

Comparative Analysis of K-Means, PSO-KMeans and Butterfly Optimization Algorithm for Road Damage Clustering

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Article History:

Submitted: 22-04-2026

Accepted: 12-05-2026

Published: 14-05-2026

Keywords:

BOA; Clustering analysis; K-Means; PSO-KMeans; Silhouette Score.

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ABSTRACT

Road damage on access routes to coastal tourism areas in Tanah Laut Regency, South Borneo has become a critical issue affecting travel safety and tourist visits. Various types of pavement distress such as cracking, depression, bump and sags, patching and potholes, polished aggregate, rutting, and swelling create complex data patterns that require robust analytical methods. This study adopts a data-driven approach to compare the performance of three clustering algorithms K-Means, Hybrid PSO-KMeans, and the Butterfly Optimization Algorithm (BOA) to determine the optimal grouping structure of road damage data. The dataset consists of seven types of road distress obtained from field surveys across three coastal locations. Data preprocessing was carried out through normalization and standardization to ensure consistency in scale, followed by clustering analysis with varying numbers of clusters ($k = 2$ to 7). The Silhouette Coefficient was used to evaluate clustering performance and determine the optimal number of clusters. The results show that the optimal clustering structure is achieved at $k = 3$, representing three levels of road damage severity: minor, moderate, and severe. Among the evaluated methods BOA produced the highest Silhouette Score of 0.7559, outperforming Hybrid PSO-KMeans (0.6583) and K-Means (0.442) indicating more compact and well-separated clusters. These findings suggest that BOA is more effective in handling complex and heterogeneous road damage data. Practically, this approach can support data-driven decision-making in prioritizing road maintenance.

INTRODUCTION

Road infrastructure plays a crucial role in supporting tourism development particularly in coastal areas where accessibility directly influences visitor mobility and safety. In Tanah Laut Regency, several coastal tourism destinations, including Swarangan Beach, Turki Beach, and Jorong Beach, exhibit road conditions with evident levels of damage such as surface cracking, subsidence, potholes, aggregate wear, and uneven road profiles. These conditions have led to a decline in tourist visits, as travel comfort and safety to these destinations are significantly compromised. Therefore, road damage constitutes a critical issue affecting transportation efficiency and infrastructure sustainability, necessitating more effective data-driven evaluation approaches (Oktopianto et al., 2026).

Previous studies have proposed several methods to assess road conditions, including Pavement Condition Index (PCI) and Surface Distress Index (SDI), which provide quantitative measures for infrastructure evaluation (Teopilus & Amrozi, 2023). However, these approaches often rely on predefined scoring systems and may not fully capture complex, high-dimensional patterns in road damage data. Recent advancements in data-driven techniques highlight the importance of machine learning and clustering methods to extract hidden patterns and support decision-making processes (Rahman et al., 2025)

Clustering techniques, such as K-Means, have been widely applied to classify road damage levels and identify similar patterns among road segments. For instance, recent studies demonstrate that clustering can effectively group road damage data and support maintenance prioritization, with Silhouette-based validation providing reliable cluster quality evaluation (Agusniar et al., 2025; Rhomadhona et al., 2025). The Silhouette Coefficient, which measures cluster cohesion and separation, is commonly used to determine the optimal number of clusters and assess clustering performance. Despite its advantages, K-Means is sensitive to centroid initialization and often converges to local optima.

To address these limitations, hybrid and metaheuristic-based clustering methods have been developed. The integration of Particle Swarm Optimization (PSO) with K-Means improves clustering accuracy by optimizing centroid initialization, while nature-inspired algorithms such as the Butterfly Optimization Algorithm (BOA) provide adaptive mechanisms that balance global exploration and local exploitation. Recent studies in infrastructure analysis also emphasize that clustering-based approaches enhance robustness and accuracy in detecting damage patterns in complex engineering systems (Bimantara & Widiartha, 2023)



However, comparative studies evaluating multiple clustering algorithms for road damage analysis remain limited, particularly in tourism infrastructure contexts. Therefore, this study aims to compare the performance of K-Means, Hybrid PSO–KMeans, and BOA in clustering road damage data based on multiple distress indicators. By using the Silhouette Coefficient as an evaluation metric, this research seeks to identify the optimal clustering structure that reflects actual road damage severity levels. The main contribution of this study lies in demonstrating that consistent clustering results across different algorithms indicate the presence of an inherent data structure, providing both methodological insights and practical implications for data-driven road maintenance prioritization.

