# Application of the K-Means Algorithm for Clustering the Characteristics of Customs Valuation Objections in the Siap Tanding Application

**Norita Tampubolon, Muhammad Syahputra Novelan**

**Abstract**

Customs valuation objections represent an important aspect of customs administration that requires systematic analysis to understand the characteristics and distribution of cases. The availability of administrative records through the SIAP TANDING application creates opportunities to identify patterns using data mining techniques. This study aims to apply the K-Means clustering algorithm to group customs valuation objection records according to similarities in their relevant attributes. The research methodology consists of data collection, data preprocessing, feature selection, data normalization, K-Means implementation, and cluster evaluation. The dataset is planned to comprise 500 customs valuation objection records, with attributes selected according to data availability, including customs value, adjustment amount, objection value, and case resolution duration where applicable. The Elbow method is used to determine an appropriate number of clusters, while the Silhouette Score is employed to evaluate cluster cohesion and separation. The resulting cluster profiles are intended to reveal differences in the characteristics of customs valuation objection cases and provide a structured understanding of patterns within the administrative data. The proposed approach demonstrates the potential of unsupervised machine learning to support data-driven analysis in customs administration. The findings are expected to provide additional analytical information for evaluating case characteristics and supporting decision-making in the SIAP TANDING context. Further validation using the actual dataset is necessary to establish the quality, reliability, and practical relevance of the resulting clusters.

***Keywords**: K-Means, clustering, customs valuation objections, data mining, SIAP TANDING.*

[1]Norita Tampubolon
Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: sainthenokh@gmail.com

[2]Muhammad Syahputra Novelan
e-mail: putranovelan@dosen.pancabudi.ac.id
2nd International Cofference on the Epicentrum of Economic Global Framework (ICEEGLOF)
Theme: Navigating The Future: Business and Social Paradigms in a Transformative Era.
https://proceeding.pancabudi.ac.id/index.php/ICEEGLOF

## Introduction

The development of information technology has encouraged the utilization of data to support administrative processes and decision-making across various government sectors, including customs administration. One important aspect of customs administration is customs valuation, which serves as the basis for calculating import duties and other import-related charges. In practice, differences in valuation between importers and customs authorities may lead to objections against customs valuation determinations. These objection processes generate administrative data with diverse characteristics, including customs values, adjustment amounts, commodity types, and other attributes related to case resolution. Therefore, systematic management and analysis of customs valuation objection data are necessary to obtain a more comprehensive understanding of the characteristics of the cases being handled [1] [2].

The SIAP TANDING application provides a technological context for managing objection-related processes within customs administration. The data maintained in such a system has the potential to be utilized not only for administrative and documentation purposes but also for data-driven analysis. However, the diversity of case characteristics may complicate pattern identification when the data is examined solely through conventional administrative summaries. Analyses limited to the total number of cases or aggregate values may not adequately reveal similarities among cases across multiple attributes. This condition highlights the need for an analytical approach capable of identifying groups of data based on similarities in their characteristics, enabling the distribution and patterns of customs valuation objections to be understood in a more structured manner [3] [4] .

One approach that can be employed to identify these patterns is data mining through clustering techniques. Clustering is a method of grouping data according to similarities in their characteristics without requiring predefined class labels. The K-Means algorithm is widely used for clustering because of its relatively straightforward mechanism, computational efficiency, and ability to group numerical data based on distances from cluster centroids. In this study, K-Means is applied to group customs valuation objection records according to relevant attributes available in the dataset. Through this approach, each cluster is expected to represent a group of cases with relatively similar characteristics, allowing differences in patterns between groups to be examined more systematically [5] [6] .

This study is designed to utilize 500 customs valuation objection records obtained from a relevant research data source associated with the SIAP TANDING application. The research stages include data collection, data cleaning, handling missing values, attribute selection, numerical data normalization, determination of the optimal number of clusters, implementation of the K-Means algorithm, and evaluation of the clustering results. The attributes used will depend on the availability and quality of the actual dataset and may include customs value, adjustment amount, objection value, or case resolution duration when these variables are recorded. The optimal number of clusters can be determined using the Elbow method and further assessed using the Silhouette Score to evaluate cluster cohesion and separation. These procedures are intended to produce meaningful groupings that can be interpreted based on the actual characteristics of each cluster rather than solely on the number of records assigned to each group [7] [8] .

