Distance Analysis Measuring for Clustering using K-Means and Davies Bouldin Index Algorithm

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Abstract **– The purpose of this research is to analyze mapping results in the form of clusters formed using clustering method measures. This is done to determine the connections that the existing clusters create. Some of the measurements used are mixed measurements, Bregman differences, and number measurements (Mixed Euclidean Distance, Generalized Divergence, Squared Euclidean Distance, Mahalanobis Distance, and Euclidean Distance). Distance measurement shall be applied on number with primary school facilities in Indonesia. The Davies Bouldin Index (DBI) is different from the cluster number test (k = 2-10) for each Distance Measure. The average DBI value in the type of measure (mixed measure) and numerical measurement (Mixed Euclidean Distance) is 0.54. The average DBI value in the type of measure (Bregman divergences) and numeric measurements (generalized IDivergence) is 0.66. The average DBI value is 0.77 for the measurement type (Bregman divergences) and numerical measurement (Squared Euclidean Distance). From the results, the measurement of distance with mixed measurement and the mixed Euclidean distance with the cluster number (k = 2), namely 0.269, have the best DBI value.**

Keywords **– Distance Measure, K-Means, Davies Bouldin Index, Clustering.**

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1. Introduction

Clustering is a data segmentation approach implemented in several areas including marketing, market segmentation and business problem analysis, computer vision patterns, object zoning and image processing [1], [2], [3], [4]. The aim of the cluster is to search for groups of objects in the same (or associated) group and various objects in other groups [5], [6], [7], [8], [9]. The k-mean method used in the clustering generally employs the Euclidean Distance measurement method [10], [11], [12]. The aim of this study is to analyze the number of clusters (k) formed by examining the parameter of distance measurement because the measurement of a distance plays an important role in determining the similarity or regularity between data and items. The number of villages in Indonesia with primary schools was used as the data set[13]. The instrument factor such as schools [14] is one of the factors that can support learning results. School facilities are directly used tools or equipment for supporting the education process, especially the teaching, scoring and learning process [14], [15], [16].

The study topic on the number of villages with school facilities [17] was carried out using the k-medoids method. The k-medoids method is proposed as a mapping solution. This contrasts with ongoing research in which we use the k-means method. In this case, the number of clusters is also determined by comparing several distance measures which have not been found in previous studies. In the previous study,

three clusters (k = 3) were used directly in mapping areas with school facilities. The study is carried out in order to see the optimal value of the clusters formed by using the Davies Bouldin Index (DBI) algorithm. The smaller the DBI, the better the cluster was formed.

Distance measurement or similar research has been done much in the resolution of data mining problems [10], [12], [18], [19]. As was done [11] with the effect of different distance measurements on the performance of the K-means algorithm with a Mathematics Laboratory (MATLAB) application on the iris and grape dataset. The results indicate the distance measurement "correlation" indicates a better interpretation of the cluster data. Further research on categorical and numerical data sets has been conducted [20], [21], [22], [23]. The paper presents a new clustering technique for large data sets. It works with large data sets and small data sets efficiently. The main idea behind this procedure is to divide the entire process into two stages. The first step involves cost-effective measured approximate distance, which divides the data into overlapping subsets, which we call stubs. Then the grouping will be conducted in the second step to measure the correct distance between the points in general stubs only. The pilot-based clustering approach reduces the calculation time and increases its efficiency during conventional clustering.

2. Methodology

2.1. Dataset

The data set used in the study is the number of villages with primary school facilities in Indonesia. The data set comes from https://www.bps.go.id/ accessible from the https://osf.io/msk6a connection. The data set includes 34 provinces (2011, 2014, 2018). Analysis supported by software Rapid Miner. The number of clusters (k) with multiple distance measurement values to obtain the optimal Davies Bouldin Index (DBI) value was determined. The following is the research design which includes a block diagram that explains the research workflow:

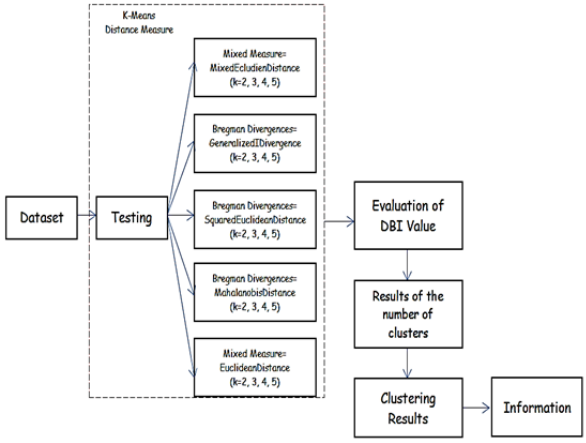


Figure 1. The proposed research flow

2.2. Distance Measure

Clustering is a way to group similar pieces of data [2], [24]. We need multiple measurements for two similar or unlike objects. The measurement is called a distance measurement [25], [26], [27] and it can be used to determine the similarity.