LITERATURE REVIEW

Recent research shows that clustering techniques are increasingly being used to analyze data in transportation and infrastructure management. For example, research has shown that K-Means can identify accident-prone areas and support decision-making in urban road safety management (Jeon et al., 2024; Wahyono et al., 2024). In addition, the clustering approach has also been applied in the analysis of urban area vulnerability using spatio-temporal K-Means, which demonstrates its ability to handle complex infrastructure data (Mutambik, 2024).

In the context of road infrastructure, clustering methods have also been used to classify road damage conditions. Previous research has shown that K-Means can cluster road damage levels based on surface distress parameters, although its performance is often affected by data complexity and sensitivity to centroid initialization (Oktopianto et al., 2026; Rahman et al., 2025). These limitations become even more apparent when applied to heterogeneous datasets with nonlinear patterns, such as road damage data, which consists of various types of damage. To address these limitations, a hybrid and metaheuristic-based clustering approach was developed. The integration of Particle Swarm Optimization (PSO) with K-Means has been shown to improve clustering performance by optimizing centroid initialization using a global search mechanism (Li et al., 2022; Yassin & Pooja, 2020).

Compared with other metaheuristic approaches, BOA has the flexibility to handle nonlinear data structures, making it suitable for clustering problems on complex real-world data.

METHOD

The research process is conducted through a structure framework. The workflow is illustrated in Fig. 1.

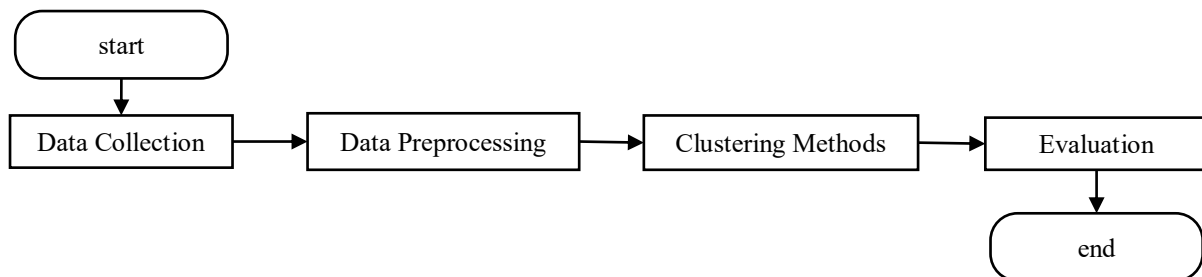


Figure 1. Workflow of Research Process

Data Collection

The research data were obtained from a field survey of road damage conducted along three coastal tourist access routes, namely Turki Beach, Swarangan Beach, and Jorong Beach, located in Tanah Laut Regency, Indonesia. The dataset consists of road segment observations, each characterized by seven types of damage: Cracking (X1), Depression (X2), Subsidence (X3), Patching and Potholes (X4), Aggregate Wear (X5), Rutting (X6), and Swelling or Heaving (X7). Each segment was also labeled according to its location allowing for cross-location comparative analysis.

Data Preprocessing

Before conducting clustering analysis, a data preprocessing stage was carried out to ensure the dataset quality and reliability. This stage consisted of three primary steps: missing value detection and treatment, data normalization, and feature scaling. These steps are crucial in clustering analysis since differences in scale or incomplete data can bias distance calculations and distort cluster formation. Both normalization and standardization are essential preprocessing strategies in data-driven clustering studies, as demonstrated in recent research highlighting their influence on clustering accuracy and computational stability (Saraswat & Raj, 2022)

- **Normalization**

Normalization is necessary to ensure that all attributes contribute equally to the clustering process, particularly when Euclidean distance is used. This study employed Min–Max Normalization, which rescales feature values into a range [0,1].

$$x'_i = \frac{x_i - x_{min}}{x_{max} - x_{min}}$$

- **Standardization**

For comparative analysis, Z-Score standardization was also applied to test the robustness of clustering results. The Z-Score method centers each attribute by its mean and scales it by its standard deviation.

$$z_i = \frac{x_i - \mu}{\sigma}$$

This transformation ensures that each variable has zero mean and unit variance, which is particularly beneficial when using optimization-based clustering methods such as BOA that are sensitive to data scale.

