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ORIGINAL STUDY

Improving Approach of Evolutionary Strategies for Clustering Technique Enhancement

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ABSTRACT

The existence of the information has been the essential aspect of the whole society. Information is concentrated in all forms to be effectively utilized. Clustering — an unsupervised learning technique. It is based on data similarity that gives rise to issues in collection, challenges and instability in data structure. It proposes an advanced evolutionary method by combining two approaches. Firstly, it adopts the evolutionary approach and integrates the advantages between two methods to design one. Among them are Differential Evolution (DE) and Genetic Algorithm (GA), Evolutionary Strategy (ES) and Genetic Programming (GP), and Evolutionary Programming (EP) and Particle Swarm Optimization (PSO). Second, it contains local search in order to improve the exploitation and to ensure the balance between exploration and exploitation within the collection (DE algorithm, ES, and EP). The enhanced approach is validated on three datasets: UTK face, Academic Group (AG) news, and weather. The next results show that the proposed approach is more efficient and flexible. It consistently obtains silhouette scores greater than 0.90 in every test scenario. This is a significant improvement over baseline metaheuristic clustering methods.

Keywords: Clustering, Evolutionary approach, Static clustering, Hybrid algorithms

1. Introduction

The abundance of images, text, and numbers on the internet these days encourages the development of algorithms that operate clustered [1]. The objective of clustering, a type of unsupervised learning, is to identify the underlying structure composed of clusters (groups

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or categories), where each cluster's objects or observations share a pertinent property (similarity) within the data domain [2]. Clustering analysis is widely used across many application domains (e.g., marketing, medicine, and bioinformatics) and addresses several research topics. In recent years, data segmentation techniques and the clustering idea have been widely employed to examine the dynamics of the underlying population [3–5].

Traditional approaches to making clusters include two methods: the partitioning method and the hierarchical method. There are numerous drawbacks to the conventional approaches, including the following: Empty clusters may be acquired because random initial centers in the assignment process lead to a structure problem, metric inadequacy relying on Euclidean distance becomes ineffective in high-dimensional data due to the curse of dimensionality, making it difficult to detect clusters with non-linear or non-spherical structures. Due to these constraints, the researchers employed evolutionary techniques to address clustering issues, such as Differential Evolution (DE) and Genetic Algorithm (GA) [6, 7].

The evolutionary approach is one of the most well-known methods in computer science and artificial intelligence because it is based on the ideas of biological inheritance and natural selection [8]. This method mimics the natural process of evolution by keeping track of a set of possible solutions and regularly applying selection, genetic crossover, and random mutation [9, 10]. The best thing about this method is that it can find solutions in complex, non-linear solution spaces very well [11, 12]. This makes it a great tool for solving optimization problems that are hard to solve with standard methods. It lets you find the best or "fittest" solutions based on the needs of the software environment around it [13–15].

Despite the soundness of these evolutionary methods, there is a gap in understanding the stability and the sensitive trade-off between exploration and exploitation when clustering heterogeneous datasets. Classical evolutionary algorithms are prone to early stopping or are not applicable to high-dimensional data, and more complex hybrid algorithms are necessary to ensure a stable data arrangement. That proposal would have two approaches: a hybrid evolutionary approach, i.e., Differential Evolutionary (DE) algorithm and Genetic Algorithm (GA), Evolutionary Strategy (ES) and Genetic Programming (GP), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO) and employing local search with the evolutionary approach (DE algorithm, ES, and EP) so as to balance exploitation and exploration.

The main contribution of this work is as follows:

– Hybrid framework development that integrates the strong points in original algorithms to get a new algorithm that overcomes the limitations in the original algorithms.
– Adaptive search mechanism by employing local search to the evolutionary approach for balancing exploration and exploitation.
– Cross-domain robustness when applying approaches on three different datasets (UTK face, Academic Group (AG) news, and weather datasets) in static models.

To help readers, this work is organized as follows: Section 2 reviews related work and its limitations. Section 3 presents the proposed methodology. Section 4 presents the experimental results. Finally, Section 5 concludes the work.

2. Related work

In addition to classification, the evolutionary approach and the synergy between clustering have been extensively developed. Clustering based on evolutionary approaches is an important field of research. This section presents important prior related work that approaches the topic from different angles and focuses on unsupervised learning.

Hybrid evolutionary algorithms have recently shown greater effectiveness in solving high-dimensional problems in a wide range of fields. In cybersecurity, metaheuristic optimization and Natural Language Processing (NLP) have been combined to improve the detection of insider attacks [16]. Moreover, these algorithms have been used in medical diagnosis: dual-classification models have been used to detect stages of Alzheimer's disease [17], and two-tiered optimization has been used to evaluate cardiovascular disease risk [18, 19].

A better version of the K-means clustering algorithm, called Adaptive Guided Differential Evolution (AGDE-KM), was introduced in [3] to overcome the shortcomings of the original algorithm. Their research identifies random selection of cluster centers as a main source of instability and slow convergence. Although their methodology supports global search with adaptive operators, it raises another enduring problem in metaheuristic clustering: the computational complexity of the exploration-exploitation balance in high-dimensional spaces. Moreover, the use of a predetermined number of clusters (K) remains a limitation that requires prior knowledge of the data set's structure.

Rongsheng et al. [20] presented A hybrid metaheuristic method (Fruit-fly Optimization Algorithm (FOA) and the K-means algorithm) by clustering text documents. This model uses FOA's global search capabilities to address the local-optima constraints of traditional K-means. Although the method showed significant improvements in clustering accuracy and convergence speed for text data, its performance might not be as efficient for extremely sparse datasets or high-dimensional feature spaces.

In 2022, Alotaibi [21] suggested incorporating optimization strategies to improve clustering outcomes. A metaheuristic algorithm called Meta Heuristic Tabu Search-Adaptive Search Memory (MHTSASM) was developed. This hybrid algorithm combines Tabu Search and K-Means with an adaptive search memory. This study addresses clustering by balancing exploration and exploitation during the search for optimal solutions, but it increases computational complexity due to the need to manage structures, multi-memory, and additional requirements. Parameter accuracy choices are needed to ensure optimal performance.

Garza-Fabre et al. [22] presented an evolutionary multi-objective clustering algorithm for analyzing multi-view data. The paper addresses the core issue of conflicting information sources inherent in complex datasets. Even though their approach uses minimum spanning trees and neighborhood relations to provide a flexible, unbiased representation of solutions, it nevertheless faces the issues associated with the high dimensionality of the search space when exploring trade-offs across a variety of data views. Also, striking the right balance among different points of view is a complex process that requires advanced methods of multi-objective optimization.

Yousif et al. [23] proposed a task-based clustering and scheduling algorithm for Internet of Things (IoT) edge computing systems, implemented via an evolutionary algorithm to improve performance and energy efficiency. Their research addresses the severe issue of computational overhead caused by the overwhelming influx of small jobs from IoT devices. Although clustering alleviates this overhead by grouping tasks, the authors note that a persistent trade-off remains between execution time and communication costs. Inaccuracies in clustering tasks can create network bottlenecks or overload resources, underscoring the need for effective optimization strategies in dynamic edge settings.

