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Original Article

Image Segmentation Recommender Using Bio-inspired Algorithms

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Abstract *- An important aspect of image processing is image segmentation. It has been applied to a wide range of tasks, including augmented reality, video surveillance, item detection, and medical picture analysis. Even though many different algorithms have been created for picture segmentation, it has never been easy to determine which approach is appropriate for a particular image. Since every image has unique characteristics, it is impossible to find an algorithm that works for every image. Thus, one of the most difficult tasks is determining which method is best for a certain image. In earlier research, we adapted three meta-heuristic clustering algorithms (Shuffled Frog Leap, firefly, and spider monkey algorithm) and demonstrated their superior performance over the widely used k-means technique. It has also been demonstrated that the three algorithms were able to get over the main drawback of the k-means algorithm, which is its automatic determination of the "k" value. The goal of this work is to create a recommendation system that can identify the optimal segmentation algorithm based on the image input within a minimal time span. The outcomes demonstrated that, in terms of SSIM, FSIM, and time required, the suggested method is capable of recommending the best segmentation algorithm. It was found that the suggested algorithms required less computing time and were more than 90% efficient. The Open Surfaces dataset, the Berkeley Segmentation Dataset and Benchmark (BSDS) were used to test the recommender system.*

Keywords *- Firefly algorithm, Image segmentation, k-means clustering, Shuffled frog leap algorithm, Spider monkey algorithm.*

1. Introduction

Image segmentation is an important area of research in the field of digital image processing. It involves partitioning a digital image into multiple segments, with the goal of simplifying analysis and understanding of the image. At its core, image segmentation aims to cluster pixels together that are similar in some defining characteristic. This defining characteristic could be grayscale value, color, texture, brightness, or other computable properties.

By clustering similar pixels together, segments are created that ideally correspond to distinct real-world objects or regions of interest within the image. Image segmentation enables a more granular, targeted analysis of images than looking at the image as a whole. For example, by segmenting an anatomical scan into segments delineating organs, bone, tissue, etc., diagnostic analysis can focus on areas of interest rather than processing unimportant regions of the image. Research into medical imaging, self-driving vehicle computer vision, satellite imagery analysis and more rely heavily on image segmentation algorithms. As applications utilizing image analysis continue to grow, there is increasing demand for more robust, efficient and accurate image segmentation methods. This has motivated the development of many new segmentation approaches leveraging machine learning and neural networks.

Key goals of novel segmentation research include achieving more precise segment borders, dealing with artifacts, shadows, or occlusion, segmenting based on higher-order features beyond pixel values, and achieving reasonable performance on standard benchmark datasets. By advancing the field of image segmentation, computer vision systems can extract more insight from images, and researchers can make progress in addressing real-world analysis challenges. The existing image segmentation algorithms lack the following aspects:

1. Achieving a high accuracy when there are images with varying levels of light, complex backgrounds or objects that are overlapping.
2. Most of the image segmentation algorithms are trained with a specific set of images. Generalizing such algorithms for all datasets is an issue.

3. Though the existing sophisticated Deep learning algorithms are able to provide better accuracy, as they are computationally intensive, those algorithms cannot be used on devices with limited resources.

Bio-inspired algorithms have the capability to adapt to different data distributions, parallelism, robustness in spite of noisy data, self-organizing capabilities, and the ability to handle multiple objectives simultaneously. This research work has focused on overcoming the gaps identified in the existing image segmentation algorithms by making use of bio-inspired algorithms.

2. Background

The Clustering groups similar data points. Image segmentation uses clustering to group pixels into coherent regions. K-means is widely used - it partitions pixels into k clusters by computing a centroid for each and optimizing to minimize in-cluster variance. Choosing the right k is challenging: too small loses detail, too large over segments. Despite widespread use, k-means has limitations: it requires pre-setting cluster number k, which is image-dependent and prone to over/under-segmentation. It risks converging to suboptimal local minima solutions based on initialization. This unpredictability necessitates repeated runs.

While k-means clustering revolutionized image segmentation, key limitations like requiring a pre-set number of clusters k and convergence on local optima motivate the exploration of more advanced techniques. One recent direction involves developing metaheuristic optimization algorithms for clustering image pixels. Metaheuristic algorithms provide flexible optimization frameworks to probe complex search spaces and avoid poor local optima effectively.