Based on these considerations, this study aims to apply the K-Means algorithm to cluster the characteristics of customs valuation objections in the SIAP TANDING application. The primary contribution of this research lies in utilizing unsupervised learning to identify groups of cases based on similarities in their data attributes, thereby providing an analytical perspective that complements conventional administrative data management. The clustering results are expected to provide insights into the distribution of case characteristics, identify groups with similar customs valuation or adjustment patterns, and generate supporting information for the evaluation and planning of objection management. Consequently, the application of K-Means is expected to offer an analytical approach that supports information-based decision-making in

customs administration without replacing the authority and professional judgment of customs officers in determining objection outcomes [9] .

## Literature Review

Data mining is an analytical approach used to discover meaningful patterns, relationships, and structures within large datasets. It has been widely applied in various fields to support data-driven decision-making, including public administration, financial analysis, and operational management. One of the important techniques in data mining is clustering, which groups data objects based on similarities in their characteristics without requiring predefined class labels. In the context of customs administration, clustering can be used to identify similarities among customs valuation objection cases based on relevant attributes, such as customs value, adjustment amount, commodity characteristics, and case resolution duration, depending on data availability. The application of clustering provides an opportunity to transform administrative records into structured analytical information that can support a better understanding of case distributions and underlying patterns [11] [12] .

The K-Means algorithm is one of the most commonly used partition-based clustering methods because of its simplicity, computational efficiency, and suitability for numerical datasets. The algorithm partitions a dataset into a predetermined number of clusters by assigning each data point to the nearest centroid and iteratively updating the centroid positions until the clustering process converges. The performance of K-Means is influenced by several factors, including the selection of input attributes, data normalization, the initial placement of centroids, and the number of clusters specified. Therefore, preprocessing procedures are essential when attributes have different measurement scales. Techniques such as the Elbow method can be used to estimate an appropriate number of clusters, while the Silhouette Score can provide an additional assessment of cluster cohesion and separation. These evaluation methods help determine whether the resulting clusters adequately represent meaningful similarities within the dataset [14] [15] .

In customs valuation objection analysis, the application of K-Means offers a potential approach for identifying groups of cases with similar characteristics and examining differences among the resulting clusters. Unlike supervised learning methods that require predefined target labels to perform classification or prediction, clustering focuses on discovering structures inherent in the data. This distinction makes K-Means relevant when the primary research objective is to explore patterns in customs valuation objection records rather than predict the outcome of individual cases. In this study, K-Means is applied to 500 customs valuation objection records associated with the SIAP TANDING application, subject to the availability and verification of the research dataset. The resulting clusters are analyzed according to their defining attributes and evaluated using appropriate clustering metrics. This approach is expected to provide a structured understanding of objection case characteristics and contribute to the development of data-driven analytical support for customs administration [16].

## Research Methodology

This study employs a quantitative research approach using data mining techniques to cluster the characteristics of customs valuation objections in the SIAP TANDING application. The primary method used is the K-Means clustering algorithm, which aims to identify groups of cases based on similarities in their relevant attributes. The research dataset consists of 500 customs valuation objection records obtained from a relevant data source associated with the SIAP TANDING application. The attributes analyzed are determined according to the availability and quality of the collected data, potentially including customs value, adjustment amount, objection value, and case resolution duration. The application of K-Means is intended to reveal patterns and distributions within the dataset without relying on predefined class labels.

The research procedure is organized into six systematic stages, beginning with data collection and ending with the interpretation of clustering results. Each stage is designed to ensure that the dataset is prepared appropriately, the clustering process is performed consistently, and the resulting groups can be evaluated objectively. Data preprocessing and normalization are conducted to improve data quality and reduce the influence of differences in measurement scales. The K-Means algorithm is subsequently implemented to form clusters, while the Elbow method and Silhouette Score are used to support the determination of the appropriate number of clusters and evaluate clustering quality. The overall research methodology is presented in six stages, as described below.