2.3. Clustering

Distance Clustering, so called distance-based clustering, is an extremely popular method for clustering objects and has produced good results [28]. The clusters are created so that two data objects in a group have a minimum distance value and a maximum distance value for two data objects across different clusters [27], [29].

2.4. Model Evaluation

For an accuracy indicator, the area under the curve (AUC) should increase the convergence between experiments. The following are the guidelines for AUC accuracy classification as shown in Table 1 [30].

Table 1. AUC accuracy classification

AUC	Meaning
0.90 - 1.00	Excellent grading.
0.80 - 0.90	Well-classified
0.70 - 0.80	Classification Fair
0.60 - 0.70	Bad Classification
< 0.60	Failure

3. Results and Discussion

The steps of this analysis process use Rapid Miner software to analyze distances and produce the best cluster of villages with elementary school facilities in Indonesia. The design model for a distance measurement using the K-means method using the software Rapid Miner in Figure 2 below is as follows:

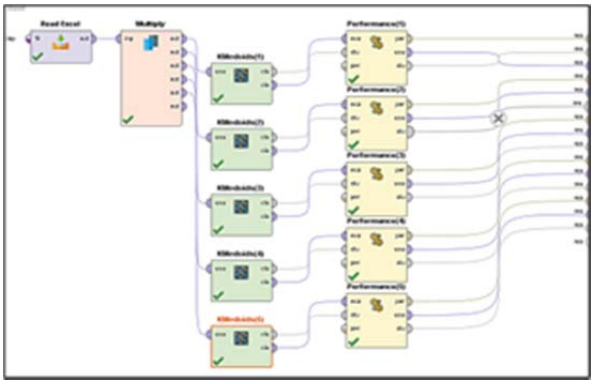


Figure 2. Design of the K-means distance measurement model

The input data set uses the "read excel" (xls) operator in Figure 2. The data is connected to several distance measurements via the operator "multiply". A multiply operator can connect several distance measurements with the k-means method. The testing is done by entering cluster values (k) from 2 to 10. The results are then recorded with the Davies Bouldin Index for comparison (DBI). The optimum number of clusters is shown with accuracy, precision, recalculation and AUC values (the smallest DBI value). The following is the recapitulation of the calculation of the analysis.

Table 2. The results of the analysis method with different Distance Measure

Measure Type	Numerical Measure	K=2	K=3	K=4	K=5
Mixed Measure	Mixed Euclidean Distance	0.269	0.294	0.478	0.37
Bregman Divergences	GeneralizedI Divergence	1.607	0.588	0.548	0.37
Bregman Divergences	Squared Euclidean Distance	0.269	1.785	1.597	0.37
Bregman Divergences	Mahalanobis Distance	0.269	0.658	0.548	1.495
Numerical Measure	Euclidean Distance	0.269	0.658	0.548	0.543

Measure Type	Numerical Measure	K=6	K=7	K=8	K=9	K=10
Mixed Measure	Mixed Euclidean Distance	1.134	0.377	1.095	0.421	0.437
Bregman Divergences	GeneralizedI Divergence	0.386	0.784	0.43	0.532	0.677
Bregman Divergences	Squared Euclidean Distance	0.349	0.774	1.015	0.409	0.4
Bregman Divergences	Mahalanobis Distance	0.816	0.359	0.502	0.778	0.437
Numerical Measure	Euclidean Distance	0.778	0.821	2.688	0.783	0.381

In table 2, it is explained that the test results for different Distance Measure for the number of clusters (k = 2 to 10) have different evaluation values (different DBI values). For measure type (Numerical Measure) and Numerical Measure (Euclidean Distance), the DBI value is not optimal, namely 2.688 (k = 8). Meanwhile, the result that the DBI value is less than optimal also occurs in the measure type (Bregman Divergences) and Numerical Measure (Squared Euclidean Distance) for k = 3 and k = 4, namely 1,785 and 1,597. In addition, the measure type (Bregman Divergences) and Numerical Measure (Generalized Divergence) also have a less optimal DBI value, namely 1.607 (k = 2). The measure type (Bregman Divergences) and Numerical Measure (Mahalanobis Distance) also have a less optimal DBI value, namely 1.495 (k = 5). The following are the results of the bar chart of each measure type as shown in Figure 3.