Some models inspired by natural phenomena like bird flocking, bioluminescent fireflies, or spider monkeys have shown promise for addressing image segmentation challenges. For example, research in [1-3] explores using the shuffled frog leaping algorithm, firefly algorithm, and spider monkey optimization algorithm respectively, for pixel clustering. Each encodes pixels as multidimensional data points and then iteratively refines cluster associations per the algorithms' defined update rules that mimic real frog, firefly, or spider monkey group behaviour.

This research explores further adapting three metaheuristic algorithms - shuffled frog leaping, firefly, and spider monkey optimization - for improved image segmentation performance. These algorithms were selected due to the prior demonstrated ability to automatically cluster pixel data effectively. The adaptations target optimizing the algorithms for two widely used image segmentation benchmark datasets:

1. Berkeley Segmentation Dataset and Benchmark (BSDS) -Contains natural images focused on evaluating boundary detection and region segmentation quality.
2. OpenSurfaces - Images of surfaces like wood, tile, metal, etc., testing algorithms' ability to segment textures and materials.

The optimized versions of the three metaheuristic algorithms are evaluated against the benchmark image collections using two key image segmentation metrics:

1. Structural Similarity Index (SSIM) - Assesses similarity of segmented regions to ground truth image patches.
2. Feature SIMilarity index (FSIM) - Quantifies preservation of perceptual features like textures and shapes.

Additionally, computational time is measured to evaluate algorithm efficiency. Finally, a recommendation engine is constructed on top of the evaluation results. For any new input image, key features are extracted and compared to benchmark performance data to intelligently recommend which of the three optimized algorithms will provide the best segmentation for the image characteristics.

This approach provides a way to achieve higher quality, efficient image segmentation through metaheuristic optimization while also automatically selecting ideal algorithms per input image needs. The contributions aim to advance real-world applications relying on fast, precise image segmentation.

3. Review of Literature

Image segmentation aims to simplify pixel-level image analysis by grouping pixels into coherent clusters reflecting real-world objects, textures or other regions of interest. [27] provide valuable perspective on algorithm options by comparing two key clustering algorithm paradigms for this task:

1. Hierarchical clustering - Builds a hierarchy of merged pixel clusters in a top-down or bottom-up fashion based on a similarity measure.
2. Partitioning clustering - Divides pixels into non-hierarchical clusters in a one-shot process based on optimization of a criterion.

The Shuffled Frog Leaping (SFL) algorithm is a metaheuristic approach drawing inspiration from evolution and memetics in frog populations to tackle combinatorial optimization problems like data clustering. Various researchers have recently built on its demonstrated potential for addressing image segmentation challenges: Chen W et al. [4] adapted the technique for segmenting breast cancer histology images, achieving more accurate multi-threshold segmentation of invasive ductal carcinoma over baseline methods.

Demokri Dizji et al. [28] integrated an SFL-based pixel classifier into a pipeline for traffic sign recognition, demonstrating its utility for identifying signs within full road scenes. Zhang X et al. [3] introduced an improved SFL with new frog position updating and memetic learning rules, leading to multi-threshold segmentation efficiency gains.

Tehami, A., & Hadria, F. [26] developed an unsupervised SFL-based image segmentation framework outperforming k-means on synthetic and real-world images like faces and textures. Across biomedical imaging, transport, faces, and more, these works demonstrate versatile SFL-driven segmentation with accuracy improvements over clustering mainstays like k-means. They also illustrate the rich potential for further enhancing efficiency and applicability via algorithmic innovations tailored for imaging data. With more research into intelligent parameter control and domain adaptation, SFL-based methodologies could see expanded use in meeting segmentation needs from scientific imaging to autonomous navigation systems.

The Firefly algorithm is a metaheuristic optimization method using principles of flashing firefly behavior as an inspiration for tackling complex high-dimensional search problems. Researchers have increasingly tailored and applied Firefly-based techniques to advance image segmentation challenges: [24] integrated Firefly with k-means clustering to partition MRI brain images, leveraging the algorithms' respective exploration and exploitation strengths. M. Sridevi [23] devised a Firefly optimization strategy to automatically find optimal multi-threshold limits for segmenting color images.