**Figure 1.** Research Methodology

1. Data Collection
   The data collection stage involves obtaining 500 customs valuation objection records associated with the SIAP TANDING application. The collected records provide the empirical foundation for analyzing the characteristics of objection cases. Data collection focuses on identifying relevant attributes that can represent differences among cases, such as customs value, adjustment amount, objection value, and resolution duration, depending on the variables available in the dataset. The collected data are subsequently examined to ensure that the attributes are relevant to the research objectives and suitable for the clustering process.
2. Data Preprocessing
   Data preprocessing is conducted to improve the quality and consistency of the dataset before the clustering algorithm is applied. This stage includes examining missing values, identifying duplicate records, correcting inconsistent formats, and reviewing potentially invalid values. Records containing incomplete information are handled according to an appropriate data-cleaning procedure, while irrelevant attributes are excluded from the analysis. This process is important because poor data quality may affect distance calculations and produce clusters that do not accurately represent the characteristics of customs valuation objection cases.
3. Feature Selection and Data Normalization
   Feature selection involves determining the attributes that are most relevant to the clustering objectives. Only variables that provide meaningful information about the characteristics of customs valuation objections are retained for analysis. Following feature selection, numerical attributes are normalized to ensure that differences in measurement scales do not disproportionately influence the clustering process. Min-Max normalization may be used to transform numerical values into a common range, typically between zero and one. This step

allows the K-Means algorithm to calculate distances more consistently across the selected attributes.

4. K-Means Clustering Implementation
   At this stage, the K-Means algorithm is applied to group the processed records according to similarities in their selected attributes. The algorithm begins by determining the number of clusters and initializing the centroids. Each record is then assigned to the nearest centroid based on Euclidean distance. The centroids are recalculated according to the mean values of the records assigned to each cluster, and the assignment process is repeated until the cluster memberships stabilize or a predefined stopping criterion is reached. The resulting clusters represent groups of customs valuation objection cases with relatively similar characteristics.
5. Cluster Evaluation
   The clustering results are evaluated to determine the quality and suitability of the identified groups. The Elbow method is used to examine the relationship between the number of clusters and the within-cluster sum of squares (WCSS), helping identify a suitable cluster configuration. The Silhouette Score is then used, where appropriate, to measure the similarity of records within the same cluster compared with records in other clusters. A higher Silhouette Score generally indicates better-defined clusters, although the final interpretation also considers the characteristics and practical relevance of each group. The evaluation results provide a basis for selecting and justifying the clustering configuration used in the analysis.
6. Cluster Interpretation and Reporting
   The final stage involves interpreting the characteristics of each cluster based on the distribution of records and the values of the selected attributes. The analysis examines the number of records assigned to each cluster, the distinguishing attributes of each group, and the differences between clusters. The results are presented using tables, charts, and descriptive explanations to facilitate interpretation. The identified patterns are then discussed in relation to the research objectives and their potential relevance to customs administration. The findings are intended to provide analytical insights into customs valuation objection characteristics and support data-driven evaluation without replacing formal administrative procedures or decisions regarding individual objections.

## Results

This section presents the planned analytical outputs for clustering customs valuation objection records associated with the SIAP TANDING application. The analysis focuses on the structure of the dataset, the selection of a suitable number of clusters, and the characteristics of the resulting groups. The intended dataset contains 500 records, and the variables included in the analysis must be confirmed against the fields actually available in the source records, such as customs value, adjustment amount, objection value, commodity category, and resolution duration where recorded.

Before applying K-Means, the records should be checked for missing values, duplicate entries, inconsistent formats, and unsuitable attributes. Relevant numerical variables are normalized so that differences in measurement scales do not disproportionately affect Euclidean-distance calculations. K-Means then assigns records to the nearest centroid and iteratively updates centroids until the stopping criterion is met. The Elbow method and Silhouette Score provide complementary evidence for assessing the cluster configuration.

