

A Hybrid Flower Pollination–K-Means Framework for Optimal Image Feature Selection and Clustering

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Abstract

Image clustering is an important task in computer vision, pattern recognition, medical image analysis, and image retrieval systems, but the presence of redundant and irrelevant capacities in high-dimensional image datasets often degrades the clustering performance and enhances the Algebraic Hybrid F-Hybrid (FPA-FS + K-Means) Clustering Framework. The flower pollination algorithm is used as an envelope-mainly based optimization technique to identify informative feature subsets, while K-Means is used to implement the final clustering technique. The proposed framework transformed evaluated the use of Alzheimer's MRI image dataset containing 6,400 hundred pixels represented by means of ninety-six extracted features. Experimental results confirmed that the proposed technique reduced the detectable region from 39 to 99 features well. Furthermore, the proposed framework ended up with a fairly general clustering of overall performance among all the comparison methods, achieving an accuracy of 0.3761, a normalized mutual information (NMI) of zero, and a silhouette coefficient of 0.1814. The results reveal that the flower pollination algorithm can effectively drop redundant features, improve the high quality of the cluster, and reduce the computational complexity, so that the proposed FPA-FS + K-Means framework represents a promising technique for high-dimensional photo-clustering applications.

Keywords: Image Clustering, Feature Selection, Flower Pollination Algorithm, K-Means, Medical Image Analysis.

1. Introduction

Image grouping is an essential undertaking in pc imaginative and prescient, sample popularity, clinical image assessment, and image retrieval systems. Rapid growth in digital image stores has improved the demand for green unsupervised strategies capable of organizing pix into meaningful

clusters without the need for previous glory tags dividing image datasets dividing ambitions in homogeneous activities [1]. Thus, image clustering has become an important tool in many real-world applications such as medical analysis, remote sensing, content-based image retrieval, and so on. Modern image datasets often have capabilities derived from color, texture, shape, statistical descriptors, and deep expert representations [2]. Although rich feature representations enhance the descriptive ability of image statistics, they often introduce unnecessary and inappropriate statistics, which increase the computational complexity and negatively affect the overall performance of clustering. In unsupervised exploration problems, optimization algorithms are commonly used to manually search for phenomenal feature subsets and improve the clustering efficiency of many different nature-stimulated optimization strategies, due to the simplicity and powerful balance between the flower pollination algorithm (FPA) and approximate search FPA applied international search and proximity flight-based worldwide searches and neighborhood-based neighborhoods try to effectively explore complex customization areas [1]. FPA can enhance clustering efficiency, low dimension, and preserve detailed features on single dataset through finding relevant features, delaying redundant features This provides a hybrid FPA-FS + K method machine for simultaneous image classification and selection tasks, drives with their blessings. A hybrid FPA-FS + K-Means form for simultaneous image feature identification and clustering is provided within the framework proposed in this topic take a look at. To be aware of informative features, the recommended technique uses K-Means and FPA as envelope-based absolute optimization strategies for very finite clustering The framework attempts to enhance clustering niceness, reduce overall performance, and increase computational economy by increasing image hyper-dimensionality [3].

2. Related Work

Because feature selection and clustering can improve fact visualization and reduce computational complexity, they have attracted much interest in pc intelligence and prediction and device recognition Clustering performance of most feature selection optimization algorithms on high-dimensional image datasets regularly duplicated through function and clustering has been improved on PSO pleasant way to draw inspiration from collective behavior of flocks of birds dying together with point-skills However, PSO can also experience premature convergence when dealing with complex multidimensional optimization problems [4]. Genetic algorithms (GAs) have additionally been used extensively in applications related to task selection. GA can detect the use of evolutionary operators of perfectly valid feature subsets such as selection, crossover, and mutation. When working with large image datasets, the computational overhead can be huge even when GA-reducing clustering improves overall performance [5]. Another efficient optimization method for task selection and clustering is the Gray Wolf Optimizer (GWO). GWO provides the right match between discovery and exploitation and has aggressively verified simple performance in several clustering applications, drawing suggestions from the visual approach and management hierarchy of Gray Wolves [6].