K-Means Clustering

The K-Means algorithm is one of the most widely used partitional clustering techniques, owing to its computational efficiency and simplicity for large-scale datasets (Sinaga & Yang, 2020). It aims to minimize the total intra-cluster variance, often referred to as the within-cluster sum of squares (WCSS). The objective function is mathematically expressed in Equation (3)

$$J = \sum_{j=1}^k \sum_{i=1}^{n_j} \|x_i^{(j)} - \mu_j\|^2$$

The algorithm iteratively performs two main steps: (1) assignment, where each data point is allocated to the nearest centroid based on the Euclidean distance; and (2) update, where centroids are recalculated as the mean of all assigned data points. This process continues until convergence, typically when changes in centroid positions fall below a predefined threshold. Despite its effectiveness in various domains, K-Means suffers from several known limitations, including sensitivity to centroid initialization, vulnerability to local minima, and the assumption of spherical and equally sized clusters.

Hybrid PSO-KMeans

The Hybrid PSO–KMeans algorithm integrates the global search capability of the Particle Swarm Optimization (PSO) metaheuristic with the local refinement strength of the K-Means algorithm (Kurniawan et al., 2023). This hybridization helps overcome K-Means dependence on random initialization and prevents premature convergence to suboptimal solutions. In PSO, a population of candidate solutions called particles moves within the search space according to individual and collective experiences. Each particle adjusts its position and velocity to balance exploration (searching new areas) and exploitation (refining the best-known solution). The velocity and position update equations are defined as follows:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i^t - x_i^t) + c_2r_2(g^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Butterfly Optimization Clustering

The Butterfly Optimization Algorithm (BOA) is a nature-inspired metaheuristic proposed by (Li et al., 2022), simulating the foraging and mating behavior of butterflies guided by their sense of fragrance. In optimization problems, each butterfly represents a candidate solution, and the intensity of fragrance correlates with the fitness of that solution. The algorithm alternates between two main phases: global search (exploration) and local search (exploitation), dynamically balancing between discovering new areas of the search space and refining the best-found solutions. The fragrance emission of each butterfly, which determines its attractiveness, is formulated as:

$$f = cI^a$$

During the global search phase, butterflies move toward the best individual discovered so far (denoted as g^*), which encourages exploration of the search space. The new position of the i^{th} butterfly is given by:

$$x_i^{t+1} = x_i^t + Levy(\lambda) \times (g^* - x_i^t) \times f_i$$

Conversely, in the local search phase, butterflies perform random walks guided by the fragrance of nearby individuals, enabling local refinement of promising solutions:

$$x_i^{t+1} = x_i^t + Levy(\lambda) \times (x_j^t - x_k^t) \times f_i$$

Testing with Silhouette Coefficient

Determining the optimal number of clusters (k) is a crucial stage in clustering analysis, as it directly affects the interpretability and performance of the resulting groups. In this study, the optimal cluster number was selected based on internal validation metrics, primarily the Silhouette Score, which measures both cluster compactness (intra-cluster cohesion) and separation (inter-cluster distance) (Schwenkreis, 2022). The metric provides a quantitative evaluation of how well each data point fits within its assigned cluster compared to neighboring clusters. The Silhouette Coefficient for a single data point *i* is computed using Equation (8):

$$S(i) = \frac{b(i) - a(i)}{\max[a(i), b(i)]}$$

A higher mean Silhouette Score reflects more distinct and cohesive clustering, indicating that the chosen number of clusters *k* yields a stable and meaningful partitioning structure. This index has been widely adopted as a robust internal validation measure in clustering research, particularly in studies involving unsupervised learning and optimization-based clustering algorithms, such as PSO-KMeans and BOA. Its application allows researchers to balance the trade-off between cluster cohesion and separation without requiring external class labels.

RESULT

Dataset Characteristic

Based on the results of the Pavement Condition Index (PCI) analysis in three coastal areas: Swarangan Beach, Turki Beach, and Jorong Beach, road condition assessments were conducted at each STA, dividing the area into 100-meter segments. Each segment was measured in detail, including the length, width, and depth of damage, to determine the area of each type of damage. The resulting damage area was then aggregated by damage type in square meters and used as a cluster variable. Seven types of road damage were used as variables: cracks (X1), depressions (X2), subsidence (X3), patches and potholes (X4), aggregate wear (X5), grooves (X6), and swelling or bulging (X7). Each variable was filled with the total area of each damage type per segment, for example, the Swarangan Beach segment was coded S0–S18, the Turki Beach segment T0–T19, and the Jorong Beach segment J0–J54. This coding facilitates the identification and analysis of damage patterns between segments and serves as the basis for developing a cluster model to determine the dominant damage characteristics of the roads at each study location.