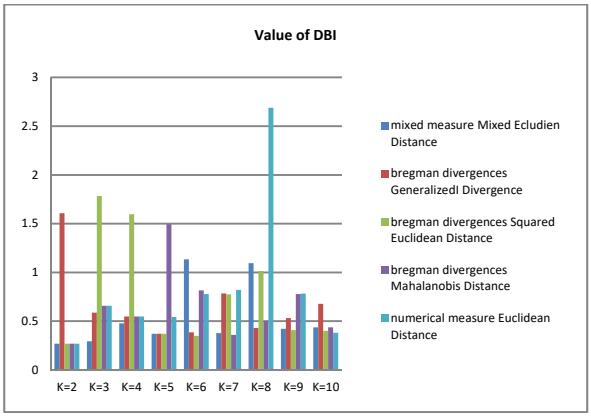


Figure 3. Diagram of the results of the analysis method with different Distance Measure

In addition, there are several results from measure types that have optimal DBI values. This is obtained by taking the DBI average value for each measure type. So that for measure type (mixed measure) and numerical measure (Mixed Euclidean Distance), the average DBI value is 0.54. This result is much better than other measure types. For measure type (mixed measure) and numerical measure (Mixed Euclidean Distance), the number of clusters (k = 2) has the most optimal DBI value of 0.269. Here are the measure types that have the optimal DBI value as shown in the following figure:

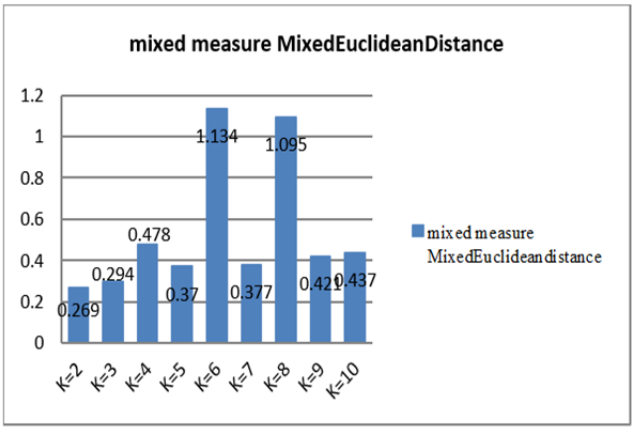


Figure 4. The measure types that have the optimal DBI value

By using a measure type (mixed measure) and a numerical measure (Mixed Euclidean Distance) at k = 2, the clustering results formed will be tested by looking at the accuracy, recall, precision and AUC values. The following are the results of the clustering formed for k = 2.

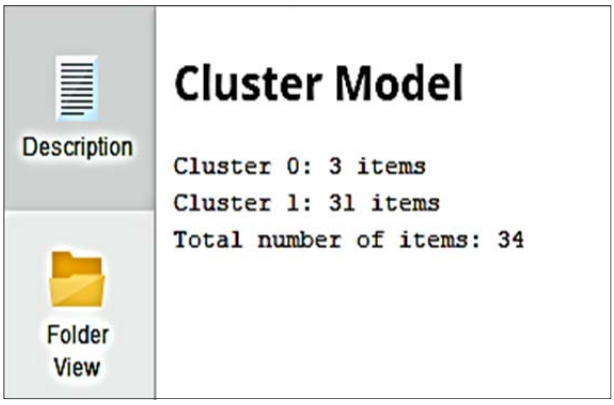


Figure 5. Clustering formed

Figure 5 shows the clusters of 34 datasets, namely 3 high cluster provinces (cluster 0), and 31 low cluster provinces (cluster 1).

This demonstrates that more than 90% of Indonesia's areas still have a minimum number of schools, particularly primary schools. The following is the exactness of the formed cluster, namely 94.17 percent.

