

Typological Analysis of Sultanate Tombs in Sumatra Using K-Means and Random Forest Clustering Methods

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ABSTRACT

The diversity of the morphological characteristics of Islamic tombs from the Sultanates in Sumatra reflects variations in cultural traditions, construction techniques, and architectural forms. However, the identification of tomb typologies is still dominated by manual observation; therefore, the classification process is relatively subjective. This study aimed to identify the typology of tombs from the Sultanates in Sumatra using the K-Means Clustering algorithm and to determine the most influential classification variables using the Random Forest algorithm. This study analyzed 85 tomb records consisting of four morphometric variables (tombstone height, length, width, and height) and several archaeological attributes. The Elbow method was used to determine the optimal number of clusters, resulting in three clusters with distinct morphometric characteristics. The evaluation of the clustering quality resulted in an average silhouette coefficient of 0.267, indicating a fairly good clustering structure. Furthermore, the Random Forest model achieved an accuracy of 68.75% with a kappa value of 0.521, indicating moderate classification performance. Variable importance analysis revealed that grave material, footstone shape, and tombstone shape were the most influential variables for distinguishing tomb typologies. These findings indicate that the combination of K-Means Clustering and Random Forest provides an effective and objective approach to identifying archaeological tomb typologies based on morphometric and physical attributes.

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1. INTRODUCTION

The spread of Islam in Indonesia since the 13th century has led to the emergence of various sultanates that serve as centers of government, trade, religious propagation, and socio-cultural development throughout the archipelago [1]. Islamization occurred through interactions between international trade networks and local communities, resulting in diverse Islamic cultural characteristics across regions [2]. The existence of these sultanates left behind not only political and governmental systems but also a variety of cultural legacies in the form of manuscripts, mosques, forts, palaces, and tomb complexes, which serve as important sources for reconstructing the history of Islam in Indonesia [3].

Archaeological remains in the form of Islamic burial complexes are an important source for reconstructing the development of the sultanates in Sumatra, as they contain historical, cultural, religious, and socio-political information. The analysis of tombstone characteristics, including shape, material, ornamentation, inscriptions, and spatial distribution, has been widely used to identify chronology, material culture, and relationships among Muslim communities in Southeast Asia [1], [4].

The development of Islamic sultanates in Indonesia has left a rich cultural legacy and remains an important source for historical and archaeological research [5]. This heritage includes not only religious buildings but also royal palaces, forts, squares, markets, and tomb complexes that formed the administrative center of the Sultanate. In traditional Islamic urban planning, the royal mosque served not only as a center of religious activities but also as a symbol of political legitimacy, closely linked to other elements such as the burial complexes of the sultan and the royal family members. The integration of these elements demonstrates the close relationship between political authority, religion, and cultural traditions during the Islamic period in the Indonesian Archipelago [5], [6].

Islamic tombs are one of the most important archaeological sources for reconstructing the history of society during the Sultanate era in Sumatra [7]. Tombstones serve as grave markers and repositories of historical information regarding the chronology, identities of important figures, and cultural developments. Through an analysis of typology, morphology, and inscriptions, the process of Islamization and the emergence of early Muslim communities can be reconstructed [8]. This suggests that the diversity of tombstones found in Rantang and Barus reflects the early development of Islam in North Sumatra and is related to the existence of the Haru Kingdom, highlighting the importance of Islamic tombs as archaeological evidence for reconstructing the history of the sultanate in Sumatra.

The study of Islamic tomb typology continues to develop as a key archaeological approach to understanding the history, culture, and social dynamics of Islamic societies in the Indonesian Archipelago. The analysis of tombstone form, materials, ornamentation, and inscriptions has been used to reconstruct chronology, identify important figures, and explain political developments within the Islamic sultanate [1]. Suprayitno and Saiful produced research results that the typology of Acehese tombstones in Kelambir Lima contributed to the reconstruction of the existence of the Aru Kingdom through variations in tombstone morphology and inscriptions. Similarly, Saptaningrum [9] emphasized that burial complexes and tombstones are an important part of Indonesia's archaeological heritage, reflecting the adaptation of Islamic culture to local society.