The results of field measurements presented in Table 1, the area of road damage for each type of distress is represented by variables X1 to X7, for example, variable X1 shows the area of damage due to cracks on the pavement surface of 3.5 m², obtained from the results of measurements of 3.5 meters in length and 1 meter in width in the initial segment of Swarangan Beach (S0). Variable X2 describes damage in the form of depressions (bumps and sags) with an area of 2.5 m², the results of measurements from a length of 2.5 meters and a width of 1 meter. Meanwhile, variable X3 shows the type of damage sinking (depression) with an area of 4.0 m², based on the results of measurements of 2 meters in length and 2 meters in width. While variables X4 to X7 each have a value of 0 m², which indicates that no damage was found in the type of patches and holes (X4), aggregate wear (X5), grooves (X6), or swelling or bulging (X7) in that segment. For more details regarding the variation in the area of each type of damage in all research segments, can be seen in Table 1.

Table 1. Results of the Road Damage Investigation Survey

Location Labels	STA		The Extent of Distress Types (m^2)						
	Start	End	X_1	X_2	X_3	X_4	X_5	X_6	X_7
S0	0+000	0+100	3,500	2,500	4,000	0,000	0,000	0,000	0,000
S1	0+101	0+200	6,292	0,000	0,000	3,200	19,000	0,000	0,000
S2	0+201	0+300	58,000	0,000	0,000	0,800	3,900	0,000	0,000
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
S18	1+801	1+900	6,100	4,600	0,000	0,000	0,000	0,000	0,000
T0	0+000	0+100	15,500	1,500	9,400	29,000	1,900	1,700	37,600
T1	0+101	0+200	19,57	0,000	0,000	5,45	1,000	0,000	0,000
T2	0+201	0+300	14,81	23,09	6,30	24,13	11,97	0,00	2,88
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
T18	1+801	1+900	102,250	12,74	5,104	161,680	1,196	20,000	0,000
T19	1+901	1+985	56,000	0,000	1,440	55,540	8,000	13,600	0,000
J0	0+000	0+100	3,500	6,250	0,000	25,550	0,000	0,000	0,000
J1	0+101	0+200	6,29	0,000	0,000	0,00	266,600	0,000	0,000
J2	0+201	0+300	1,200	0,000	0,000	0,000	0,000	0,000	0,000
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
J53	5+301	5+400	7,65	0,000	4,88	2,28	7,65	0,000	0,000
J54	5+401	6+700	800	0,000	0,000	800	0,000	0,000	0,000

Source: Field Survey Results, 2025

Descriptions X_1 = Cracking S = Label for Swarangan
 X_2 = Bumb and Sags T = Label for Turki
 X_3 = Depression J = Label for Jorong
 X_4 = Patching and Potholes
 X_5 = Polished agregat
 X_6 = Rutting
 X_7 = Swelling

K-Means Clustering Peerformance

The experiments in this study were conducted six times, each with a different number of clusters (k). The clustering results were evaluated using the Silhouette Coefficient, a metric used to assess the quality and validity of the clustering structure. The Silhouette score indicates how well each data point fits within its assigned cluster compared to its proximity to other clusters. The results of these evaluations are presented in Table 2.

Table 2. Result of Silhouette Score K-Means

K	Silhouutte score
2	0.442
3	0.278
4	0.332
5	0.442
6	0.338
7	0.330

Table 2 presents the Silhouette Score for various values of k using the K-Means method. The highest scores are observed at $k=2$ and $k=5$, both with a value of 0.442, while the lowest score occurs at $k=3$ with a value of 0.278. The fluctuating pattern indicates that the K-Means clustering results lack stability when the number of clusters is varied. This instability occurs because K-Means is highly sensitive to the initial selection of centroids. If the initial centroids do not align well with the data distribution, the iterative process may converge at a local minimum rather than the global optimum. Furthermore, in cases of unbalanced data, centroids may gravitate too close to one another, leading to suboptimal clustering. This fluctuation is also illustrated in Fig 2, where the Silhouette scores vary significantly across different values of k . The graph confirms that the K-Means method does not yet produce consistent clustering results for this dataset.