Qiu et al. [24] developed an Evolutionary Multi-Objective Clustering (EMOC) algorithm with an autoencoder to overcome the issue of high-dimensional data clustering. They are working to reduce the curse of dimensionality, which, in many cases, leads to poor clustering performance for traditional evolutionary methods due to feature redundancy and the increased complexity of the search space. Although deep learning enables efficient feature extraction, research has shown that balancing data reconstruction rates with maintaining cluster structures remains a challenge. Moreover, the method is sensitive to neural network hyperparameters, which can compromise the robustness and stability of the multi-objective optimization process.

Gálvez et al. [25] have applied image clustering as a preprocessing step in a hybrid GA-PSO methodology to the automatic reconstruction of colored fractal images. A major constraint of this method is its high dependence on the quality of the primary clustering, and any error in the color partitioning process is pronounced during the evolutionary optimization stage. Also, the algorithm has a weakness in automatically determining the optimal number of clusters, an important parameter that balances image reconstruction fidelity and total computational overhead.

El Dine et al. [26] combined K-means clustering with a GA that prioritizes resources in Narrow Band IoT (NB-IoT) networks. Their work concerns the essential problem of packet loss and high latency in emergency situations, using clustering devices to prioritize and meet communication needs. One notable limitation of this method, however, is that the IoT environment is dynamic, and the benefit of predefined clusters can be less than expected because changes in device states may require frequent re-clustering. Moreover, resource-constrained base stations cannot implement evolutionary algorithms at scale due to the algorithms' computational complexity.

3. Methodology

This work aims to improve the clustering approach for handling multiple data types (UTKFace, AG News, and Weather datasets). To achieve that, this work improved the evolutionary approach. The proposed methodology steps are presented in detail in Fig. 1.

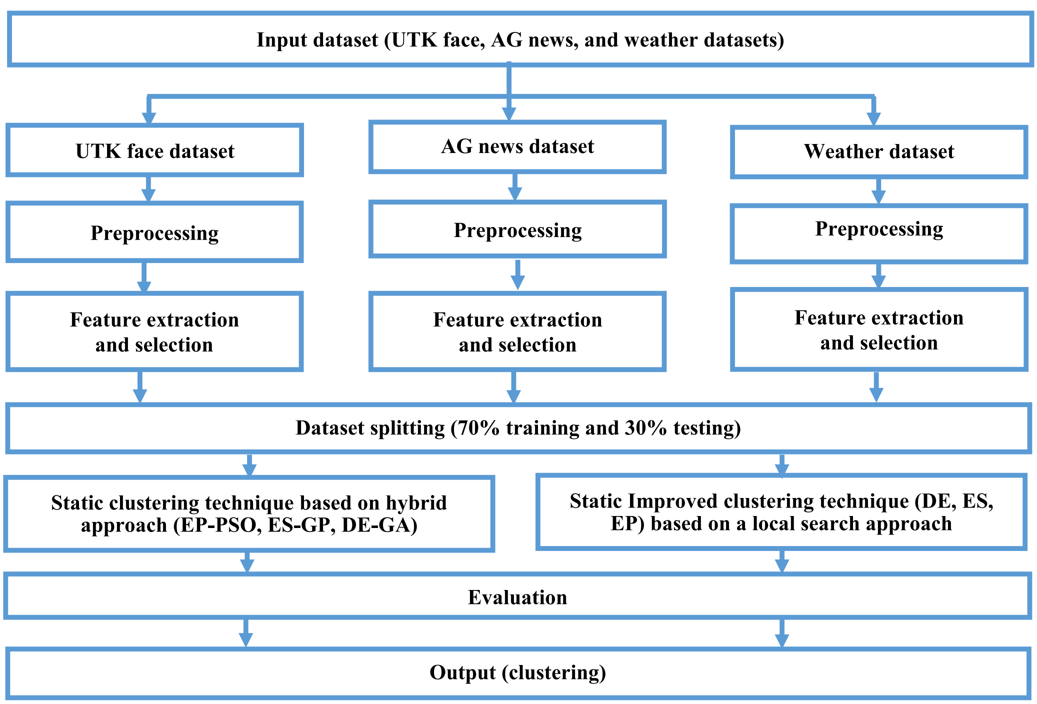


Fig. 1. The proposed methodology.

3.1. Input dataset

Data are essential raw materials for any machine learning task. Machine learning techniques build the models by discovering the hidden structures or relationships already present in the training data. Therefore, machine learning models heavily depend on the quality of the dataset. A robust dataset should be diverse, representative, and balanced to ensure the model generalizes well to unseen data.

To rigorously evaluate the versatility and robustness of the proposed approach, three heterogeneous datasets were strategically selected. These datasets represent different data modalities and structures: UTK face dataset that related with the field of computer vision to test the model's performance on high-dimensional, unstructured visual data, AG news dataset for the NLP purposes to assess the ability to capture semantic relationships in sequential text data, and finally, the weather dataset which is tabular/numerical to evaluate the approach on structured, and time-variant numerical data. This diversity ensures that the proposed method is not overfit to a specific type of problem but is instead a general-purpose solution capable of handling varied real-world data distributions. Table 1 summarizes the datasets used.

Table 1. Datasets summarization.

Dataset Name	Data type	Dataset Description
UTK Face [27]	Image datasets	Content 4112 images about (man, woman, and children)
Academic Group (AG) News [28]	Text datasets	Content from 7600 sample talk about news (political, economic, sports, and artistic)
Weather [29]	Numeric datasets	Numeric dataset content from 8785 samples talks about weather (sunny, rainy, warm, and cold)

3.2. Preprocessing

This section presents the preprocessing steps applied to the datasets used. For the UTK face dataset, the images are first resized to 240 $\times$ 240 pixels to maintain a high spatial resolution, then normalized to prepare the data digitally.

For AG news dataset, the text is first transformed into numeric through four steps, (1) tokenizing sentences into tokens, (2) standardization by transforming all letters into lowercase, (3) vocabulary building by checking tokens and giving all tokens unique number, (4) finally, padding making all text in length specific (300 tokens), if the length is large, it is cut, else padding is zero.

While the weather dataset converts all words to numeric values and handles missing values by filling them with the column's mean, it does not delete entire rows; instead, it uses the mean to save space. Processing outliers will be handled using the Interquartile Range (IQR) method. The purpose of handling outliers is to reduce their negative impact on clustering results and to standardize all columns to a common scale.

3.3. Feature extraction and feature selection

Feature extraction is the process of computing a collection of feature vectors that provide a summary and compact view of the data. Refining existing features is known as feature selection. When datasets have a large number of features, only the most relevant are used, and the others are ignored [14].

To extract features, ResNet50 is used for the UTK face dataset, Convolutional Neural Networks (CNNs) are used for the AG news dataset, and a variance threshold is used for the weather dataset. The variance method has been used as a feature selection method for all the datasets.

3.4. Dataset splitting

The dataset was divided into one training subset (70%) and one test subset (30%). The training partition was used to fine-tune the method and the parameters and the test partition was an independent hold-out sample as a demonstration of the predictive value of the method and the generalization power. Select this ratio in order to mitigate the risk of overfitting and strike a good learning/testing balance.

3.5. Improved approaches design

To improve clustering capabilities, it has been developed using two approaches: first, a hybrid of evolutionary approaches, and second, by adding local search technique to evolutionary approach. The efficiency of the evolutionary algorithms proposed in this work depends on the fitness function; the search process leads towards an optimal solution. Table 2 presents the specific parameter settings used for both improved approaches.

Table 2. Parameters of algorithms.