Recent advances in data analysis have encouraged the application of machine learning techniques in archaeology, particularly for artifact classification, archaeological site identification, and cultural heritage analyses. Compared with conventional approaches, machine learning can process large and complex datasets more efficiently while uncovering hidden patterns within the data [10], [11]. However, the application of unsupervised learning methods, particularly clustering techniques, remains relatively limited in archaeological studies compared with supervised learning approaches. This situation presents an opportunity to develop machine learning-based methods to identify tomb typologies more objectively and determine the variables that contribute most to the classification process [6].

Among clustering techniques, the K-means algorithm is widely used because it groups objects based on similar characteristics without requiring predefined labels, making it effective for discovering the natural structure of multivariate data [12], [13]. Furthermore, the Random Forest algorithm was chosen because of its high classification accuracy, resistance to overfitting, and ability to quantify variable importance, thus enabling the identification of attributes that contribute most to the formation of archaeological typologies [14].

Unlike previous studies that generally classify Islamic tomb typologies using a descriptive approach based on morphology, ornamentation, and inscriptions, this study proposes a quantitative machine-learning approach to identify the typological patterns of Sultanate tombs in Sumatra. The novelty of this research lies in the integration of K-Means Clustering to construct typological groups based on morphometric characteristics and Random Forest to determine the most influential variables contributing to each group. This integrated approach provides a more objective classification framework while supporting quantitative archaeological interpretations of the development of Islamic tombs during the Sultanate period in Sumatra.

Based on these considerations, this study aims to apply the K-Means Clustering algorithm to classify Sultanate tomb typologies in Sumatra based on morphometric characteristics and use the Random Forest algorithm to identify the variables that most significantly contribute to the formation of each typological group. These findings are expected to provide a quantitative framework that supports archaeological interpretation and contribute to future studies of Islamic tombs in Indonesia.

2. METHOD

The data used in this study comprise 85 sultanate graves in Sumatra. The research variables included four numeric variables: gravestone height, base length, base width, and base height, and eight categorical variables: gravestone type, gravestone shape, gravestone material, gravestone decorative motif, footstone

shape, footstone material, footstone decorative motif, and base material. Numerical variables were used in the clustering process using the K-Means Clustering method, while categorical variables were used in a Random Forest analysis to identify the attributes most significantly influencing cluster formation.

The descriptive statistics in Table 1 indicate significant variation in the morphometric measurements of the graves. The average gravestone height was 69.05 cm, with a range of 0–158 cm, while the average grave mound length was 263.50 cm, with a range of 0–727 cm. The average grave border width and height were 106.00 cm and 45.53 cm, respectively. The results also showed that the data contained no missing values; therefore, all observations could be used in the analysis.

The variation in the size of tombstones and grave markers indicates the diversity of physical characteristics among the sultanate tombs in Sumatra. In archaeological studies, morphometric differences are used to distinguish the typology of artifacts and archaeological structures, as they reflect variations in the shape and size of an object [15]. Therefore, the morphometric data in this study were deemed adequate for use in the clustering process using the K-Means Clustering method. The details of the study variables are presented in Table 1.

Table 1. Research Variables

NO	Variable	Data Type	Description
1	Tombstone height	Numeric	Headstone Height (cm)
2	Base length	Numeric	Base Length (cm)
3	Strap width	Numeric	Band Width (cm)
4	Jirat height	Numeric	Ridge Height (cm)
5	Types of tombstones	Categorical	Tombstone Type
6	Tombstone Shape	Categorical	
7	Tombstone Material	Categorical	Tombstone Material
8	Decorative Motifs on Tombstones	Categorical	Decorative Tombstone Motifs
9	Tombstone Shape	Categorical	Footstone Shape
10	Tombstone Material	Categorical	Treadstone Material
11	Tombstone Ornament Style	Categorical	Decorative Tombstone Motifs
12	Grave marker material	Categorical	Grave Marker Material

Prior to analysis, the data underwent a pre-processing stage that included checking for missing values, verifying data types, and standardizing all numerical variables using the Z-score method. Standardization was performed because morphometric variables have different units and value ranges, which can affect the calculation of the Euclidean distance in the K-means algorithm. This process aims to ensure that each variable contributes equally to the clustering process and produces more representative groups [16].