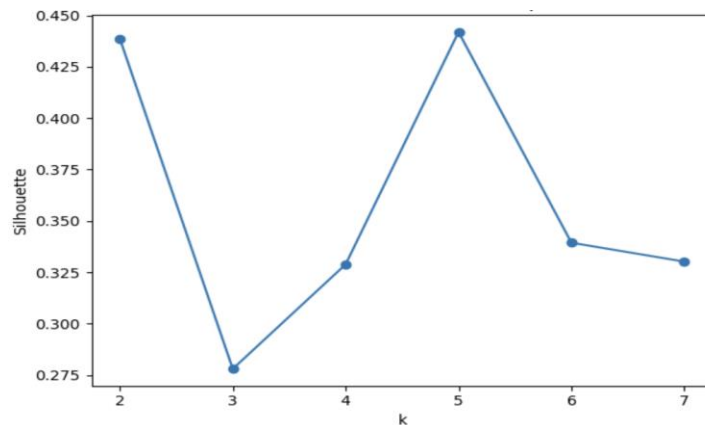


Figure 2. Comparison of Silhouette Scores for Various k Values

Hybrid PSO-K-Means Performance

The Hybrid PSO–KMeans method was applied to cluster road damage data consisting of seven (7) attributes: cracking, depression, subsidence, patching and potholes, aggregate wear, rutting, and swelling. The experiments were conducted six (6) times with varying numbers of clusters, ranging from $k = 2$ to $k = 7$. The Silhouette Score values obtained from these experiments are presented in the following Table 3.

Table 3. Result of Silhouette Score Hybrid PSO-K Means

K	Silhouette score
2	0.6264
3	0.6583
4	0.6360
5	0.6513
6	0.5759
7	0.4834

Based on Table 3, the highest Silhouette score was achieved at $k=3$ with a value of 0.6583. This indicates that partitioning the data into three clusters yielded the optimal clustering structure, where data points within each cluster exhibit high similarity, while being distinctly separated from other clusters. The improvement in the Silhouette score at $k=3$ demonstrates that the Particle Swarm Optimization (PSO) integration successfully optimized the initial centroid selection for the K-Means algorithm. By mitigating the risk of falling into local optima, the hybrid approach resulted in more stable and superior cluster separation compared to the standard K-Means method.

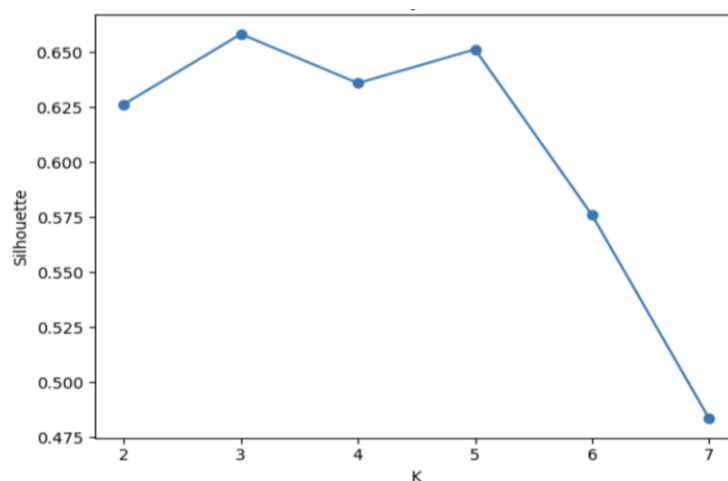


Figure 3. Comparison of Silhouette Scores for Various k Values

BOA Method Performance

The Butterfly Optimization Algorithm (BOA) was evaluated using the same parameters and objective function to ensure a pair performance comparison with the K-Means and PSO–KMeans algorithms. The Silhouette Score values for the different numbers of clusters are presented in Table 4 below.

Table 4. Result of Silhouette Score BOA Method

K	Silhouette score
2	0.7534
3	0.7559
4	0.7392
5	0.7559
6	0.7305
7	0.7356

The results in Table 4 show that the Butterfly Optimization Algorithm (BOA) achieved the highest Silhouette Score of 0.7559 at $k = 3$ and $k = 5$. This value is significantly higher than that obtained using the PSO–KMeans method, indicating that BOA is capable of producing clusters with a more distinct and cohesive structure. The superior performance of BOA is attributed to its fragrance-based global search mechanism, which mimics the foraging behavior of butterflies. This mechanism facilitates adaptive exploration of the solution space while maintaining a robust balance between global exploration and local exploitation (Arora et al., 2021). During the global search phase, individuals are guided toward the global best solution, whereas in the local search phase, they refine their positions relative to nearby individuals. This adaptive process effectively prevents premature convergence, a common limitation in conventional swarm-based algorithms. From an interpretive perspective, the peak performance at $k=3$ suggests the formation of three primary groups representing distinct road conditions. Notably, BOA produced a substantially higher Silhouette margin compared to PSO–K-Means (0.7559 vs. 0.6583), demonstrating clearer cluster separation. This suggests that BOA is more sensitive in detecting subtle variations between road segments, particularly in datasets characterized by complex patterns and varying degrees of damage intensity.