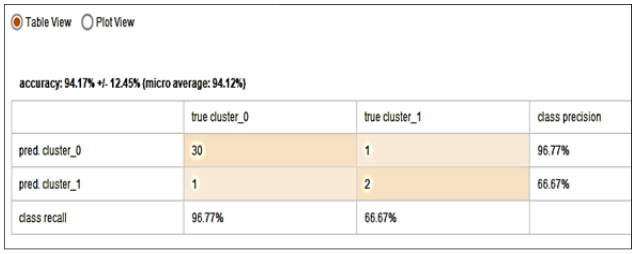


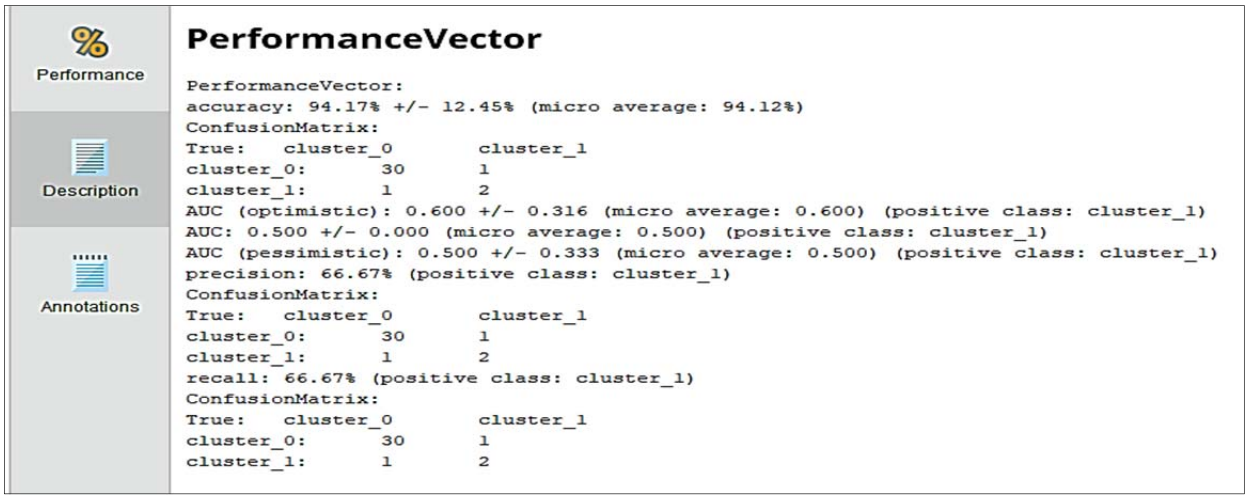
Table View Plot View

accuracy: 94.17% +/- 12.45% (micro average: 94.12%)

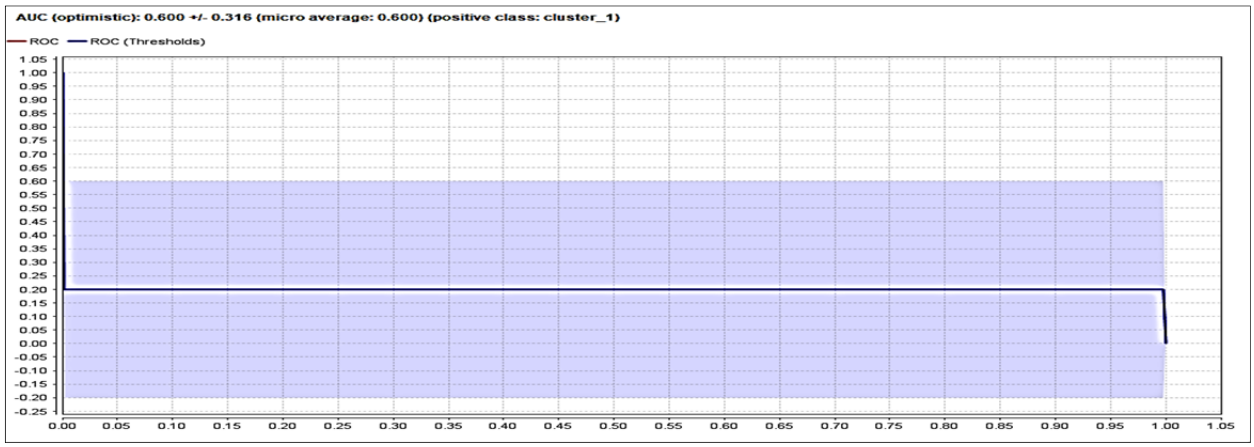
	true cluster_0	true cluster_1	class precision
pred. cluster_0	30	1	96.77%
pred. cluster_1	1	2	66.67%
class recall	96.77%	66.67%	

Figure 6. Accuracy value on the cluster formed

Moreover, from the results of the confusion matrix and the ROC curve testing the value k-means algorithm produces an precision value of 66.67, a recall value of 66.67% and an AUC value of 0.6%. The k-means algorithm is therefore an algorithm and technique to map the number of villages in Indonesia with have elementary school facilities. Then there are statistical data and AUC graphs, as shown in the figure below.



(a)



(b)

Figure 7. Recall, Precision and AUC values on the cluster formed

4. Conclusion

In this study, it can be explained that selecting a measure type will produce a different cluster. Where in the study the number of villages that have potentials for elementary schools in Indonesia can be applied and the appropriate clustering is produced. The clustering process is carried out by looking at the most optimal DBI value from a series of measure type tests. In addition, the results of the clustering that are formed will be evaluated by looking at the accuracy, recall, precision and AUC values. For the mapping of the clusters that were formed, it was found that 3 provinces were in the high cluster and 31 provinces were in the low cluster.

Data availability

The data in this study can be accessed at: https://www.bps.go.id/ accessible from the https://osf.io/msk6a

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