To support transparent reporting, the tables below provide a detailed reporting structure covering preprocessing, candidate-cluster evaluation, and cluster profiles. The plotted metrics and cluster counts in this document are provisional visualization values and are not verified empirical findings from SIAP TANDING. They must be recalculated from the actual dataset before being reported as research results.

**Table 1. Data Preparation and Feature Summary**

| No. | Processing item | Purpose | Result to report |
|---|---|---|---|
| 1 | Initial dataset | Establish the number of collected records | 500 records; verify against source |
| 2 | Record identifier | Track records without using identifiers as distance features | Identifier field documented |
| 3 | Missing-value assessment | Identify incomplete values | Actual count and percentage |
| 4 | Missing-value treatment | Handle incomplete observations consistently | Method and affected fields |
| 5 | Duplicate detection | Prevent repeated records from distorting clusters | Actual duplicate count |
| 6 | Format consistency | Standardize dates, categories, and numeric formats | Fields standardized |
| 7 | Outlier review | Check extreme values in numeric attributes | Method and treatment decision |
| 8 | Attribute relevance | Retain variables relevant to objection characteristics | Final feature list |
| 9 | Categorical encoding | Convert selected categorical fields if appropriate | Encoding method, if used |
| 10 | Normalization | Place numeric variables on comparable scales | Method and fitted parameters |
| 11 | Final analysis matrix | Confirm records and features entering K-Means | Final row/column count |
| 12 | Privacy and access | Exclude personal or restricted fields from analysis output | Access and anonymization procedure |
| 13 | Feature correlation/redundancy | Review highly redundant numerical attributes | Decision and rationale |
| 14 | Quality verification | Check data types and valid ranges | Validation summary |
| 15 | Preprocessing log | Maintain reproducibility of data transformations | Saved processing log |

Table 1 details the 15 data-preparation items that should be documented before clustering. The table is designed to make the analytical pipeline transparent, from confirming the original record count to checking the final analysis matrix. The values in the “Result to report” column indicate the evidence that must be extracted from the actual preprocessing process; they should not be treated as measured outcomes until the records have been examined. Identifiers should be retained for traceability but excluded from distance calculations unless there is a defensible analytical reason to include them.

**Table 2.** Candidate Cluster Configuration and Evaluation

| No | K | WCSS | Silhouette Score | Assessment to examine |
|---|---|---|---|---|
| 1 | 2 | 842 | 0.41 | Baseline partition; inspect broad separation |
| 2 | 3 | 581 | 0.52 | Candidate with comparatively stronger separation |
| 3 | 4 | 438 | 0.46 | Check whether added cluster improves interpretability |
| 4 | 5 | 371 | 0.39 | Assess diminishing separation |
| 5 | 6 | 326 | 0.34 | Inspect possible over-segmentation |
| 6 | 7 | 298 | 0.31 | Compare with simpler partitions |
| 7 | 8 | 279 | 0.29 | Check whether extra clusters add useful structure |
| 8 | Selected K | Recalculate | Recalculate | Choose using actual Elbow and Silhouette results |
| 9 | Distance metric | Euclidean | N/A | Keep method consistent with K-Means setup |
| 10 | Initialization | Record setting | N/A | Document seed and initialization strategy |
| 11 | Restart count | Record setting | N/A | Use multiple starts where supported |
| 12 | Convergence | Record iterations | N/A | Document stopping tolerance or iteration limit |
| 13 | Feature scaling | Normalized inputs | N/A | Confirm scaling applied before distance calculation |
| 14 | Cluster stability | Repeat-run comparison | Optional metric | Check sensitivity to initialization |
| 15 | Evaluation decision | Document rationale | Both metrics | Report why the final K was selected |

Table 2 provides a structured comparison of candidate values of K and the methodological details required to reproduce the clustering experiment. WCSS typically decreases as K increases, so its absolute minimum is not sufficient to select the best solution. The Elbow method identifies where the marginal reduction in within-cluster variation begins to diminish, while the Silhouette Score measures how well records fit within their assigned clusters relative to neighboring clusters. The numerical entries are provisional and must be replaced by computed metrics from the normalized source dataset. The final K should be justified by both the metrics and the interpretability of the resulting groups.