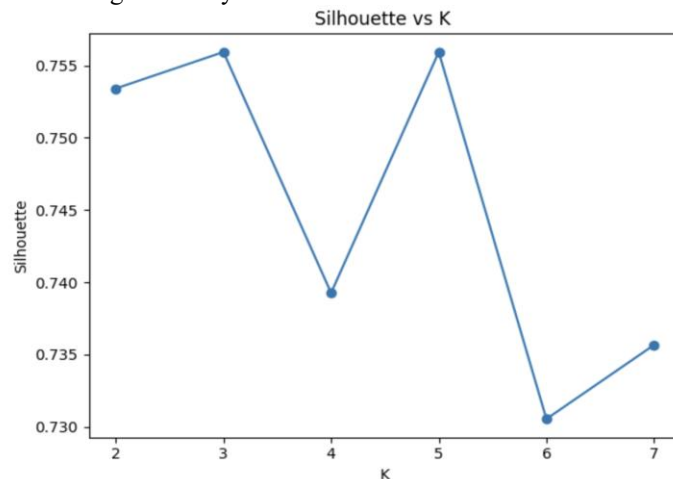


Figure 4. Comparison of Silhouette Scores for Various k Values

Comparative Analysis of Clustering Methods

To evaluate the effectiveness of the proposed approaches, a comparative analysis was performed among K-Means, Hybrid PSO–K-Means, and BOA. The Silhouette Scores for all tested values of k are summarized in Table 5.

Table 5. Comparison of Silhouette Score across Mehods.

K	K-Means	Hybrid PSO-K Means	BOA Method
2	0.442	0.6264	0.7534
3	0.278	0.6583	0.7559
4	0.332	0.6360	0.7392
5	0.442	0.6513	0.7559
6	0.338	0.5759	0.7305
7	0.330	0.4834	0.7356

Based on the comparison results, the Butterfly Optimization Algorithm (BOA) consistently achieved the highest Silhouette Scores across all cluster variations, ranging from 0.73 to 0.76. This indicates that BOA effectively balances global exploration and local exploitation resulting in more compact and well-separated clusters. In contrast, the Hybrid



PSO–KMeans method demonstrated relatively stable performance, with a peak Silhouette Score of 0.6583 at $k = 3$, and values remaining above 0.6 for most cluster configurations. The standard K-Means algorithm exhibited a lower and more fluctuating trend (0.27–0.44), highlighting its sensitivity to initial centroid selection and its limited capability in capturing complex patterns in road damage data.

The performance differences among the algorithms are substantial. BOA outperformed K-Means by approximately 71% (0.7559 vs. 0.442), while Hybrid PSO–KMeans showed an improvement of about 49% over K-Means (0.6583 vs. 0.442). Furthermore, BOA demonstrated an additional improvement of approximately 15% compared to Hybrid PSO–KMeans, indicating its higher efficiency in identifying globally optimal solutions compared to particle swarm-based approaches.

From a methodological perspective, this improvement can be explained by the ability of both BOA and PSO-based methods to optimize the K-Means objective function through global search mechanisms. Consequently, the optimal number of clusters for grouping road damage segments is identified as $k = 3$. The highest Silhouette Score at $k = 3$ was achieved by BOA (0.7559), followed by Hybrid PSO–KMeans (0.6583), while K-Means produced lower values due to its sensitivity to centroid initialization. The consistency of the optimal cluster number across BOA and Hybrid PSO–KMeans aligns with real-world road conditions, which can be naturally classified into three levels of severity: minor, moderate, and severe.

DISCUSSION

These findings are consistent with the results presented in Section 3. The results of this study demonstrate that clustering performance is strongly influenced by the optimization mechanism embedded within each algorithm. The superior performance of the Butterfly Optimization Algorithm (BOA), which achieved the highest Silhouette Score (0.7559), indicates its ability to effectively balance global exploration and local exploitation in complex datasets. This finding is consistent with previous studies showing that nature-inspired metaheuristic algorithms outperform conventional clustering methods when dealing with nonlinear and high dimensional data structures (Kaveh & Mesgari, 2023). In contrast, the relatively low and fluctuating performance of K-Means confirms its well-known limitation namely its dependence on initial centroid selection (Sinaga & Yang, 2020). In datasets characterized by heterogeneous and overlapping features such as road damage data K-Means tends to converge to local optima, resulting in less stable clustering structures. This behavior has also been reported in previous studies on clustering performance and initialization sensitivity.