Algorithms	Parameters	Values
All	Population Size P	400
All	Numbers of generation G	30
All	Number of Independent Runs N	10
DE-GA and DE based on local Search	Mutation Factor F	0.7
DE-GA	refinement rate R	0.5
EP-PSO and EP based on local Search	mutation rate	0.5
EP-PSO	w_max, w_min	0.9 – 0.4
EP-PSO	c_1, c_2	2.0
ES-GP	Crossover Rate	0.8
ES-GP and ES based on local Search	Parent Population size μ	400
ES-GP and ES based on local Search	Offspring Population size	100

As a mathematical tool to apply genetic operators (mutation and crossover), each solution (chromosome) is represented as a real-valued vector. A vector of K cluster centers represents the coordinates of the clusters. Suppose that in a dataset with D dimensions, each individual has a length of $K \times D$. This representation allows the algorithm to find the best position of the cluster centers in the search space for optimal clustering. In addition, the computational complexity of the obtained approaches is $O(N \times G \times P \times f(i))$, where f(i) represents the cost of calculating the Silhouette score for i data points. This formulation guarantees the algorithm achieves a trade-off between high clustering accuracy and computational efficiency.

3.5.1. Hybrid technique based on improved clustering approach

In this case, hybridize evolutionary approaches by combining the strengths of two algorithms to generate a distinct algorithm. This choice is further justified by Wolpert's No Free Lunch (NFL) theorem, which states that no single optimization algorithm is universally superior for every problem. In integrating algorithms such as DE and GA, the goal is to have a good balance between exploration and exploitation. Three hybrid techniques have been proposed. These hybrid techniques are: (1) DE and GA, (2) EP and PSO, and (3) ES and GP.

3.5.1.1. Hybrid differential evolution and genetic algorithm technique. The suggested hybrid algorithm (DE-GA) is procedurally organized around the idea of functional succession to balance space exploration and exploitation in pursuit of promising solutions. The algorithm starts with a DE stage as a global search tool and generates mutant solutions to maintain population diversity and avoid stagnation in weak local solution areas. As the algorithm transitions to the second phase, an elite local optimization strategy based on GA is adopted, sorting individuals and directing them only toward elite solutions. This incorporation guarantees very precise refinement of cluster location, and the system operates as a push-pull mechanism. DE provides the required strength to overcome the mathematical barriers, whereas GA produces world-best accuracy, creating a hybrid model that is highly stable and better able to handle complex data with minimal clustering error. Algorithm 1 presents the proposed DE-GA.

Algorithm 1: DE-GA.

```
Input:dataset, P = 400, G = 30, F = 0.7, R = 0.5
Output:best clusters
Begin
  Initialize P:
  For each G do
    step 1: DE
    For each individual in P do
      mutant ← a + F × (b − c)
      crossover between target and mutant
     If fitness(trial) > fitness(target) then
      Replace target with trial
     End If
    End For
    step 2: GA Local Refinement
    Rank population by fitness
    Select top (individuals × R)
    For each selected individual do
     If fitness(refined) improves then
      Accept refined solution
     End If
     Select P best individuals
    End For
  End For
End
```

3.5.1.2. Hybrid evolution programming and particle swarm optimized technique. This is a hybrid technique that is characterized by the adaptation of the balance between exploration and exploitation. Whereas PSO is more effective at exploitation—fine-tuning solutions by converging on the global optimum, Evolutionary Programming (EP) strengthens exploration. When the swarm's diversity decreases and the search process stalls, the model activates EP processes to escape local optima. This synergy makes the model resistant to premature convergence and, at the same time, very accurate in determining optimal clusters. Algorithm 2 presents the steps of the proposed EP-PSO.

Algorithm 2: EP-PSO

Input: dataset, P = 400, G = 30, **EP** mutation rate = 0.5, w_max = 0.9, w_min = 0.4, c_1= 2.0, c_2= 2.0
Output: best clusters
Begin
  Initialize P:
  For each G do
    Step 1: PSO Update
    For each **individual** do
      Update **personal**-best if improved
      Update **global**-best if improved
      Update **velocity** using: $V_{t+1} = w \times v + c_1 \times r_1 \times (\text{pBest} - \text{position}) + c_2 \times r_2 \times (\text{gBest} - \text{position})$
      Update **position**: $x_{t+1} = x_t + V_{t+1}$
    End For
    Step 2: EP Mutation
    For each individual do
      If stagnation > threshold, then
        Apply strong EP mutation
      Else
        Apply EP mutation
      End If
    End For
    Step 3: EP Selection
    Combine parents and offspring
    Rank by fitness
    Select P best individuals
  End For
End

3.5.1.3. Hybrid evolutionary strategy and genetic programming technique. In this section, the proposed hybrid between ES and GP is discussed. As a tree represents each individual, it is randomly constructed from function nodes and terminal nodes. Terminal nodes took numeric inputs and displayed clusters of presented centers, while function nodes performed calculations. The strength of the hybrid algorithm lies in the mutation and crossover of GP for discovering the structures of the clustering function, followed by an evolution strategy for exploiting and fine-tuning the numerical values (center coordinates). In addition, the adapted subtree mutation rate and mutation strength are automatically updated based on changes in the cluster's efficiency, ensuring a steady, dynamic equilibrium between exploration of the solution space and convergence to the optimal solution. Eventually employ selection on the blending of the two parents and offspring, and sorting based on the fitness of the offspring to pass to the next generation. The proposed ES-GP is explained in Algorithm 3.

3.5.2. Improved technique clustering approach based on local search

In another case, it was improved by adding local search to evolutionary approaches, thereby enhancing exploitation and balancing exploitation and exploration. This integration is crucial to maintaining a proper balance between exploration (searching the entire space) and exploitation (refining the best-found solutions). As suggested by the NFL theorem, no single algorithm can optimally solve all clustering problems; therefore, adding a local search layer allows the proposed models to overcome the limitations of standard metaheuristics. These improved techniques are: (1) DE based on local search, (2) EP based on local search, and (3) ES based on local search.

3.5.2.1. Differential evolution based on local search. This work improves the DE algorithm with a two-stage local search mechanism to increase optimization efficiency. The first part of the algorithm goes through the standard DE operations — mutation, crossover and

Algorithm 3: ES-GP

Input: dataset, P = 400, G = 30, Crossover Rate = 0.8, μ = 400, λ = 100
Output: best clusters
Begin
  Initialize P:
    For each individual in P do
      Generate GP tree with terminals and function nodes
    End For
  While generations not finished do
    Step 1: ES and GP
    Adaptive Mutation Update
    Update subtree_mutation_rate based on variance
    Update ES mutation strength based on best fitness
    Step 2: Offspring Generation
    While offspring < P do
      Selecting parents using Tournament Selection
      If rand < crossover_rate then
        Apply GP-subtree crossover → produce child1, child2
      Else
        Copy parents
      End If
      Step 4: Selection
    Select the next population using (μ + λ) selection
    Evaluate all individuals Sort by fitness
    Select P best individuals
  End While
End

selection — to efficiently explore the search space globally. This step allows the algorithm to find useful parts and minimizes the early convergence to suboptimal local solutions. In the second phase, a dual-stage local-refinement approach is proposed to optimize exploitation. This refinement is done in two steps sequentially. Smart centroid refinement adjusts the positions of cluster centers by moving them to the appropriate location in the cluster, reducing intra-cluster variance and improving cluster compactness. Second, local swap refinement improves the overall clustering quality, as boundary data points are re-assessed and reassigned to new clusters where the reassignment of points results in better overall clustering performance. It combines global exploration with a two-level local refinement process to reach a better balance between exploration and exploitation, providing more accurate and stable clustering results. The proposed DE according to the local search algorithm is shown in Algorithm 4.