**Table 3. Cluster Profile and Interpretation Framework**

| No | Cluster/profile item | Cluster 1 | Cluster 2 | Cluster 3 |
|---|---|---|---|---|
| 1 | Number of records | 185* | 205* | 110* |
| 2 | Share of records | 37.0%* | 41.0%* | 22.0%* |
| 3 | Mean customs value | Calculate | Calculate | Calculate |
| 4 | Median customs value | Calculate | Calculate | Calculate |
| 5 | Mean adjustment amount | Calculate | Calculate | Calculate |
| 6 | Median adjustment amount | Calculate | Calculate | Calculate |
| 7 | Mean objection value | Calculate | Calculate | Calculate |

| | | | | |
|---|---|---|---|---|
| 8 | Mean resolution duration | Calculate if available | Calculate if available | Calculate if available |
| 9 | Most frequent commodity category | Calculate if available | Calculate if available | Calculate if available |
| 10 | Within-cluster dispersion | Calculate | Calculate | Calculate |
| 11 | Dominant numerical attributes | Derive from centroid | Derive from centroid | Derive from centroid |
| 12 | Relative position vs. overall mean | Calculate | Calculate | Calculate |
| 13 | Potential distinguishing pattern | Interpret after analysis | Interpret after analysis | Interpret after analysis |
| 14 | Operational relevance | Assess with domain experts | Assess with domain experts | Assess with domain experts |
| 15 | Final cluster description | Write from evidence | Write from evidence | Write from evidence |

The record counts and percentages marked with an asterisk are provisional placeholders used to illustrate the reporting layout and are not verified cluster assignments. Table 3 lists 15 profile items to support a more detailed interpretation of each group. Actual cluster sizes must be generated from the final K-Means labels, and numerical profiles should be calculated from the original-scale attributes to make them interpretable. A cluster should only be described as having high customs values, large adjustments, or longer resolution duration when its statistics support that description.