2.1. Data Preprocessing

Data preprocessing was performed to ensure good-quality data before the analysis process began. This stage included checking for missing values, verifying data types, and separating numerical and categorical variables according to the analysis requirements. The results showed that no variables had missing values; therefore, all data could be used in the next analysis stage.

Next, all numerical variables were standardized using the Z-score method, so that each variable was on the same scale. Standardization is necessary because the K-means algorithm uses Euclidean distance, which is sensitive to differences in data scale; thus, variables with a wider range of values can dominate the clustering process if normalization is not performed [16]. After the standardization process was completed, the numerical data were used as input for the K-means algorithm, while the categorical data were prepared as predictor variables for the Random Forest analysis.

2.2. K-Means Clustering Analysis

The cemetery data were clustered using the K-Means Clustering algorithm, an unsupervised learning method that groups objects based on their similar characteristics by minimizing within-cluster variation [17]. In this study, the clustering process used eight standardized numerical variables: headstone height, headstone width, headstone thickness, footstone height, footstone thickness, frame length, frame width, and frame height. The degree of similarity between objects was calculated using the Euclidean distance; therefore, each object was grouped into a cluster with the closest centroid.

The K-means process was performed by minimizing the sum of the squares of the distances between each object and the cluster center (centroid), which is expressed as follows:

$$J = \sum_{i=1}^k \sum_{x_j \in C_i} \|x_j - \mu_i\|^2 \quad (1)$$

Where:

$$J = \text{fungsi objektif}$$

k = number of clusters,

C_i = data set in the i -th cluster,

x_j = j-th data point,

μ_i = centroid of the first cluster

The optimal number of clusters was determined using the Elbow and Silhouette methods. The clustering process was then performed using the K-means algorithm with $nstart = 25$ to obtain more stable results.

2.3. Cluster Evaluation and Characteristics

The quality of the clustering results was evaluated using the Silhouette Coefficient, which measures the degree of cohesion within a cluster and the degree of separation between clusters [18]. The silhouette coefficient ranges from -1 to 1, with values closer to 1 indicating a high level of suitability for an object within its cluster, whereas values closer to -1 indicate a better fit for another cluster [19]. This evaluation was used to assess the quality of the clustering results obtained from the k-means algorithm.

Next, the characteristics of each cluster were analyzed using the average value (centroid) of all the numeric variables within each cluster. A comparison of centroid values was used to identify differences in the morphometric characteristics of the graves, allowing each cluster to be interpreted based on its dominant physical dimensions. This approach facilitated the identification of grave typologies and provided a basis for analyzing key variables using the Random Forest algorithm [20].

2.4. Random Forest Analysis

The Random Forest algorithm was used to identify the variables with the greatest influence on differentiating tomb typologies resulting from K-means clustering [21]. Random Forest is an ensemble learning method that constructs multiple decision trees from randomly selected data samples (bootstrap sampling) and then combines the predictions from each tree through a majority voting mechanism, resulting in a more stable classification model with good generalization capabilities [22].

The model performance was evaluated using a confusion matrix, accuracy, and Kappa to measure the accuracy of the classification results. Furthermore, the importance of each variable was analyzed using the Mean Decrease Gini, where variables with higher values indicated a greater contribution to the classification process. This analysis was used to identify the tomb characteristics that are most influential in differentiating the typologies of sultanate tombs in Sumatra [23].