3.5.2.2. Evolutionary programming based on local search. In this regard, the integration of EP with an intensive local search mechanism is aimed to achieve higher performance with optimization and higher accuracy in solution. The algorithm proposed follows a systematic process with 3 stages. First, genetic diversity (in other words EP mutation), is used on the present population to create new progeny. This process of mutation encourages diversity within the population by creating a wider search space and prevents premature convergence to non-optimal solutions. Secondly, a dual-phase local search strategy is used to make exploitation and optimizing candidate solutions more robust. This phase has two stages in two phases. The smart centroid refinement updates the center positions of the cluster to reduce the intra-cluster dispersion and promote compactness. Afterwards, local swap refinement adjusts boundary points and then places them in other clusters if these adjustments improve clustering accuracy. Third, competitive selection occurs by joining parent and offspring populations and a strict fitness-based selection is adopted. Therefore only the most promising solutions can be kept for the future generations. In general, the

Algorithm 4: DE based on local Search

Input: dataset, P = 400, G = 30, F = 0.7
Output: Best cluster
Begin
  Step1: DE
  Initialize P:
    For each individual i in P do
      mutant $\leftarrow$ a + F $\times$ (b − c)
      Perform crossover between target and mutant
      If fitness(trial) > fitness(target) then
        Replace target with trial
      End If
      Select better solution
  Step2: Local Search
    Select top individuals
    For each selected individual do
      Apply dual phase of local search
    End For
    Select best P individuals
    Update global best solution
  End For
End

presented framework strikes a balance between global discovery and local exploitation in a more robust way and provides a high accuracy in clustering process. Algorithm 5 presents the proposed EP with the use of locally searched parameters.

Algorithm 5: EP based on local Search

Input dataset, P = 400, G = 30, mutation rate = 0. 5
Output: Best cluster
Begin
  Step1: EP
  Initialize population P
  For each generation do
    Mutation
    For each individual i in P do
      Generate offspring using EP mutation
    End For
    Step2: Local Search
    Select top-performing offspring
    For each selected offspring do
      Apply dual phase of local search
    End For
    Combine parents and offspring
    Select best P individuals
    Update the global best solution
  End For
End

3.5.2.3. Evolutionary strategy based on local search. ES is enhanced, here, by adding a local search mechanism to enhance optimization performance. The proposed approach is divided into three major phases. To begin with, guided mutation is used rather than random mutation. At this step, mutation is performed using an adaptive mutation coefficient allowing more informed perturbations of candidate solutions. This approach enhances the search efficiency by redirecting exploration into search regions with greater potential. A second option of dual-phase local search is implemented to improve the exploitation and obtain the optimized offspring. This phase consists of the following two optimization steps. Then the smart centroid refinement adjusts the cluster center coordinates to minimize intra-cluster dispersion and increase cluster compactness. Next, local swap refinement is

Algorithm 6: ES based on local Search

Input: dataset, P = 400, G = 30, $\mu = 400$, $\lambda = 100$
Output: Best cluster
Begin
  Step 1: ES
  Initialize P:
  For each generation do
    Generate λ using ES mutation
      Adapt strategy parameters σ
    Step2: Local Search
    Select top-performing offspring
    For each selected offspring do
      Apply dual phase of local search
    End For
      Select the next population using $(\mu + \lambda)$ selection
      Update the global best solution
  End For
End

undertaken, in which the boundary data points are reassigned between clusters so as to increase clustering accuracy. Third, a selection mechanism merges parent and offspring populations and selects the best individuals to form the next generation. This ensures that high-quality solutions are preserved while maintaining population diversity. Algorithm 6 is an example of the proposed ES framework combined with local search.

3.6. Evaluation metrics

Five evaluation metrics have been used to evaluate the proposed approaches. These metrics are the silhouette score, Davies-Bouldin index, Dunn Index, Calinski-Harabasz index, and standard deviation.

The silhouette score assigns an individual to a specific cluster and compares it with another cluster; its value ranges between (-1, +1). When the result is near (+1), it means that it is in a good cluster [10]. The reason for choosing it is that it balances the trade-off between compactness within each group and separation between groups. The evolutionary algorithm objective is to maximize the fitness function based on the silhouette score, which is calculated for each data sample i according to the following equation:

$$f(i) = \frac{\boldsymbol{b}(\boldsymbol{i}) - \boldsymbol{a}(\boldsymbol{i})}{\mathbf{max}\{\boldsymbol{a}(\boldsymbol{i}),\ \boldsymbol{b}(\boldsymbol{i})\}} \tag{1}$$

where a(i) is the average distance between sample i and all other points within the same cluster (measurement of cohesion) is represented. b(i) is the minimum average distance between sample i and points in adjacent clusters, which is represented (spacing measurement) [30].

The Davies-Bouldin index has the average similarity measures between each grouping and the nearest; its best value is near (0), which presents good clusters and far distances between each one [25].

The Dunn Index measures the relationship between the minimum distance between points in different clusters and the maximum distance between points in the same cluster. Higher values are better [30].

The Calinski-Harabasz index is the ratio of between-group variance (divergence) to within-group variance (cohesion) [8, 9].

The standard deviation is a measure of how far the data is spread out from the mean. A lower standard deviation indicates that the clusters are more homogeneous and compact, meaning the data points are closely distributed around their cluster centers [31].

4. Experimental results

The proposed algorithms were evaluated using 10 independent runs to ensure statistical stability. In each run, the optimization process was executed for 30 generations, providing a consistent basis for performance comparison.

4.1. Evaluation of the hybrid techniques based on an improved clustering approach

This section presents the experimental results used to evaluate the performance of the proposed hybrid clustering approach. The proposed framework consists of three hybrid methods: (1) DE and GA, (2) EP and PSO, and (3) ES and GP.

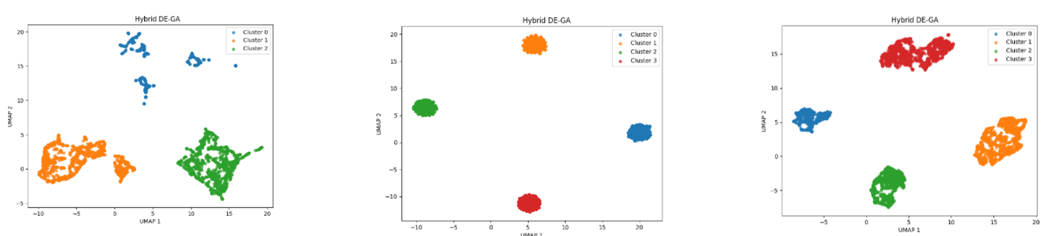
4.1.1. Evaluate the hybrid differential evolution and genetic algorithm technique

Table 3 presents the mean performance results of the hybrid DE-GA technique.

Table 3. Mean performance results of the hybrid DE-GA technique.