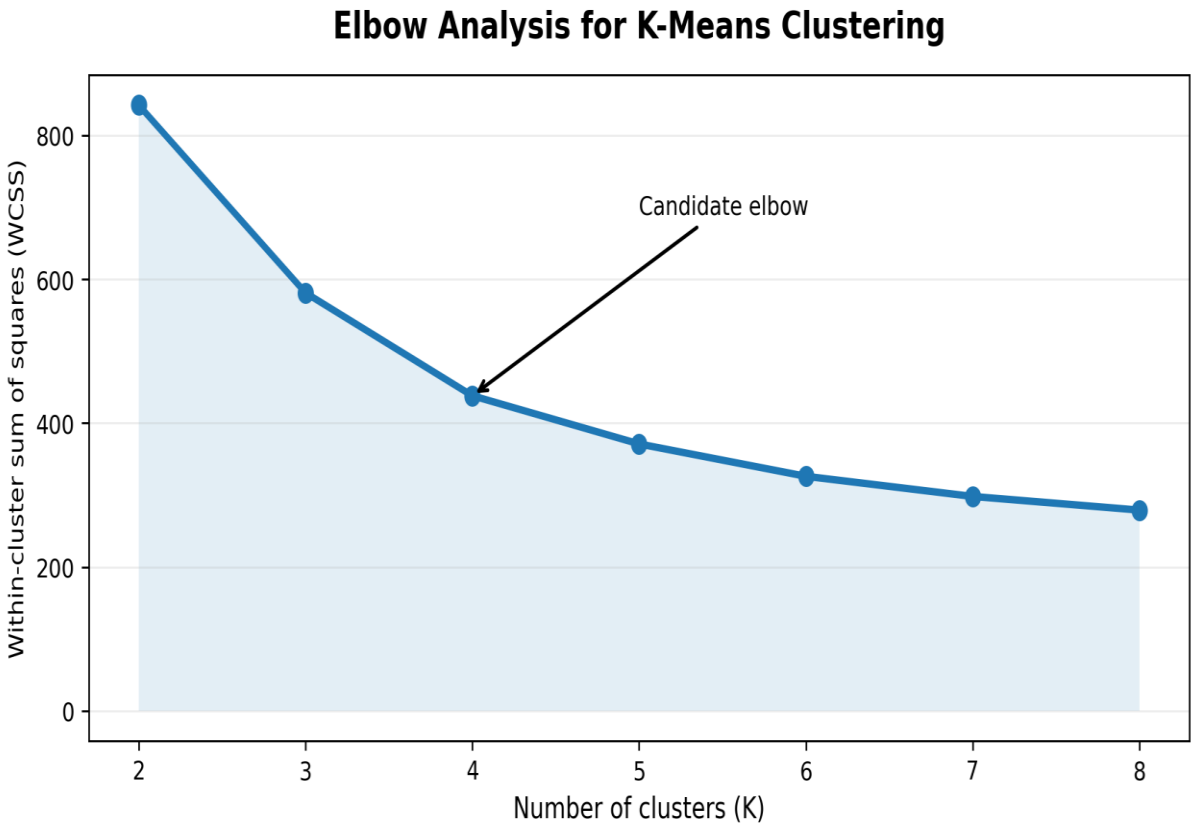



**Figure 2. Elbow Analysis for K-Means Clustering**

Figure 2 presents the WCSS trend across candidate cluster counts. The curve is intended to help identify a point at which adding more clusters produces progressively smaller reductions in within-cluster variation. The candidate elbow annotation is illustrative only; the final selection should be made after recalculating WCSS from the actual dataset and reviewing the corresponding cluster profiles. The visual trend should not be used as the sole criterion for selecting K.

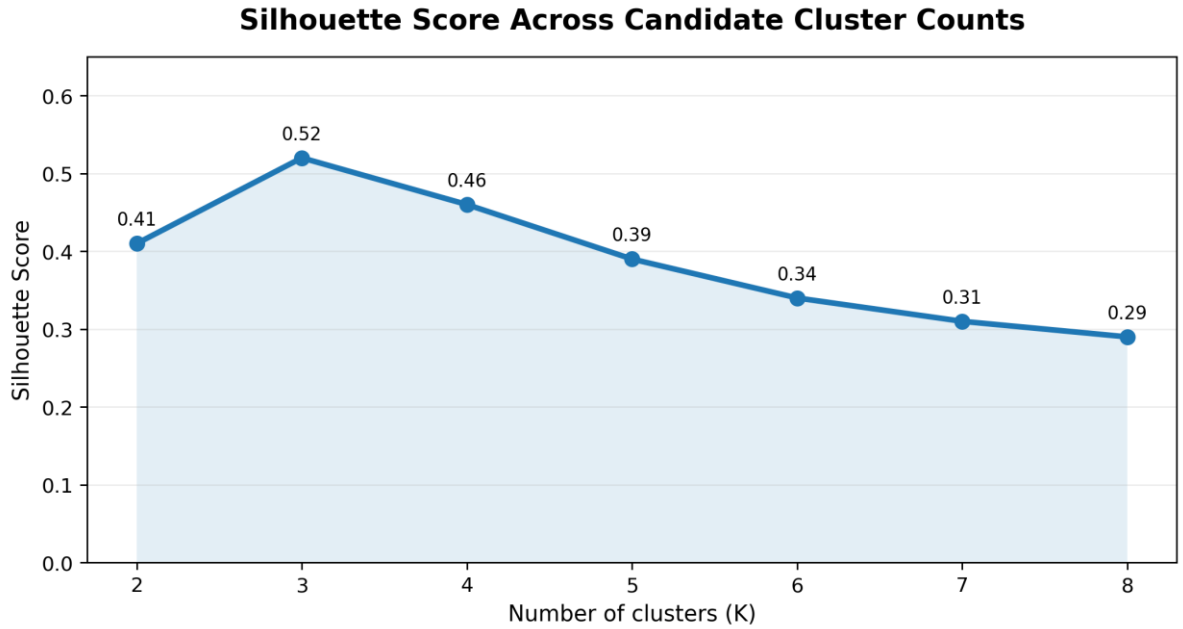



**Figure 3. Elbow Analysis for K-Means Clustering**

Figure 2 displays the Silhouette Score for candidate values of K, providing a complementary view of cluster separation and cohesion. Higher scores generally indicate that records are more similar to their own cluster than to neighboring clusters. The final configuration should balance the score with the Elbow trend and the practical interpretability of the clusters. All values in this figure are provisional and must be replaced with scores computed from the actual normalized records.