The Hybrid PSO–KMeans method shows a significant improvement over standard K-Means demonstrating the effectiveness of integrating global optimization strategies into clustering processes. By leveraging Particle Swarm Optimization (PSO), the hybrid approach enhances centroid initialization and reduces the risk of premature convergence. However, although PSO–KMeans improves clustering compactness and separation, its performance remains slightly inferior to BOA. This suggests that while PSO effectively enhances global search capability, BOA provides a more adaptive and flexible search mechanism, allowing for finer adjustments in both global and local search phases.

A key finding of this study is the consistent identification of the optimal number of clusters ($k = 3$) across all evaluated methods. This consistency represents a significant contribution, as it provides empirical evidence that the clustering structure is not merely influenced by the choice of algorithm but reflects an inherent and stable pattern within the data. In this research, the three clusters correspond to natural groupings of road damage severity: minor, moderate, and severe. The use of the Silhouette Coefficient as an internal validation metric supports this interpretation, as it evaluates both intra-cluster cohesion and inter-cluster separation (Schwenkreis, 2022).

The consistency of $k = 3$ across algorithms with different computational mechanisms further indicates that the clustering result is not a methodological artifact but an intrinsic property of the dataset. This finding suggests that road damage characteristics naturally form three distinct levels of severity, reflecting the hierarchical progression of pavement deterioration observed in real-world conditions. This research extends existing research by not only comparing multiple clustering algorithms but also interpreting the agreement among different methods as evidence of intrinsic data structure. While previous studies typically focus on identifying the best-performing algorithm, this research highlights that consistency across methods can serve as a stronger validation of the underlying data pattern. Therefore, the identification of $k = 3$ is not only statistically optimal but also physically meaningful in representing actual road damage conditions.

From a practical standpoint, the findings offer important implications for infrastructure management and decision-making. The classification of road segments into three distinct severity levels enables policymakers to prioritize maintenance strategies more effectively. Segments classified as severe can be addressed immediately, while moderate and minor segments can be incorporated into medium- and long-term maintenance planning.

Despite these contributions, this study has several limitations. The dataset is limited to three coastal locations, which may restrict the generalizability of the findings. In addition, the evaluation relies solely on internal validation (Silhouette Coefficient) without incorporating external validation or expert judgment. Future research may integrate additional validation indices, such as Davies Bouldin or Calinski Harabasz, and explore hybrid approaches combining clustering with predictive modeling to further enhance analytical robustness.

CONCLUSION

This study compares three clustering methods K-Means, Hybrid PSO–KMeans, and the Butterfly Optimization Algorithm (BOA) to analyze road damage data on access routes to coastal tourism areas in Tanah Laut Regency, South Kalimantan. The dataset consists of seven types of pavement distress, including cracking, depression, subsidence, patching and potholes, aggregate wear, rutting, and swelling. The results indicate that the optimal number of clusters is $k = 3$, representing three levels of road damage severity: minor, moderate, and severe. Among the evaluated methods, BOA achieved the best performance, with the highest Silhouette Score of 0.7559, followed by Hybrid PSO–KMeans (0.6583), while K-Means exhibited lower and less stable performance.

These findings demonstrate that metaheuristic-based algorithms, particularly BOA, are more effective in handling complex and heterogeneous road damage data. Furthermore, the consistent identification of the optimal number of clusters across different methods suggests that the clustering structure reflects an intrinsic pattern within the data, rather than being merely a computational outcome. From a practical perspective, this approach can support data-driven decision-making in prioritizing road maintenance, enabling more objective and efficient allocation of resources. From an academic standpoint, this study contributes by demonstrating that consistency across multiple clustering methods can serve as an indicator of inherent data structure. Future research is recommended to apply this approach to larger and more diverse datasets, as well as to incorporate external validation or predictive modeling techniques to further enhance the robustness and generalizability of the results.

ACKNOWLEDGMENT

This research was supported by the Directorate of Research and Community Service (DPPM) under the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia. The authors also acknowledge the Study Program of Road and Bridge Construction Engineering Technology, Politeknik Negeri Tanah Laut, for its institutional support throughout this study.