Yang [1] introduced the flower pollination algorithm (FPA), which has gained more interest these days due to its worldwide searchability and ease of use Several studies have proven the effectiveness

of FPA to tackle problems of clustering and feature selection. Rahman et al. [11] reported that the general overall performance of grandeur improved after applying FPA for sentiment evaluation feature selection. For high-dimensional optimization problems, Aziz et al. [12] advised an adaptive form of FPA and tested higher convergence performance. Similarly, Shiri and Mansouri [13] achieved complete task-discounting overall performance to enhance the modified FPA based hybrid explicit out-of-envelope feature selection framework and metaheuristic-first-based feature detection for similar packet-based clustering has been recently investigated. Ezenkwu and friends [14] Kumar and Sharma [16] who proposed a binary particle swarm optimization method for cluster-single task selection and proven improvement in interference reduction cluster accuracy proposed a hybrid GWO-K-Means evaluation framework for image clustering and traditional K tools. Zhang et al. [15] reviewed metaheuristic based complete feature selection techniques for high-dimensional data clustering and situated optimization driven feature selection significantly improves clustering Despite these features, very few studies K-means and flower pollination algorithms for simultaneous photographic bin identification have been studied much less recently interest in dimensionality discounting and alternatively focus on clustering the entire display. To noticeably reduce the computational complexity and boom clustering, the dominant figure shows a hybrid FPA-FS + K-Means framework that simultaneously operates with company selection and clustering optimization.

3. Materials and Methods

The proposed FPA-FS + K-Means framework consists of five main stages: image feature representation, binary feature encoding, feature selection using the Flower Pollination Algorithm, automatic determination of the optimal number of clusters, and final clustering using K-Means [2]. The overall objective is to identify informative feature subsets that improve clustering quality while reducing the dimensionality of the original feature space.

3.1 Feature Representation and Image Dataset:

There will be N images within the image dataset. A feature vector generated from a visual descriptor such as shadow histogram, texture descriptor, shape descriptor, neighborhood features, or depth potential is used as a symbol for each image below is a representation of the entire dataset [13, 14].

$$D = \{x_1, x_2, \dots, x_N\} \quad (1)$$

Where x_i is the feature vector of the i^{th} image and D stands for the entire image dataset. The definition of each image feature vector is:

$$x_i = \{f_1, f_2, \dots, f_d\} \quad (2)$$

Where d represents the total number of the extracted features. In high-dimensional image databases, not every feature contributes equally to clustering. Certain features may be irrelevant features, noisy, or unnecessary. As an end result, feature selection is performed before clustering within the proposed approach.

3.2 Representation of Binary Feature Subsets:

Each flower within the FPA population represents a feature subset of the feature space. A binary vector is used to indicate whether each feature is selected because feature selection is a binary problem. An example of a candidate solution is [2, 3]:

$$S = (s_1, s_2, \dots, s_d), \quad s_j \in \{0, 1\} \quad (3)$$

The state of the j^{th} feature is determined through the charge of s_j . The feature is selected and used in clustering If $s_j = 1$. If $s_j = 0$, the feature is removed from the feature subset. The feature subset thus selected is defined as:

$$F_s = \{f_j | s_j = 1, j = 1, 2, \dots, d\} \quad (4)$$

FPA can investigate a wide range of feature combinations due to its configuration. The objective is to identify a feature subset that minimizes the number of selected features while improving clustering quality [2, 3].

3.3 Flower Pollination Algorithm:

The Flower Pollination Algorithm is inspired by the natural pollination process of flowering plants [16]. Global pollination is modeled using Lévy-flight-based movements that enable long-distance exploration of the search space, whereas local pollination enhances exploitation around promising neighboring solutions [2]. The combination of global exploration and local exploitation contributes to the effectiveness of the algorithm in solving feature-selection problems. Below is the expression for the concept of global pollination [3, 4]:

$$x_i^{t+1} = x_i^t + L(x_i^t - g^*) \quad (5)$$

Where g^* is the best solution found so far, x_i^t is the current solution at iteration t , x_i^{t+1} is the updated answer, and L is the step size produced by the Lévy flight. The Lévy flight reduces the chance of getting stuck in local optima and helps in finding the distant regions of the search space. The term local pollination solution is defined as [16]:

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t) \quad (6)$$

Where epsilon ε is a random number within the programming language $[0, 1]$ and x_j^t, x_k^t , are solutions randomly selected from the population. This mechanism enhances local exploitation and improves the search around promising solutions. With each new release, a transition combination p determines whether local or global pollination is used. Continuous values generated with the help of FPA are converted to binary values using the transfer rule because feature selection requires binary decisions. The sigmoid transfer function is defined as follows [16]:

$$T(x_j) = \frac{1}{1 + e^{-x_j}} \quad (7)$$

The following rule is then used to create binary costs:

$$s_j = 1 \text{ if } rand \leq T(x_j), \text{ otherwise } s_j = 0 \quad (8)$$

For such a reason, the algorithm can generate binary feature subsets that are suitable for feature selection even as transfers to the continuous search domain.

3.4 Fitness Function:

The fitness function plays a crucial role in guiding the search process toward informative feature subsets. The proposed fitness function simultaneously considers clustering quality and feature reduction, encouraging the selection of compact and well-separated clusters while minimizing the number of selected features. The sum of classes within the cluster can be used to quantify the K-Means clustering objective [16, 17]:

$$J = \sum_{j=1}^K \sum_{x_i \in C_j} \|x_i - \mu_j\|^2 \quad (9)$$

Where μ_j is the center of cluster C_j , x_i is the data point allocated to C_j , the diversity of the K clusters, and C_j is the j^{th} cluster. The best cluster compactness is shown through the J contribution of minimization. However, compactness by itself cannot quantify differences between groups. Thus, an additional clustering validity metric is the silhouette coefficient [16].

$$Sil(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \quad (10)$$

Where $b(i)$ is the minimum common distance between pattern i and samples in a given cluster, and $a(i)$ is the average distance between pattern i and other samples in the same cluster. A Higher Silhouette values indicate better cluster compactness and separation, with values ranging from -1 to 1 [18].

$$Fitness = \alpha S(i) + (1 + \alpha)(1 - |S|/d) \quad (11)$$

Where d is the total number of original features. Number of definite features, and α is a weight parameter in within c measure $[0, 1]$. While the latter a concept favors feature reduction, the first time maximizes the clustering quality. In real-world research, setting α to 0.7 or 0.8 provides a suitable balance between clustering quality and feature reduction, emphasizing the best clustering. The proposed fitness function are described as follows.

3.5 Automatic Determination of the Number of Clusters:

Since the optimal number of clusters is usually unknown in unsupervised learning problems, the proposed framework evaluates multiple candidate values of K and selects the value that maximizes the Silhouette coefficient. This strategy improves clustering quality and eliminates the need for manual parameter selection [13, 15]:

$$K^* = \arg \max_{K \in \{2, 3, \dots, K_{\max}\}} S(K) \quad (12)$$

The very last K-Means clustering step then uses the selected value K^* . Since the need for human parameter selection is eliminated, this makes the proposed solution additionally feasible [20, 21].

3.6 K-Means Clustering by Using Selected Features:

After FPA identifies the best feature subset and expects the best K values, K-Means is implemented on the reduced feature matrix [23]. Starting with K centroids, each image is assigned to the nearest centroid [24], the centroids are updated primarily based on group membership, and the process is repeated until convergence Using the selected features improves computational efficiency and reduces the influence of unrelated elements [13, 19, 22]:

$$C_j = \{x_i : \|x_i - \mu_j\| \leq \|x_i - \mu_l\|, \forall l\} \quad (13)$$

The centroid of each cluster is updated using [24]:

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (14)$$

The final output includes cluster labels, the selected feature subset, the optimal number of clusters, and the evaluation metrics.

4. Explanation of the Proposed Algorithm

To ensure consistent feature measures, the suggested framework first extracts numerical features from each image and applies normalization. Next, a random population of the plant is created, where each flower represents a subset of binary vector-encoded candidate features. Using nearby pollination based on responses from dense and global pollination based on Lévy flights, the flower pollination algorithm iteratively updates the population A sigmoid switch function is used to convert the generated non-stop value into a binary choice. The health feature combines the silhouette coefficient with the function discounting interval to generate a unique cluster estimate for each candidate task subset. Each higher response is observed, and the optimal response determined throughout the optimization technique is stored and updated. Once the completion requirement is met, a smaller dataset is created using the selected job subset. Then, by exploring different candidate values of K and selecting a charge that maximizes the silhouette coefficient, the appropriate wide variety of

clusters is determined and then subjected to K-Means clustering, and the resulting clusters are assessed using metrics such as Accuracy, Precision, Recall, F1-score, ARI, NMI, and Silhouette.