Dataset	Silhouette score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.938	0.081	332210.906	4.365	0.204
AG News	0.972	0.045	1634154.25	15.973	0.081
Weather	0.921	0.104	131238.562	4.363	0.633

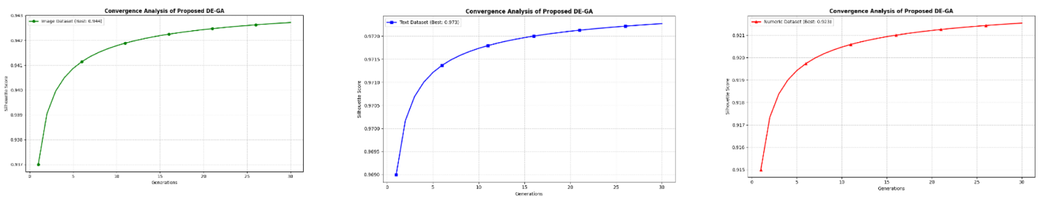
As can be seen in Table 3, the hybrid DE-GA achieves the best performance on the AG news dataset with a high Silhouette score (0.972) and low Davies-Bouldin index (0.045). These results suggest well-separated and cohesive clusters, confirming the capacity of DE-GA hybrid to handle discriminative feature representations in the AG news dataset. However, the dual approach gives relatively low performance for the weather dataset with Silhouette of 0.921. This decrease can be explained by the higher density and overlap of weather-related numerical features, which complicate the separation of clusters. Moreover, as shown in Fig. 2, the clusters in the AG news dataset have more distinct structure and less overlap which indicate the performance of hybrid DE-GA in these cases.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 2. Distributed cluster when applying the hybrid DE-GA technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

Furthermore, Fig. 3 shows that the hybrid technique achieves its best performance within the first 10 iterations, after which the accuracy stabilizes at its peak. This behavior indicates fast convergence and stable learning dynamics of the hybrid approach.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 3. Convergence analysis of the hybrid DE-GA technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

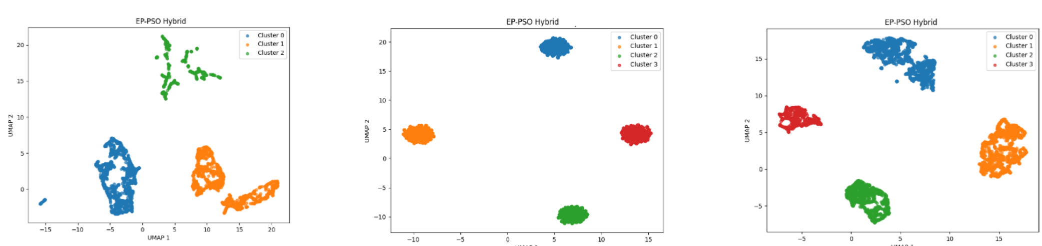
4.1.2. Evaluate the hybrid evolutionary programming and particle swarm optimization technique

Table 4 presents the mean results of the hybrid EP-PSO technique.

Table 4. Mean performance results of the hybrid EP-PSO technique.

Daatset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.933	0.091	301206.468	3.924	0.220
AG News	0.973	0.037	2545568.75	16.268	0.084
Weather	0.920	0.110	132038.578	3.898	0.687

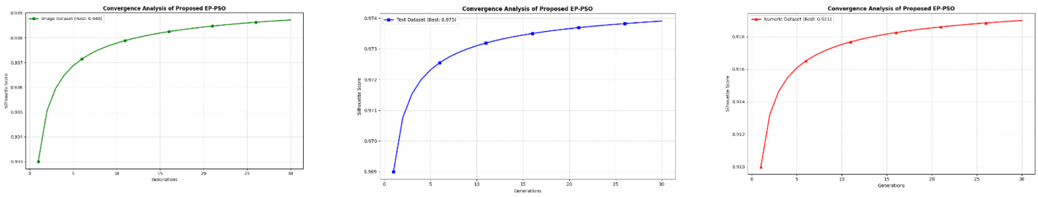
Table 4 reveals the results of the hybrid EP-PSO technique, which offers good clustering performance on the AG news dataset. The hybrid approach is also shown with a high Silhouette score (0.973), and a very high Calinski-Harabasz index (2545568.75), which means that the clusters are separated and much compact. The high performance indicates that it is very effective to combine the strong mutation capability of EP, which is exploration, with the fast convergence behavior of PSO, i.e., exploitation in high-dimensional text representations. The model obtained a Silhouette score of 0.933 on the UTK face dataset, which is slightly worse than on the AG news dataset, as the visual features became more complex and variable. That said, the results remain competitive. Of note, the standard deviation (0.084) on the AG news dataset shows that the hybrid EP-PSO technique gives stable and consistent clustering performance across multiple runs. According to comparison with Table 3 and Table 4, the hybrid EP-PSO is superior to the hybrid DE-GA procedure for the next domain applications where the velocity-based update of PSO is shown to be efficient in enhancing cluster centroids in high-dimensional feature spaces. The clustering data obtained by the hybrid EP-PSO technique shows excellent separation between the clusters (Fig. 4). This is the case even in challenging data conditions which also highlights the fact that its representation is really strong.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 4. distributed cluster when applying the hybrid EP-PSO technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

Fig. 5 shows that the hybrid technique reaches its best performance within the first 10 iterations, where accuracy stabilizes at peak values, indicating fast convergence and stable learning behavior.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 5. Convergence analysis of the hybrid EP-PSO technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

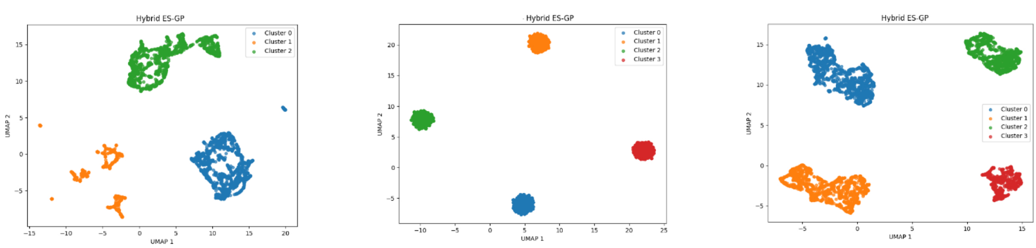
4.1.3. Evaluate the hybrid evolutionary strategy and genetic programming technique

Table 5 presents the mean performance results of the proposed hybrid ES-GP technique.

Table 5. Mean performance results of the hybrid ES-GP technique.