REFERENCES

- Agusniar, C., Ulfa, S. M., & Rhomadhona, H. (2025). Utilizing K-Means clustering for grouping student achievement data to evaluate learning activeness. *Journal of Advanced Computer Knowledge and Algorithms*, 2(3), 56–59.
- Bimantara, I. M. S., & Widiartha, I. M. (2023). OPTIMIZATION OF K-MEANS CLUSTERING USING PARTICLE SWARM OPTIMIZATION ALGORITHM FOR GROUPING TRAVELER REVIEWS DATA ON TRIPADVISOR SITES. *Jurnal Ilmiah Kursor*, 12(1), 1–10. <https://doi.org/10.21107/kursor.v12i01.269>
- Jeon, W., Kim, J., & Lee, J. (2024). A Data-Driven Decision-Making Support Method for Priority Determination for an Intelligent Road Problem Reporting System. *Applied Sciences*, 14(23), 10861. <https://doi.org/10.3390/app142310861>
- Kaveh, M., & Mesgari, M. S. (2023). Application of Meta-Heuristic Algorithms for Training Neural Networks and Deep Learning Architectures: A Comprehensive Review. *Neural Processing Letters*, 55(4), 4519–4622. <https://doi.org/10.1007/s11063-022-11055-6>
- Kurniawan, M., Muhima, R., Hakimah, M., Agustini, S., & Putri, R. (2023). Modified Particle Swarm Optimization for Clustering. *Proceedings of the 4th International Conference on Advanced Engineering and Technology*, 89–96. <https://doi.org/10.5220/0012111800003680>
- Li, Y., Yu, X., & Liu, J. (2022). Enhanced Butterfly Optimization Algorithm for Large-Scale Optimization Problems. *Journal of Bionic Engineering*, 19(2), 554–570. <https://doi.org/10.1007/s42235-021-00143-3>
- Mutambik, I. (2024). Assessing Urban Vulnerability to Emergencies: A Spatiotemporal Approach Using K-Means Clustering. *Land*, 13(11), 1744. <https://doi.org/10.3390/land13111744>
- Oktopianto, Y., Antonius, A., & Rochim, A. (2026). Classification of Urban Road Damage Levels Using Surface Distress Index Parameters and K-means Algorithm. *Jurnal Ilmiah Dinamika Rekayasa*, 22(1), 126–135.
- Rahman, F. I., Lukman, L., & Hildayati, H. (2025). Sistem Klasifikasi Kerusakan Jalan Metode Machine Learning dengan Algoritma K-Means dan Random Forest. 3(1), 116–6. <http://jurnal.ardenjaya.com/index.php/ajst>
<http://jurnal.ardenjaya.com/index.php/ajst>
- Rhomadhona, H., Kusriani, W., Aprianti, W., & Permadi, J. (2025). Implementation of K-Means clustering for social assistance recipients with Silhouette Score evaluation. *Brilliance: Research of Artificial Intelligence*, 5(1), 136–143.
- Saraswat, P., & Raj, S. (2022). DATA PRE-PROCESSING TECHNIQUES IN DATA MINING: A REVIEW. *International Journal of Innovative Research in Computer Science & Technology*, 10(1), 122–125.



- <https://doi.org/10.55524/ijirest.2022.10.1.22>
- Schwenkreis, F. (2022). Using the Silhouette Coefficient for Representative Search of Team Tactics in Noisy Data. *Proceedings of the 11th International Conference on Data Science, Technology and Applications*, 193–202. <https://doi.org/10.5220/0011100600003269>
- Sinaga, K. P., & Yang, M.-S. (2020). Unsupervised K-Means Clustering Algorithm. *IEEE Access*, 8, 80716–80727. <https://doi.org/10.1109/ACCESS.2020.2988796>
- Teopilus, C. D., & Amrozi, M. R. F. (2023). The Evaluation of Pavement Condition Assessment Methods for Road Assets in Coastal Areas. *INERSIA Lnformasi Dan Ekspose Hasil Riset Teknik Sipil Dan Arsitektur*, 19(2), 183–193. <https://doi.org/10.21831/inersia.v19i2.61089>
- Wahyono, H., Setiaji, H., Hartati, T., & Wiliani, N. (2024). K-Means Clustering for Identifying Traffic Accident Hotspots in Depok City. *Journal of Applied Research In Computer Science and Information Systems*, 2(1), 159–170. <https://doi.org/10.61098/jarcis.v2i1.182>
- Yassin, S. S., & Pooja. (2020). Road accident prediction and model interpretation using a hybrid K-means and random forest algorithm approach. *SN Applied Sciences*, 2(9), 1576. <https://doi.org/10.1007/s42452-020-3125-1>