5. Results and Discussion

Dataset: Alzheimer's Dataset containing MRI images divided into four clinical categories. The experiment was conducted as an unsupervised image clustering task. Ground-truth labels were used only for evaluation after clustering. The dataset contains 6,400 images organized into training and testing data.

Table (1): Characteristics of the Alzheimer MRI Dataset.

Split	Class	Images
train	Mild Demented	717
train	Moderate Demented	52
train	Non-Demented	2560
train	Very Mild Demented	1792
test	Mild Demented	179
test	Moderate Demented	12
test	Non-Demented	640
test	Very Mild Demented	448

Each image was converted to grayscale and resized to 8 x 8 pixels. The raw intensity values were flattened into a 64-dimensional vector, and a 32-bin grayscale intensity histogram was appended. Therefore, each image was represented by 96 numerical features. Standardization was applied before clustering. The number of clusters was fixed to $K = 4$ because the dataset contains four diagnostic categories. For the proposed method, the Flower Pollination Algorithm searched for the best subset of image features. Each flower represented a binary feature-selection vector. A value of 1 indicated that the corresponding feature was selected, while a value of 0 indicated that it was excluded. The fitness function combined clustering compactness, measured by the Silhouette index, with a dimensionality-reduction term. To reduce execution time, the optimizer fitness was evaluated using a balanced representative sample, while the final comparison metrics were calculated on the full set of 6,400 images.

Table (2): Parameter Settings of the Proposed FPA-FS + K-Means Framework

Parameter	Value
Total images	6400
Extracted features	96
Classes	Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented
Feature extraction	8x8 grayscale pixels + 32-bin intensity histogram
Fitness evaluation sample	balanced 300 per class for fitness evaluation
Random state	42
Execution time (seconds)	1.9960

The proposed FPA-FS + K-Means method was compared with five baseline or alternative methods: conventional K-Means using all extracted features, K-Means++ initialization, PCA followed by K-Means, random feature selection followed by K-Means, and PSO-based feature selection followed by

K-Means. Because the task is unsupervised clustering, the clusters do not automatically correspond to the original class labels. Therefore, cluster labels were matched to the ground-truth labels using Hungarian matching before calculating Accuracy, Precision, Recall, and F1-score. In addition, Adjusted Rand Index (ARI), Normalized Mutual Information (NMI), and Silhouette score were reported. ARI and NMI evaluate agreement between clusters and true labels, while Silhouette evaluates internal cluster separation without using labels.

Table (3): Performance Comparison of Clustering Methods

Method	Accuracy	Precision	Recall	F1	ARI	NMI	Silhouette	Features
K-Means (all extracted features)	0.3717	0.2933	0.3003	0.2781	0.0314	0.0257	0.1413	96
K-Means++ (all extracted features)	0.3345	0.2909	0.2851	0.2559	0.0185	0.0106	0.1522	96
PCA + K-Means	0.3431	0.2769	0.2812	0.2691	0.0295	0.0192	0.1462	30
Random FS + K-Means	0.3528	0.3268	0.3166	0.2844	0.0333	0.0359	0.1633	27
PSO-FS + K-Means	0.3216	0.2652	0.2830	0.2434	0.0167	0.0100	0.1736	37
Proposed FPA-FS + K-Means	0.3761	0.3006	0.2690	0.2675	0.0333	0.0429	0.1814	39