Dataset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.937	0.091	220123.656	3.872	0.23 8
AG News	0.971	0.056	24433712.5	15.800	0.098
Weather	0.920	0.132	131121.501	4.520	0.699

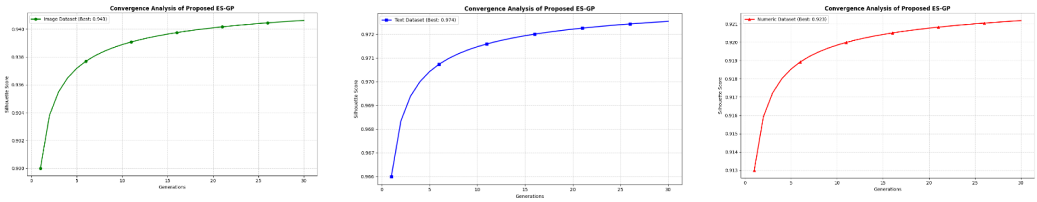
Table 5 shows the output of the hybrid ES-GP approach. The hybrid ES-GP method has a Calinski-Harabasz index of 24433712.5 which is very high on the AG news dataset compared with the previous hybrid methods. This suggests that the tree-based representation of GP is very effective for modeling such complex non-linear correlations of feature space of the AG news dataset, where the clusters are well-separated and exhibit high inter-cluster variance. Also, the Silhouette score is still relatively high, it stays 0.971, confirming that the hybrid technique shows good clustering. For the UTK face dataset, the hybrid technique leads to better performance than the previous hybrids, having a Silhouette of 0.937. On the other hand, the performance results on the weather dataset are relatively consistent (Silhouette score 0.920). It indicates strong challenges due to high data density and a lot of feature overlap among weather variables, which poses a hard time in separating clusters. The hybrid ES-GP method's clustering distribution is shown in Fig. 6. It shows solid separation of clusters even in complicated data ecosystems. This reflects its strong capabilities of representation.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 6. Distributed cluster when applying the hybrid ES- GP technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

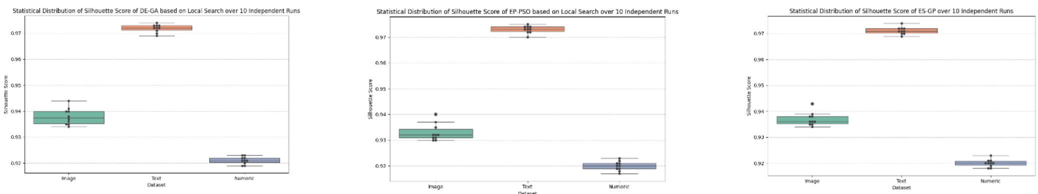
Fig. 7 shows that the hybrid technique reaches its best performance within the first ten iterations, where accuracy stabilizes at peak values, indicating fast convergence and stable learning behavior.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 7. Convergence analysis of the hybrid ES-GP technique. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

Fig. 8 presents the stability and performance consistency of the hybrid DE-GA, EP-PSO, and ES-GP techniques over 10 independent runs.



a. DE-GA b. EP-PSO c. ES-GP

Fig. 8. Performance comparison of the hybrid techniques over 10 independent runs. a. DE-GA. b. EP-PSO. c. ES-GP.

4.2. Evaluating improved technique clustering approach based on local search

This section presents the results of the improved technique clustering approach based on local search.

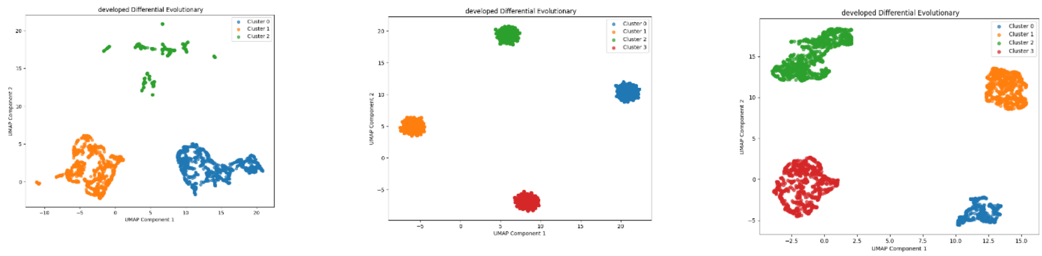
4.2.1. Evaluate differential evolution based on local search

Table 6 presents the mean results of the DE based on local search.

Table 6. Mean performance results of DE based on local search.

Dataset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.939	0.085	355462.25	3.992	0.213
AG News	0.979	0.033	2564788.75	19.782	0.086
Weather	0.929	0.116	135637.58	3.998	0.750

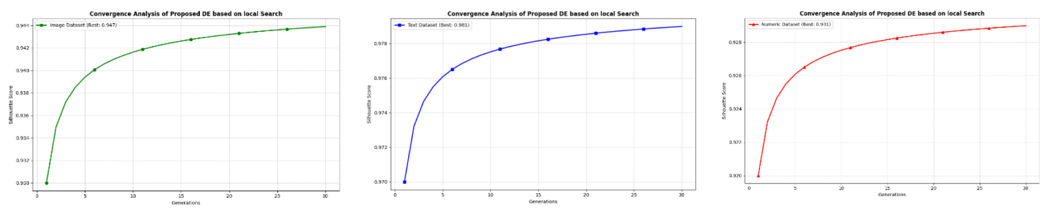
Table 6 shows the performance of the better DE method improved by local search. Results indicated that the performance on the AG news dataset showed the highest Silhouette score of 0.979 and a strong Dunn index of 19.782 in our study, pointing to a relatively compact and well-separated cluster. These results indicate that DE can be more efficient global exploration is feasible; nevertheless, the combination of smart centroids refinement and local swap mechanisms can have greater effectiveness towards boundary-optimization in the high-dimensional feature space. For the UTK face dataset, the model shows significantly improved performance compared to previous hybrid types with a Silhouette score of 0.939 and a reduced Davies-Bouldin index of 0.085, which indicates that separation and compactness are better. The weather dataset demonstrates improvements in stability based on its Silhouette score of 0.929, confirming that the data can better handle overlapping and dense feature distributions. The results of the quantitative test itself are shown in Fig. 9, which illustrates the clustering distribution in relation to other similar data, showing highly compact clusters in distinct segments, emphasizing the success of the proposed improvement modes.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 9. Distributed cluster when applying DE based on local Search. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

Furthermore, Fig. 10 shows that the model reaches its optimal performance within the first 10 iterations, where accuracy stabilizes at peak values, demonstrating fast convergence and consistent learning behavior.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 10. Convergence analysis of the proposed DE based on local search. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

4.2.2. Evaluate evolutionary programming based on local search

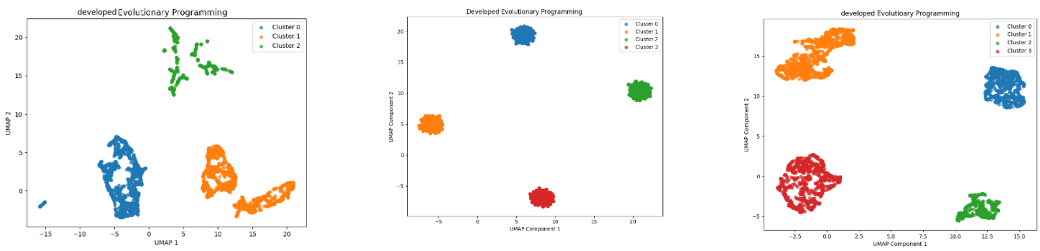
Table 7 presents the mean results of the EP based on local search calculated.

Table 7. Mean performance results of EP based on local search.