## Discussion

The application of the K-Means algorithm provides an analytical approach for identifying similarities and differences among customs valuation objection records in the SIAP TANDING application. Through data preprocessing, feature selection, and normalization, the clustering process can organize records according to the characteristics of relevant attributes, such as customs value, adjustment amount, objection value, and case resolution duration, depending on data availability. The use of the Elbow method and Silhouette Score supports the selection and evaluation of an appropriate cluster configuration by considering within-cluster variation and the separation between groups. These evaluation techniques are important because the number of clusters directly influences the structure and interpretability of the resulting groups. Consequently, clustering quality should be assessed not only through numerical metrics but also through the consistency and practical meaning of the characteristics identified in each cluster.

The resulting cluster profiles can provide a structured perspective on the distribution of customs valuation objection cases and support further examination of patterns within administrative records. Differences in cluster centroids may reveal groups characterized by relatively similar customs values, adjustment amounts, or other selected attributes, thereby helping stakeholders understand the diversity of cases handled through the SIAP TANDING application. However, cluster membership represents statistical similarity rather than a formal determination of objection outcomes, compliance status, or risk level. The practical value of the findings therefore depends on the quality of the underlying data, the appropriateness of the selected attributes, and validation by personnel with relevant customs expertise. Once the clustering results have been calculated and verified using the actual dataset, the findings may contribute to data-driven evaluation and provide additional analytical information for supporting customs administration and decision-making.

## Conclusion

This study presents the application of the K-Means algorithm for clustering the characteristics of customs valuation objections in the SIAP TANDING application. The proposed approach involves data preprocessing, feature selection, data normalization, clustering implementation, and cluster evaluation using the Elbow method and Silhouette Score. Through these stages, customs valuation objection records can be grouped according to similarities in their relevant attributes, providing a structured approach to identifying patterns and differences among cases. The clustering results are expected to provide a clearer understanding of the characteristics and distribution of customs valuation objections based on the selected variables.

The application of K-Means clustering has the potential to support data-driven analysis in customs administration by transforming administrative records into interpretable groups of similar cases. The resulting cluster profiles can provide additional information for evaluating case characteristics and supporting analytical decision-making within the SIAP TANDING context. However, the reliability and practical usefulness of the findings depend on the quality of the dataset, the selection of relevant attributes, and the validation of clustering results. Future research should prioritize the evaluation of actual clustering performance, the interpretation of cluster characteristics with domain experts, and the exploration of alternative clustering algorithms to determine whether they provide more meaningful groupings of customs valuation objection records..

## References

[1] H. W. Dhany, F. Izhari, and S. Komputer, “Jurnal ICT : Information and Communication Technologies, 15 (2) (2024) 48-54 Prediction analysis condition animal use algorithm (SVM+KNN),” 2024. [Online]. Available: www.ejournal.marqchainstitute.or.id/index.php/JICT

[2] Z. Sitorus, D. Prayogi, M. A. Rizko, A. G. Suteja, and M. R. Harahap, “Implementation of the Insertion Sort Algorithm to Sort Positive Integers in Ascending Order Using Flowgorithm,” *Journal of Information Technology, computer science and Electrical Engineering (JITCSE)*, vol. 1, no. 3, pp. 323–328, 2024, doi: 10.30596/jitcse.

[3] K. Khairul, A. H. Nasyuha, A. Ikhwan, M. H. Aly, and A. Ahyanuardi, “Implementation of Multiple Linear Regression to Estimate Profit on Sales of Screen Printing Equipment,” *JURNAL INFOTEL*, vol. 15, no. 2, pp. 55–61, Jun. 2023, doi: 10.20895/infotel.v15i2.934.