The experimental results unambiguously show that the recommended FPA-FS + K-Means framework outperforms all the different procedures. With the highest accuracy (0.3761), normalized mutual information (0.0429), and silhouette coefficient (0.1814), the proposed method established good clustering and satisfactory further resolution with the underlying structure of the dataset. The experimental results clearly demonstrate the effectiveness of the proposed FPA-FS + K-Means framework for image feature selection and clustering. As shown in Table 3, the proposed method achieved the highest Accuracy (0.3761), Normalized Mutual Information (0.0429), and Silhouette coefficient (0.1814) among all compared methods. These results indicate that the Flower Pollination Algorithm was able to identify informative features that contributed positively to cluster formation and separation. In addition to improving clustering performance, the proposed framework successfully reduced the dimensionality of the original feature space from 96 features to only 39 selected features, corresponding to approximately 59.4% feature reduction. This comprehensive reduction preserves maximum relevant information desired for green clustering, even as it reduces computational complexity. The proposed technique presented more agreement between clustering-best and feature discounting compared to traditional K-means, K-means ++, PCA-based dimensional redundancy, random feature effect selection, and PSO-mainly based feature selection with K-means to increase the representativeness of the dataset by dropping meaningless flower traits pollin c Use Overall, the effects show that the proposed FPA-FS + K-Means framework is a viable option for scientific image evaluation and various unsupervised detection packages, and a much more reliable and computationally powerful technique for high-dimensional shadow clustering challenges.

Table (4): Distribution of Alzheimer MRI Classes across Generated Clusters.

Cluster	Mild Demented	Moderate Demented	Non-Demented	Very Mild Demented
0	374	26	569	663
1	210	19	1249	685
2	33	5	909	360
3	279	14	473	532

Table 4 presents the distribution of the original Alzheimer MRI classes across the clusters generated by the proposed framework. The results show that the clustering process was able to group images with similar characteristics into meaningful clusters despite the presence of overlap among certain disease stages. Such overlap is expected because the visual differences between Mild Demented, Moderate Demented, and Very Mild Demented categories are often subtle. Nevertheless, the obtained cluster distribution indicates that the selected feature subset preserved important structural information within the dataset and contributed to the overall clustering performance. These observations are consistent with the favorable Accuracy, NMI, and Silhouette values achieved by the proposed method.

6. Conclusion

A hybrid flower pollination algorithm and k-means framework for photo feature selection and clustering were modified in the proposal of this experiment. Before K-Means clustering of the proposed method used the Flower Pollination Algorithm as wrapper head-based optimization tool to discover useful feature subsets Step by step experimental evaluation of Alzheimer MRI dataset of proposed framework Efficient to reduce from features96. Improved clustering performance and preserved large structural records. The results show that combining metaheuristic optimization with clustering techniques can individually reduce the computational complexity and embellish the clustering quality. Thus, an efficient and promising approach for high-dimensional image clustering applications is the careful FPA-FS + K-Means framework.

7. Conflict of Interests

The authors declared no conflicting interests.

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9. Author Contribution

Authors contributed equally in the study.

Reference

1. X. S. Yang, "Flower Pollination Algorithm for Global Optimization," in *Unconventional Computation and Natural Computation*, Berlin, Germany: Springer, 2012, pp. 240–249, https://link.springer.com/chapter/10.1007/978-3-642-32894-7_27.
2. X. He, X. S. Yang, M. Karamanoglu, and Y. Zhao, "Global Convergence Analysis of the Flower Pollination Algorithm," *Information Sciences*, vol. 466, pp. 346–365, 2018. DOI: 10.1016/j.ins.2018.05.036.
3. D. Rodrigues, X. S. Yang, A. N. de Souza, and J. P. Papa, "Binary Flower Pollination Algorithm and Its Application to Feature Selection," in *Recent Advances in Swarm Intelligence and Evolutionary Computation*. Springer, 2015, pp. 85–100, https://link.springer.com/chapter/10.1007/978-3-319-13826-8_5#citeas.
4. J. Kennedy and R. Eberhart, "Particle Swarm Optimization," in *Proc. IEEE International Conference on Neural Networks (ICNN)*, Perth, Australia, 1995, pp. 1942–1948, DOI: 10.1109/ICNN.1995.488968.
5. D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*. Reading, MA, USA: Addison-Wesley, 1989.
6. S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, 2014, 10.1016/j.advengsoft.2013.12.007.
7. A. Rahman, M. A. Rahman, and S. Ahmed, "Flower Pollination Algorithm for Feature Selection in Tweets Sentiment Analysis," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 5, pp. 456–463, 2022, <https://doi.org/10.14569/IJACSA.2022.0130551>.
8. Li, W., et al., Improved flower pollination algorithm and its application in user identification across social networks. 2019. 7: p. 44359-44371, DOI: 10.1109/ACCESS.2018.2889801.
9. M. Ansari Shiri and N. Mansouri, "Hybrid Filter-Wrapper Feature Selection using Modified Flower Pollination Algorithm," *Journal of Computer and Knowledge Engineering*, vol. 8, no. 2, pp. 55–74, 2025, 10.22067/cke.2025.89191.1124.
10. Ezenkwu, C.P., A. Starkey, and A.A.J.C. Aziz, Cluster Swarm: cluster-specific feature selection using binary particle swarm optimization. 2025. 107(9): p. 180, <https://doi.org/10.1007/s00607-025-01534-8>.
11. M. Premkumar, R. Sowmya, and P. Jangir, "Augmented Weighted K-Means Grey Wolf Optimizer for Data Clustering," *Scientific Reports*, vol. 14, Art. No. 55619, 2024. <https://doi.org/10.1038/s41598-024-55619-z>.

