) to the nearest cluster.
c) Randomly select objects in each cluster as candidates new medoid.

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d) Calculate the distance of each object in each cluster with a new medoid candidate.
e) Calculate the total deviation (S) by calculating the total distance value new - long total distance. If S <0, then swap object with data cluster to form a collection of k new objects as medoids.
f) Repeat steps 3 to 5 until there is no change in medoid, so that we get the cluster and their respective cluster members.

3. Results and Discussion

3.1. Centroid and Cluster with Rapidminer

In using the K-Medoids algorithm, the midpoint or centroid's value can be determined randomly or randomly from the data obtained, provided that the desired clusterization is 5. The determination of the clusters in this paper is divided into five parts, namely very high clusters, high clusters, medium clusters, the cluster is low, and the cluster is very low. The following is the grouping process and the results of the K-Medoids algorithm carried out with Rapidminer.

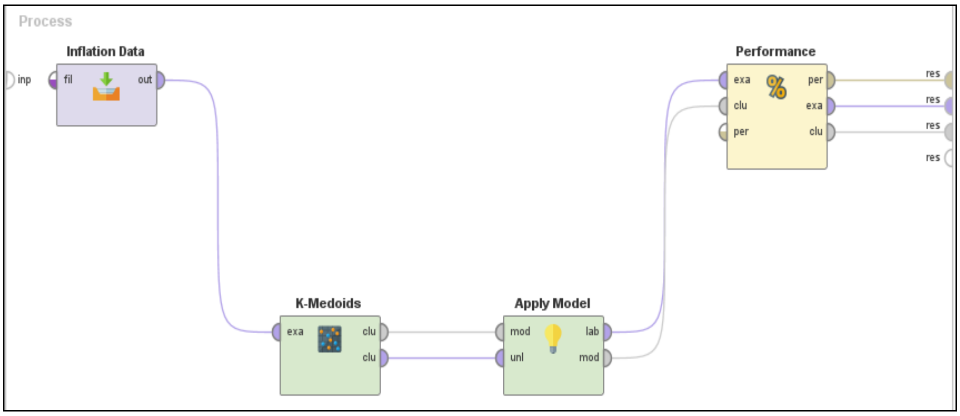

Figure 2. Process K-Medoids (K Value = 5)

Figure 2 describes the process of clustering the K-Medoids algorithm using Rapidminer, which begins with importing excel data on inflation data for 90 cities in Indonesia, then continues with selecting the K-Medoids algorithm operator for the clustering. Value K = 5, the measure types used are MixedMeasures. After that, it is connected to the Apply Model operator to apply the model that has been learned or trained. The aim is to obtain predictions on unlabeled data (testing data) that do not have a label. The next stage is connecting to the Performance operator to evaluate the performance of the model, which provides a list of performance criteria values automatically according to the given task.

Cluster Model

```
Cluster 0: 4 items
Cluster 1: 2 items
Cluster 2: 79 items
Cluster 3: 4 items
Cluster 4: 1 items
Total number of items: 90
```

Figure 3. Cluster Model (K-Medoids)

Figure 3 is a cluster model produced using Rapidminer, Cluster 0: 4 items, Cluster 1: 2 items, Cluster 2: 79 items, Cluster 3: 4 items, and Cluster 4: 1 item. For the final result, the Centroid table can be seen in Figure 4.

Attribute	cluster_0	cluster_1	cluster_2	cluster_3	cluster_4
January	0.980	0.420	0.270	0.680	1
February	-0.040	0.930	0.400	-0.290	0.810
March	0.390	-1.530	0.070	-0.550	-1.910
April	-0.800	0.560	-0.240	0.310	0.720
May	0.060	0.700	0.220	0.650	0.900
June	-0.300	0.200	0.080	1.070	0.920
July	-0.490	-0.480	-0.080	-0.340	1.450
August	-0.480	-0.640	-0.040	-0.570	0.410
September	0.220	0.210	0.030	0.210	-0.830
October	0.180	-0.610	0.080	-0.090	0.240

Figure 4. Centroid table

The detailed results of the inflation clustering for 90 cities in Indonesia can be seen in Figure 5.