2.5. Model Evaluation

The performance of the Random Forest model was evaluated using a confusion matrix, accuracy, and Kappa [24]. A confusion matrix was used to compare the model predictions with the actual classes to determine the number of correct and incorrect classifications. Furthermore, the Accuracy metric was used to measure the proportion of all predictions that were correctly classified, while Kappa was used to evaluate the level of agreement between the classification results and the actual data, considering the possibility of agreement occurring by chance [25].

In addition to evaluating the model performance, this study used Balanced Accuracy to assess the classification performance for each cluster. The use of this metric is important because it provides a more objective picture of the model performance on data with an imbalanced class distribution. Models with high Accuracy, Kappa, and Balanced Accuracy values indicate good classification ability, allowing for a more reliable interpretation of the grave typology identification results [26].

3. RESULTS AND DISCUSSION

3.1. Research Data Characteristics

The research dataset comprised 85 sultanate tombs in Sumatra, which were described using four morphometric variables: tombstone height, base length, base width, and base height. The data characteristics are presented using descriptive statistics, including the minimum, quartile, median, mean, and maximum values, as shown in Table 2. The data review also revealed that no variables had missing values; therefore, all data could be used in the analysis without the need for imputation or deletion of observations.

Table 2. Descriptive Statistics of Research Variables

Variable	Min	Q1	Q2	Mean	Q3	Max
Tombstone height (cm)	0,00	49,00	70,00	69,05	94,00	158,00
Rope length (cm)	0,00	210,00	250,00	263,50	316,00	727,00
Edge width (cm)	0,00	70,00	112,00	106,00	141,00	276,00
Jirat Height (cm)	0,00	22,00	40,00	45,53	54,00	270,00

Based on Table 2, the four morphometric variables had a fairly wide range of values. The average height of the tombstone is 69.05 cm, and the average base length is 263.50 cm. The average width and height of the tomb fence were 106.00 cm and 45.53 cm, respectively. The differences in the minimum, maximum, and quartile values for each variable indicate that the physical dimensions of the tombs are not uniform.

This morphometric variation indicates differences in the physical characteristics of the tombs, which may reflect the diversity of typologies, construction techniques, and cultural traditions during the sultanate period. This diversity of characteristics provides an important basis for applying the K-Means Clustering method, as the clustering process is based on the degree of similarity in the morphometric dimensions of each tomb. Thus, tomb typological patterns can be identified more objectively based on the physical characteristics of each object.

The number of clusters was determined using the Elbow and Silhouette methods to identify the most appropriate number of clusters before the clustering process began. The visualization results in Figure 1 show that the within-cluster sum of squares (WSS) curve decreases sharply up to $k = 3$, then begins to level off as the number of clusters increases. This pattern indicates that adding clusters beyond $k = 3$ results in only a relatively small reduction in within-cluster variation; therefore, three clusters were considered sufficient to adequately represent the data structure.

In contrast, the Silhouette Method produced the highest average silhouette coefficient at $k = 8$. However, the use of eight clusters was deemed inappropriate for the research objectives, as it resulted in an overly detailed grouping for a dataset consisting of only 85 graves. Furthermore, an excessive number of clusters could complicate the interpretation of tomb typological characteristics. Therefore, this study used three clusters as the optimal number, considering the results of the Elbow Method, ease of interpretation, and alignment with the research objectives, namely, identifying the typology of sultanate tombs in Sumatra.