Dataset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.938	0.086	346362.5	3.850	0.212
AG News	0.979	0.053	1562513.25	18.947	0.079
Weather	0.928	0.123	133138.5	3.898	0.696

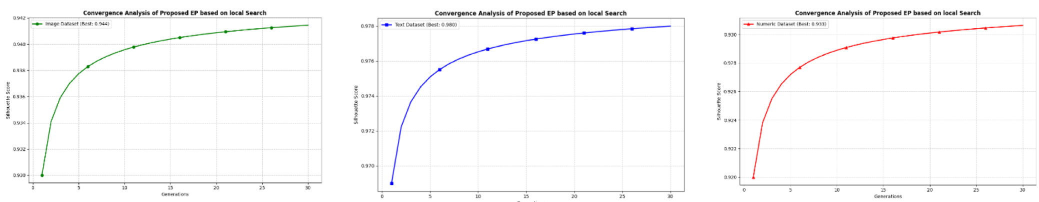
Table 7 details the performance of the enhanced EP method which also incorporated a local search mechanism. The output reveals that the model performs best on the UTK face dataset. Overall, it is achieving a high Calinski-Harabasz index (1562513.25), reflecting highly compact and well-separated clusters. This is evidence for the success of incorporating dual-phase local search with EP. The refinement process drastically facilitates centroid positioning and exploitation in high-dimensional feature spaces. In the AG news dataset, the model gives a very high Silhouette score (0.979) and Dunn index (18.947), indicating that even with sparse, high-dimensional text, this method effectively avoids local optima. In the weather dataset, stable performance can be found, with a Silhouette score of 0.928. The clustering distribution shows that clusters have been very compact, as in Fig. 11. The separation from adjacent groups indicates that this technique is robust.

Fig. 12 shows that the model achieves optimal performance within the first 10 iterations, with accuracy stabilizing at peak values, demonstrating fast convergence and stable learning behavior.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 11. Distributed cluster when applying EP based on local search. a. UTK face dataset. b. AG news dataset. c. Weather dataset.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 12. Convergence analysis of the proposed EP based on local Search. a. UTK face dataset. b. AG news dataset. c. Weather dataset.

4.2.3. Evaluate evolutionary strategy based on local search

Table 8 presents the mean results of the ES based on local search.

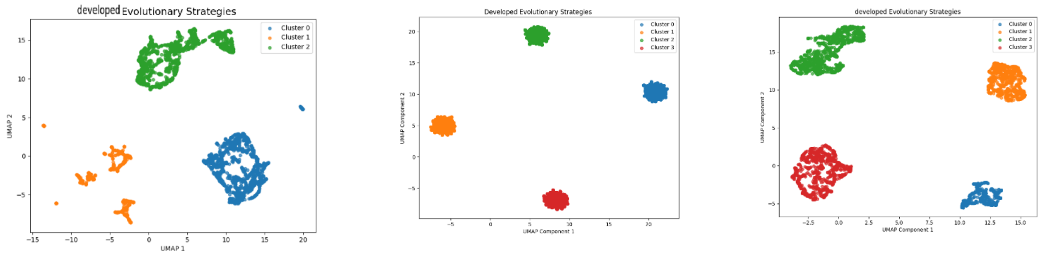
Table 8. Mean performance results of ES based on local search.

Dataset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
UTK Face	0.939	0.084	313429.25	3.956	0.211
AG News	0.978	0.062	3565313.5	17.912	0.081
Weather	0.925	0.110	135132.549	3.988	0.769

Table 8 compares the performance results of the improved Evolutionary Strategy (ES) algorithm with a local search mechanism. This approach successfully splits datasets into more distinct, well-defined clusters and displays the best Calinski-Harabasz index (3565313.5) on the AG news dataset in all models studied. This experiment demonstrates that integrated use of adaptive ($\mu + \lambda$) selection in ES combined with a dual-phase local search results in better inter-cluster segmentation and optimization of intra-cluster compactness in high-dimensional areas. The model retains high performance on the UTK face dataset, where Silhouette scores are 0.939 and Dunn indices are 3.956, indicating it is highly stable to visual data. For the weather feature set, results also hold, with a Silhouette score of 0.925, implying uniform clustering success depending upon data distributions. Plotting the clusters visually (Fig. 13), the proposed technique can be seen to take effective advantage of the very compact clusters that form in most cases with clear separation from adjacent groups.

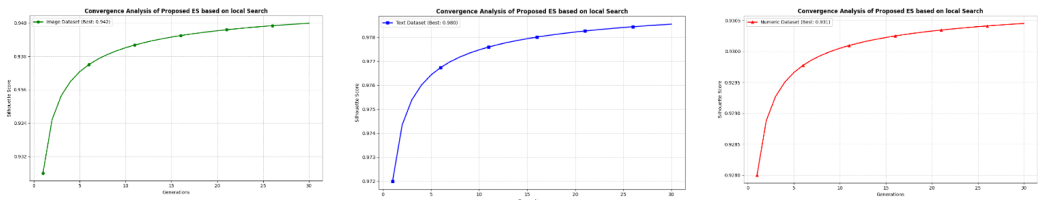
Fig. 14 shows that the technique reaches its optimal performance within the first 10 iterations, where accuracy stabilizes at peak values, indicating fast convergence and stable learning behavior.

Fig. 15 presents the stability and performance consistency of the DE, EP, and ES techniques with a local search mechanism over 10 independent runs.



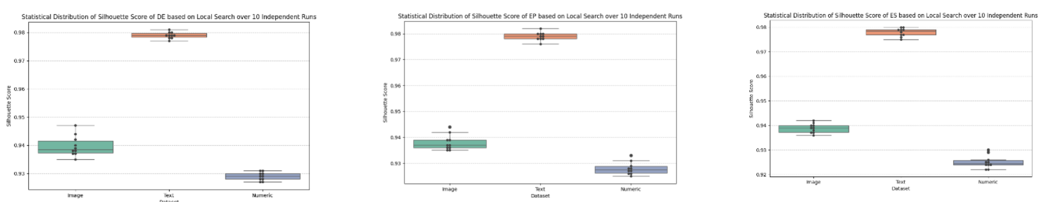
a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 13. Distributed cluster when applying ES based on local search. a. UTK face dataset. b. AG news dataset c. Weather dataset.



a. UTK face dataset b. AG news dataset c. Weather dataset

Fig. 14. Convergence analysis of the proposed ES based on local search. a. UTK face dataset. b. AG news dataset. c. Weather dataset.



a. DE based on local search b. EP based on local search c. ES based on local search

Fig. 15. Performance comparison of evolutionary techniques based on local search mechanism. a. DE based on local search. b. EP based on local search. c. ES based on local search.

4.3. Compared results

This section provides an overview and performance comparison for standard and improved approaches as presented in Table 9. The initial six rows correspond to the standard evolutionary techniques. The next three rows relate to the hybrid evolutionary approach - DE-GA, EP-PSO, and ES-GP. Lastly, the last three rows present the enhanced evolutionary techniques incorporating local search mechanisms, specifically, DE, EP, and ES, with a local refinement approach.

The Wilcoxon signed-rank test was performed in the UTK face, AG news, and weather datasets. Up to now, the p-values obtained have been below the 0.05 level, even though the feature spaces were all complex. It shows that the improvements in performance attained by hybrid techniques and the local search-enhanced techniques are strong and statistically significant, and therefore attest to the fact that the improvements are not a result of random fluctuations.

Table 9. Compared the results between standard techniques and improved techniques.