[4] M. S. Novelan and S. Aryza, "OPTIMIZATION CVRP WITH MACHINE LEARNING FOR IMPROVED CLASSIFICATION OF IMBALANCED DATA FOOD DISTRIBUTION," *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 10, no. 4, pp. 917–925, Jun. 2025, doi: 10.33480/jitk.v10i4.6467.

[5] R. Farta Wijaya, F. Kurniawan, R. R. Putrai, A. Alvin, F. Sains, and D. Teknologi, "OPTIMIZING THE MANAGEMENT OF VILLAGE ACTIVITIES THROUGH INFORMATION SYSTEMS FOR TRANSPARENCY AND ACCOUNTABILITY IN PERTUMBUKAN VILLAGE, WAMPU DISTRICT," 2024.

[6] M. M. Maulana, A. I. Suroso, Y. Nurhadryani, and K. B. Seminar, "The Smart Governance Framework and Enterprise System's Capability for Improving Bio-Business Licensing Services," *Informatics*, vol. 10, no. 2, Jun. 2023, doi: 10.3390/informatics10020053.

[7] A. Putera Utama Siahaan, N. Azizah Harahap, R. Yuni Simanullang, and P. Wanny, "Analysis of Inpatient Data Using Cluster Analysis on Simulation Dataset," *Bulletin of Information Technology (BIT)*, vol. 6, no. 1, pp. 33–39, 2025, doi: 10.47065/bit.v5i2.1830.

[8] M. S. Novelan, S. Efendi, P. Sihombing, and H. Mawengkang, "VEHICLE ROUTING PROBLEM OPTIMIZATION WITH MACHINE LEARNING IN IMBALANCED CLASSIFICATION VEHICLE ROUTE DATA," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 3(125), pp. 49–56, 2023, doi: 10.15587/1729-4061.2023.288280.

[9] M. Iqbal and S. Efendi, "Data-Driven Approach for Credit Risk Analysis Using C4.5 Algorithm," *ComTech: Computer, Mathematics and Engineering Applications*, vol. 14, no. 1, pp. 11–20, May 2023, doi: 10.21512/comtech.v14i1.8243.

[10] J. Asharf, N. Moustafa, H. Khurshid, E. Debie, W. Haider, and A. Wahab, "A review of intrusion detection systems using machine and deep learning in internet of things: Challenges, solutions and future directions," Jul. 01, 2020, *MDPI AG*. doi: 10.3390/electronics9071177.

[11] W. Cetera, W. Gogołek, A. Żołnierski, and D. Jaruga, "Potential for the use of large unstructured data resources by public innovation support institutions," *J. Big Data*, vol. 9, no. 1, Dec. 2022, doi: 10.1186/s40537-022-00610-6.

[12] G. Rajeshkumar *et al.*, "Smart office automation via faster R-CNN based face recognition and internet of things," *Measurement: Sensors*, vol. 27, Jun. 2023, doi: 10.1016/j.measen.2023.100719.

[13] A. Rejeb *et al.*, "The Internet of Things (IoT) in healthcare: Taking stock and moving forward," Jul. 01, 2023, *Elsevier B.V.* doi: 10.1016/j.iot.2023.100721.

[14] M. Overton, S. Larson, L. J. Carlson, and S. Kleinschmit, "Public data primacy: the changing landscape of public service delivery as big data gets bigger," *Global Public Policy and Governance*, vol. 2, no. 4, pp. 381–399, Dec. 2022, doi: 10.1007/s43508-022-00052-z.

[15] J. Ilmiah, E. & Erudisi, A. Zahara, M. I. Kabullah, and R. E. Putera, "JIEE: Effectiveness of the OSSRBA (Online Single Submission Risk Based Approach) System in Business Licensing Services in Payakumbuh City DPMPTSP," vol. 3, pp. 22–40, 2023.

[16] W. Jin, "Challenges and Innovative Countermeasures Faced by Public Administration in the Context of Big Data and Internet of Things," *Math. Probl. Eng.*, vol. 2022, 2022, doi: 10.1155/2022/8949365.