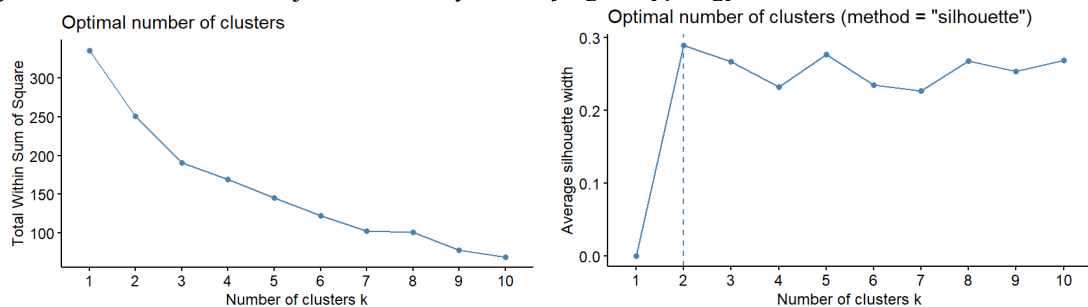


Figure 1. Number of clusters: (a) Metode Elbow; (b) Silhouette Metode

3.2. Characteristics of Each Cluster

The characteristics of each cluster were determined based on the average values of the morphometric variables used during the grouping process. The differences in the average values of each variable indicate that each cluster has distinct physical characteristics. The average morphometric characteristics of each cluster are listed in Table 3.

Table 3. Average Physical Characteristics of Graves in Each Cluster

Variables	Klaster 1	Klaster 2	Klaster 3
Tombstone height (cm)	40.14	99,96	79,25
Grave length (cm)	233,89	354,86	190,50
Web width (cm)	114,65	147,93	31,29
Shoe height (cm)	42,84	68,21	18,75

Based on Table 3, Cluster 1 is characterized by a relatively lower tombstone height compared to the other clusters, with an average tombstone height of 40.14 cm. The length of the grave markers in this cluster was moderate, while the width and height were relatively larger than those in Cluster 3. These characteristics indicate that Cluster 1 consists of graves with relatively simple physical dimensions.

Cluster 2 has the highest average values for all morphometric variables. The tombstone height reached 99.96 cm, grave length was 354.86 cm, grave width was 147.93 cm, and grave depth was 68.21 cm. These results indicate that Cluster 2 comprises a group of graves with the largest physical dimensions compared to the other clusters. This difference suggests the presence of a group of graves with more monumental dimensions, which may represent graves with more complex constructions.

Meanwhile, Cluster 3 has relatively tall tombstones, measuring 79.25 cm, but their base length, width, and height are smaller than those of the other two clusters. The width of the grave rim in this cluster is only 31.29 cm, whereas the average height is 18.75 cm. These characteristics indicate that Cluster 3 consists of graves with relatively tall tombstones but with more modest grave rim dimensions.

In general, the clustering results indicate that variations in grave morphometrics are influenced not only by the height of the tombstone but also by the dimensions of the jirat. The differences in characteristics within each cluster indicate that the K-means method is capable of grouping graves based on similar physical dimensions, thus providing initial insight into the typological variations of sultanate tombs in Sumatra.

3.3. Evaluation of Clustering Results

The clustering results were evaluated using the Silhouette Coefficient to measure the level of compactness and separation between clusters.

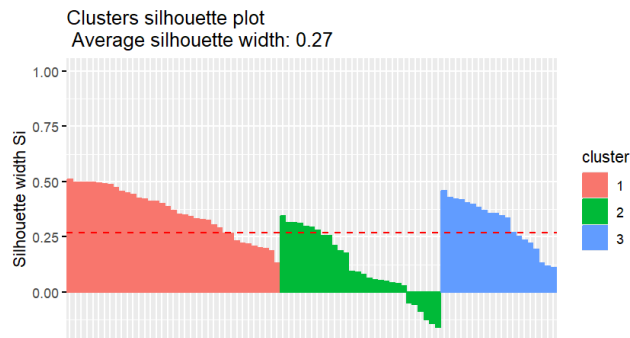


Figure 2. Plot of K-Means

The evaluation results using the silhouette coefficient yielded an average value of 0.27, indicating that the cluster structure fell into the “fairly good clustering” category. Cluster 1 had the best clustering quality because most of its members had high and positive Silhouette values. Conversely, Cluster 2 shows a lower clustering quality, characterized by several objects with negative Silhouette values, indicating characteristics like those of other clusters. Meanwhile, Cluster 3 mostly has positive silhouette values, indicating a good clustering consistency. Overall, these results indicate that the K-means method can identify tomb typological patterns based on morphometric characteristics, although there are still some objects located on the boundaries between clusters due to the diversity of the physical characteristics of the tombs.