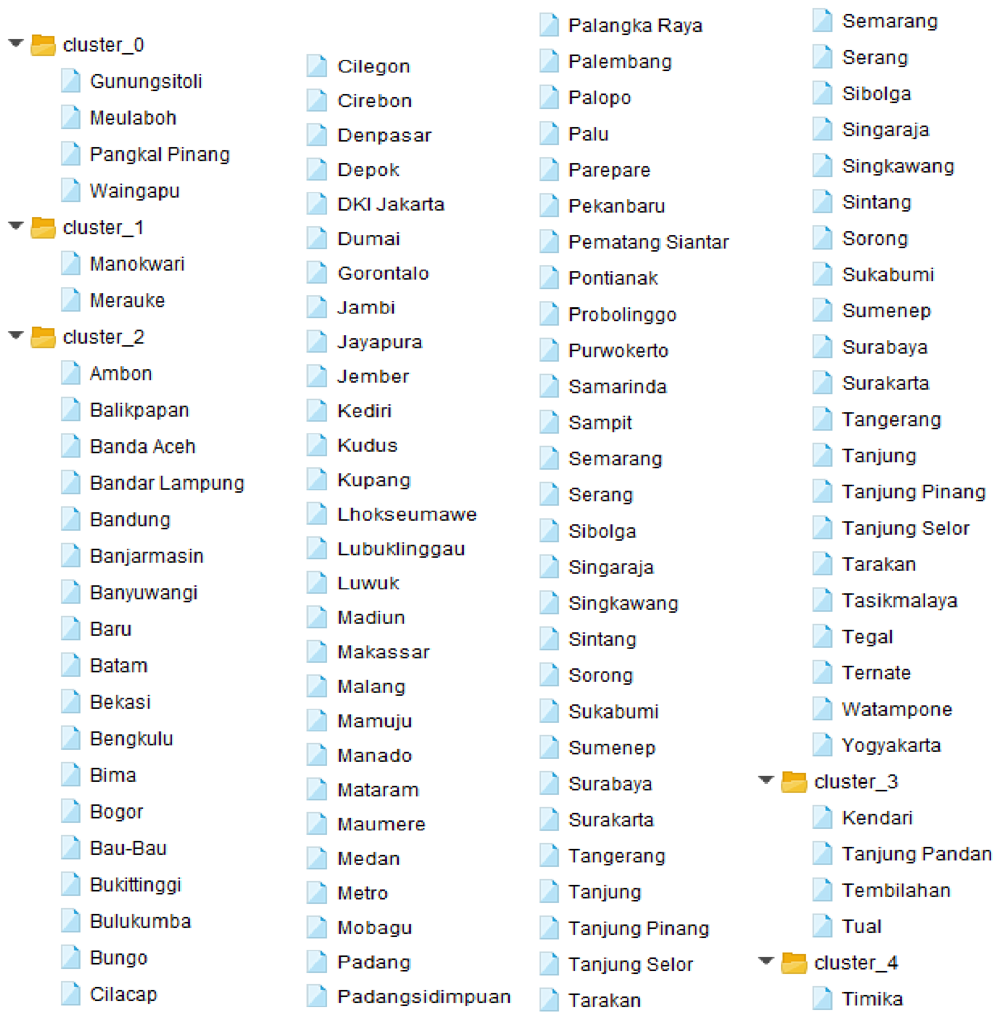

Figure 5. Folder View Inflation of 90 Cities in Indonesia

Cluster_0 based on figure 5 consists of 4 cities (Gunung Sitoli, Meulaboh, Pangkal Pinang and Waingapu). Cluster_1 consists of 2 cities (Manokwari and Merauke). Cluster 2 consists of 79 cities (Ambon, Balikpapan, Banda Aceh, Bandar Lampung, Bandung, Banjarmasin, Banyuwangi, Baru, Batam, Bekasi, Bengkulu, Bima, Bogor, Bau-bau, Bukittinggi, Bulukumba, Bungo, Cilacap to Yogyakarta). Cluster_3 consists of 4 cities (Kendari, Tanjung Pandan, Tembilahan and Tual). While Cluster_4 consists of 1 city (Timika).