Algorithms	Dataset	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
DE	UTK Face	0.919	0.217	266657.021	3.324	0.757
	AG News	0.963	0.128	1928229.25	15.452	1.246
	Weather	0.909	0.214	102804.15	2.981	0.776
EP	UTK Face	0.917	0.194	217049.328	2.967	0.734
	AG News	0.962	0.123	1132143	10.209	3.908
	Weather	0.910	0.235	19269.5	3.854	0.798
ES	UTK Face	0.915	0.194	198354.51	3.809	0.797
	AG News	0.961	0.172	989933.5	12.102	3.979
	Weather	0.908	0.235	100245.5	3.100	0.778
GP	UTK Face	0.918	0.129	294036.5	3.928	0.745
	AG News	0.960	0.160	1758255.65	15.715	5.879
	Weather	0.907	0.283	101236.355	3.963	3.867
GA	UTK Face	0.918	0.291	195058.55	3.924	0.832
	AG News	0.962	0.190	1139190.5	12.874	4.973
	Weather	0.905	0.253	102930.5	3.101	0.981
PSO	UTK Face	0.913	0.197	189651.607	3.236	0.834
	AG News	0.960	0.245	1025445.25	11.763	1.971
	Weather	0.902	0.198	9845046.5	3.101	0.912
DE-GA	UTK Face	0.938	0.081	332210.906	4.365	0.204
	AG News	0.972	0.045	1634154.25	15.973	0.081
	Weather	0.921	0.104	131238.562	4.363	0.633
EP-PSO	UTK Face	0.933	0.091	301206.468	3.924	0.220
	AG News	0.973	0.037	2545568.75	16.268	0.084
	Weather	0.920	0.110	132038.578	3.898	0.687
ES-GP	UTK Face	0.937	0.091	220123.656	3.872	0.23 8
	AG News	0.971	0.056	24433712.5	15.800	0.098
	Weather	0.920	0.132	131121.501	4.520	0.699
DE with local search	UTK Face	0.939	0.085	355462.25	3.992	0.213
	AG News	0.979	0.033	2564788.75	19.782	0.086
	Weather	0.929	0.116	135637.58	3.998	0.750
EP with local search	UTK Face	0.938	0.086	346362.5	3.850	0.212
	AG News	0.979	0.053	1562513.25	18.947	0.079
	Weather	0.928	0.123	133138.5	3.898	0.696
ES with local search	UTK Face	0.939	0.084	313429.25	3.956	0.211
	AG News	0.978	0.062	3565313.5	17.912	0.081
	Weather	0.925	0.110	135132.549	3.988	0.769

4.4. Compared results with related work

This section presents a comparative analysis that evaluates the proposed improved techniques against related work and established techniques in the field. The results of this comparison are summarized in Table 10.

The first six rows of Table 10 show the results of the proposal approaches with respect to related works, in which each approach adopts its own clustering strategy. The results confirm that the improvement techniques proposed do outperform existing ones. Conventional clustering methods like K-Means and DBSCAN are available, but they are problematic given the datasets utilized in this work. K-Means is very sensitive to the initialization of cluster centroids and tends to converge to local optima, preventing it from effectively exploring the global search space. Conversely, DBSCAN largely depends on parameter settings (ϵ and min_samples) and suffers from the curse of dimensionality in high-dimensional feature spaces, leading to much lower clustering quality. Therefore, the proposed work provides a metaheuristic hybrid clustering framework that integrates evolutionary optimization with

Table 10. Comparison of the results between the proposed improved techniques and related work.

Algorithms	Dataset Type	Silhouette Score	Davies Bouldin	Calinski Harabasz	Dunn Index	Standard Deviation
DE and GA	UTK Face	0.938	0.081	332210.906	4.365	0.204
	AG News	0.972	0.045	1634154.25	15.973	0.081
	Weather	0.921	0.104	131238.562	4.363	0.633
EP and PSO	UTK Face	0.933	0.091	301206.468	3.924	0.220
	AG News	0.973	0.037	2545568.75	16.268	0.084
	Weather	0.920	0.110	132038.578	3.898	0.687
ES and GP	UTK Face	0.937	0.091	220123.656	3.872	0.23 8
	AG News	0.971	0.056	24433712.5	15.800	0.098
	Weather	0.920	0.132	131121.501	4.520	0.699
DE with local search	UTK Face	0.939	0.085	355462.25	3.992	0.213
	AG News	0.979	0.033	2564788.75	19.782	0.086
	Weather	0.929	0.116	135637.58	3.998	0.750
EP with local search	UTK Face	0.938	0.086	346362.5	3.850	0.212
	AG News	0.979	0.053	1562513.25	18.947	0.079
	Weather	0.928	0.123	133138.5	3.898	0.696
ES with local search	UTK Face	0.939	0.084	313429.25	3.956	0.211
	AG News	0.978	0.062	3565313.5	17.912	0.081
	Weather	0.925	0.110	135132.549	3.988	0.769
[32]	AG News	0.85	0.48	N/A	N/A	N/A
[33]	Westher	0.784	0.42	2450.5	0.65	N/A
[34]	Weather	0.45-0.55	0.7-0.9	N/A	N/A	N/A
[35]	AG News	0.58- 0.65	N/A	N/A	0.42-0.51	N/A
[36]	AG News	0.60	N/A	N/A	0.45	N/A

local search mechanisms. This architecture enables enhanced global exploration and local exploitation, leading to better clustering performance overall than that of convolutional techniques.

5. Conclusion

Inspired by natural processes, evolutionary approaches offer powerful solutions to issues that traditional clustering methods face in that they exhibit high response time, are sensitive to initial cluster selection and are particularly sensitive to local optima. This strong exploration and exploitation of the solution space makes finding more optimal grouping schemes, especially those characterized by good inter-cluster separation and strong intra-cluster cohesion, more probable. We show that the methods found here show effectiveness in two main directions. First, it combines the features of evolutionary algorithms with the clustering method. Second, it improves performance by adding a local search algorithm to the evolutionary architecture. These contributions improve clustering for different classes of datasets like UTK face, AG news and weather. Evolutionary methods are generally considered as a good starting point for more precise and flexible clustering strategies. Several limitations should be acknowledged, but the proposed approach is very well-performed. First, as the method is a hybrid approach, it also induces computational complexity over typical K-means or simple metaheuristic methods, and leads to higher computation times on higher scale for big data. Second, this means that the current approach requires a baseline value of clusters (K), and prior knowledge of the data structure is essential to be able to apply these into practice. Future work may then look at self-adaptive methods for automatically deciding the optimal number of clusters. To extend the findings from this research, the following directions are pointed out in future work:

- Processing large data flows: exploring the scalability of the proposed hybrid method to large-scale and streaming data platforms.
- Multi-objective clustering: Building on the proposed method, extending it to a multi-objective optimization framework, considering both the clustering validity indices and computational efficiency, and in particular to determine Pareto optimal solutions. Real world application: The performance of proposed approach over UTK face, AG news and weather datasets confirms its feasibility in real-world application. More than that, the proposed model can also be applied for the cluster of multi-modal diagnostic information in the healthcare domain for more advanced patient-stratified management. In terms of smart city environment, this algorithm can be combined with ITS for smart transportation system in which an intelligent system can be designed to increase traffic signal control, reducing congestion and reducing the fuel consumption and the carbon footprint of real-time traffic and sensor information. Furthermore, for the financial industry, the procedure proves to play a powerful role in the domain of fraud detection and customer segmentation, in which accurate clustering is necessary for informed decision-making.

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None.

Authors' contributions

Duaa Mahde Saleh: conceptualization, data collection, methodology, and interpretation of results. Hasanen S. Abdullah and Ahmad Zamsuri: review and editing.

Conflict of interest

None.

Data availability

The data used in this work are publicly available and can be accessed from online sources.

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