Table 4. Random Forest Model Performance

Evaluation Metric	Nilai
Accuracy	68,75%
Kappa	0,5210

Based on Table 4, the Random Forest model achieved an accuracy of 68.75%, indicating that most of the test data were successfully classified into the appropriate clusters. A Kappa value of 0.521 indicates a moderate level of classification agreement after accounting for the possibility of random agreement. These results indicate that the model performs well in identifying the characteristics of each cluster based on the archaeological attributes used.

3.4. Classification Variables Using Random Forest

A Random Forest model was built using 500 decision trees (ntrees) to classify the clustering results obtained from the K-means method. Model performance was evaluated using Out-of-Bag (OOB) Error, Accuracy, Kappa, and Balanced Accuracy. The model evaluation results are shown in Table 4.

Table 5. Model of Random Forest

Parameters	Value
Number of trees (n)	500
OOB Error	46,38%
Precision	68,75%
Kappa	0,5210
Balanced Accuracy for Cluster 1	0.8016
Balanced Accuracy, Cluster 2	0,7636
Balanced Accuracy Cluster 3	0.7083

Based on Table 5, the Random Forest model achieved an accuracy of 68.75% with a kappa value of 0.521, indicating a moderate level of classification agreement. Furthermore, the OOB Error value of 46.38% indicates some classification errors, particularly for objects with overlapping morphometric characteristics. However, the Balanced Accuracy values, which ranged from 0.708 to 0.802, indicate that the model is sufficiently capable of distinguishing the characteristics of each cluster, making it suitable for identifying variables influencing grave typology.

3.5. Key Variables Shaping Grave Typology

The results of the Random Forest analysis showed that each variable contributed differently to the differentiation of grave types.

Table 6. Average Gini Index

Rank	Variable	Decreased Average Gini Index
1	Grave materials	6.712
2	Grave marker shapes	4.724
3	Tombstone shapes	4.415
4	Tombstone materials	2.846
5	Tombstone types	2.458
6	Tombstone materials	2.401
7	Decorative footstone motifs	2.116
8	Tombstone ornaments	1.707

The results of the Random Forest analysis show that each variable contributes differently to distinguishing grave typologies. Based on the Mean Decrease Gini values in Table 6, tombstone material is the variable with the highest contribution, with a value of 6.712, followed by the shape of the footstone (4.724) and the shape of the headstone (4.415). Conversely, the decorative patterns on the headstone and footstone have relatively lower significance than the other variables.

The high Mean Decrease Gini value for the grave structure material indicates that the type of material used in the grave structure material makes the greatest contribution to distinguishing the characteristics of each group. Meanwhile, the shapes of the tombstone and footstone also play a significant role in the classification process because they are effective in separating objects into different groups. These results indicate that the main physical attributes of the tomb have a greater influence on typology formation than decorative attributes, such as ornamental motifs. This finding is also consistent with the variable importance analysis in Random Forest, which can identify attributes that make the most significant contribution to the classification process and help explain the characteristics of the objects being analyzed [22],[21].

4. CONCLUSION

This study successfully grouped 85 Sultanate tombs in Sumatra into three clusters using the K-Means Clustering method based on morphometric characteristics: tombstone height, base length, base width, and base height. The clustering results showed that each cluster had distinct physical characteristics, illustrating variations in tomb typology based on similarities in their morphometric dimensions. The evaluation using the Silhouette coefficient yielded an average value of 0.267, indicating that the resulting cluster structure fell into the "fairly good" category.

The Random Forest model achieved an accuracy rate of 68.75% with a Kappa value of 0.521, indicating that the model performed reasonably well in classifying tomb types based on archaeological attributes. Variable importance analysis revealed that the tomb lining material, foot tombstone shape, and head tombstone shape were the most significant variables contributing to the differentiation of the characteristics of each cluster. These findings suggest that the primary physical attributes of tombs play a more dominant role than decorative attributes in the process of identifying Sultanate tomb typology in Sumatra.

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