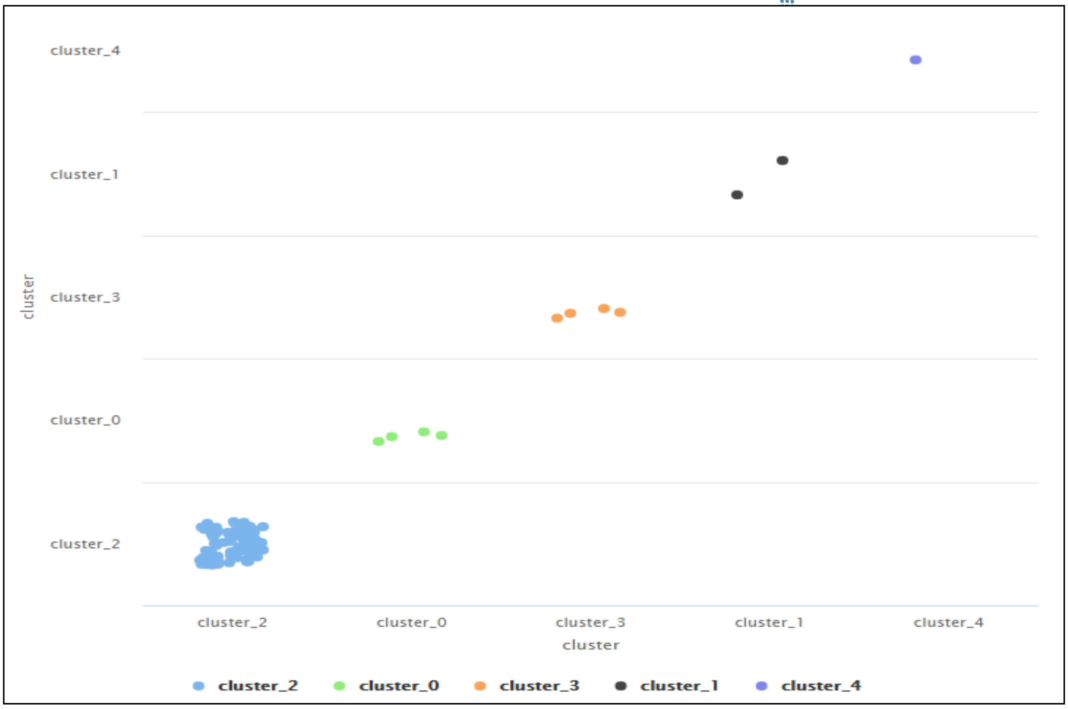

Figure 6. Visualization of Inflation Clusters for 90 Cities in Indonesia

Based on Figure 6, it is explained that the green dots belong to the Cluster_0 group. The black dots represent the Cluster_1 group. The light blue color points belong to the Cluster_2 group. Orange dots represent Cluster_3 groups and blue dots represent Cluster_4 groups.

4. Conclusion

Data Mining K-Medoids can be used for estimating the inflation rate of 90 cities in Indonesia. Based on the results of clustering analysis using rapidminer, for cities with a very high inflation rate category consists of 1 city (Available on Cluster_4), high category consists of 4 cities (Cluster_0), medium category consists of 4 cities (Cluster_3), low category consists of 79 cities (Cluster_2), and deficient category consisted of 2 cities (Cluster 1). Performance Vector K-Medoids in this study resulted in the value Avg._within_centroid_distance = -1.095 and Davies_Bouldin = -1.232.

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