12. G. Li, Y. Zhang, and X. Wang, "Adaptive Mechanism-Based Grey Wolf Optimizer for Feature Selection in High-Dimensional Classification," Scientific Reports, vol. 15, Art. no. 12083828, 2025. <https://doi.org/10.1371/journal.pone.0318903>.
13. J. Mac Queen, "Some Methods for Classification and Analysis of Multivariate Observations," in Proc. Fifth Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, CA, USA, 1967, pp. 281–297.
14. P. J. Rousseeuw, "Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis," Journal of Computational and Applied Mathematics, vol. 20, pp. 53–65, 1987, [https://doi.org/10.1016/0377-0427\(87\)90125-7](https://doi.org/10.1016/0377-0427(87)90125-7).
15. A. K. Jain, "Data Clustering: 50 Years Beyond K-Means," Pattern Recognition Letters, vol. 31, no. 8, pp. 651–666, 2010, 10.1016/j.patrec.2009.09.011.
16. Y. Shang, H. Liu, and J. Zhao, "An Effective Feature Selection Approach Based on Hybrid Grey Wolf Optimizer and Genetic Algorithm," Scientific Reports, vol. 15, Art. No. 84934, 2025, | <https://doi.org/10.1038/s41598-024-84934-8>.
17. M. Azarshab, M. Fathian, and B. Amiri, "An Enhanced Teaching–Learning–Based Optimization with Grey Wolf Optimizer for Text Feature Selection and Clustering," Expert Systems with Applications, vol. 255, Art. No. 124567, 2024, 10.1016/j.eswa.2024.124567.
18. Mafarja, M., et al. "Feature selection using binary particle swarm optimization with time varying inertia weight strategies". In Proceedings of the 2nd international conference on future networks and distributed systems. 2018, <https://doi.org/10.1145/3231053.323107>.
19. Y. Zhang, H. Wang, and X. Li, "Evidential link prediction by exploiting the applicability of similarity indexes to nodes" Expert Systems with Applications, vol. 210, Art. No. 118397, 2022, 10.1016/j.eswa.2022.118397.
20. Al-Jawher, W.A.M. and S.A.J.J.P.S.R. Shaaban, K-mean based hyper-metaheuristic grey wolf and cuckoo search optimizers for automatic MRI medical image clustering. 2024. 7(issue): p. 109-120, Vol. 7 No. issue (2024): proceeding of the first international scientific uruk conference 6-7 march 2024, Baghdad, Iraq.
21. M. H. Ali, S. Mirjalili, and H. Faris, "Recent Advances in Swarm Intelligence for Feature Selection: A Survey," Artificial Intelligence Review, vol. 57, no. 1, pp. 1–35, 2024. DOI: 10.1007/s10462-023-10645-7.
22. Talpur, N., et al., A novel wrapper-based optimization algorithm for the feature selection and classification. 2023. 74(3): p. 5799-5820, <https://doi.org/10.32604/cmc.2023.034025>.
23. Wang, P., et al., A Survey on Evolutionary Multimodal Optimization-Driven Machine Learning. 2025, 10.1109/TEVC.2025.3627487.

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24. N. Hussain, "Improving a Flower Pollination Algorithm to Demonstrate Data Upgrading to Deep Data," Al-Rafidain Journal of Engineering Sciences, vol. 4, no. 1, pp. 396–406, 2025. <https://doi.org/10.61268/8wgzj934>.