Capor-Hrosik et al. [25] combined a Firefly variant with Otsu's thresholding method to effectively detect brain tumors in MRI scans, outperforming other algorithms on quantitative metrics. [22]Sharma et al. further improved tumor image segmentation by incorporating Kapur and fuzzy entropy criteria into their Firefly optimizer with superior results over particle swarm optimization and evolutionary algorithms.

Moreover, [30] Sharma, A. et al. recently advanced Firefly further by integrating opposition-based learning for faster, more robust MRI color image segmentation. Through bespoke modifications targeting image data needs, Firefly algorithms demonstrate significant promise in advancing biomedical imaging, fingerprint recognition, machine vision and other vital segmentation use cases.

S. Bhattacharyya et al. [31] have proposed a quantum version of the spider monkey optimization algorithm for image clustering, which makes use of a rotation gate in Hilbert hyperspace to drive towards better convergence. The improvisation was also compared with the classical SMO and demonstrated better efficiency. Prabhat R. Singh et al. [29] have modified the spider monkey optimization algorithm to solve global optimization problems. In this work, they have used the transformations of the Nelder-Mead (NM) to improve the ability of local leader phase selection, thereby improving the efficiency of the SMO algorithm. [32] Pal, Swaraj, et al. have proposed adding histogram-based bi-level and multi-level segmentation for gray scale images and compared it with the PSO algorithms and were able to obtain the optimum threshold values and CPU time.

3.1. Objectives

1. To implement image segmentation using the three modified clustering algorithms (Shuffled Frog algorithm, firefly algorithm, Spider monkey algorithm)
2. To check and compare the performance of those algorithms for image segmentation
3. To recommend the best clustering algorithms for the given image datasets (color, grayscale and black and white)

4. Methodology

4.1. Shuffled Frog Leaping (SFL) Algorithm

As described by [1], the SFLA is an optimization technique that draws inspiration from memetic algorithms and Particle Swarm Optimization (PSO). Integrating these concepts allows the SFLA to balance both exploration of the solution space and exploitation of promising solutions, key capabilities of an effective optimizer. Specifically, the SFLA encodes candidate solutions to a target problem as a population of logical "frogs", with each frog essentially representing one solution vector.

The frog population gets partitioned into disjoint memeplexes or subgroups. Local search occurs within each memeplex, rapidly refining frogs by incorporating successful memes from fitter local frogs. This enables local optima exploitation.

Meanwhile, frogs also get shuffled around between memeplexes, spreading promising solutions more globally. This facilitates exploration beyond just local optima. As a result of this hybrid approach, SFLA has demonstrated high convergence speeds while remaining simple to implement and apply.

The location of the i-th frog is defined mathematically as follows, assuming that D is the issue dimensions and that p is the number of randomly created individuals:

$$X_i = (x_{i1}, x_{i2}, x_{i3}, \dots\dots\ x_{iD}) \tag{1}$$

Figure 1 provides a visual illustration of this frog assortment scheme into memeplexes before local search iterations proceed.

The key outcomes are focused clusters where local improvements can be rapidly explored while also maintaining diversity globally across clusters to escape poor local optima later via shuffling between groups.

Next, the bad frog's position is optimised using the following equations (X_{new})

$$S = rand\,(\,) \times (X_b - X_w) \tag{2}$$

$$X_{new} = X_w + S\,, S_{max} \geq S - S_{max} \tag{3}$$

Where the frog's worst and greatest locations in each memeplex are indicated by X_w and X_b, respectively. Moreover, the maximum leap made by the frog is represented by S_m, and rand() is a random integer in the range [0, 1]. In this way, if the bad frog's position is improved, X_{new} takes its place; if not, X_b is replaced with the elite frog's position. After that, X_{new} is computed.

After that, if the specified position is improved, X_{new} takes the place of X_b; if not, X_w is given a random value. Until the predetermined number of updates is reached, this process keeps going. Ultimately, every individual within every memeplex is combined and rearranged into V memeplexes.

4.2. Modification in Shuffled Frog Algorithm

The modified shuffled frog algorithm starts with randomly forming k number of clusters. The mean/median of the cluster is taken as the central tendency, and the outliers or the data points that lie far away (based on distance) are identified from each cluster. This outlier is moved in a circular fashion across the clusters till it gets placed in the correct cluster. Though this is similar to the k-means, in terms of the quality of the clusters, the time taken by the algorithm is lesser than k-means, and the number of iterations is nearly (n/2)-2 as against n for k-means.

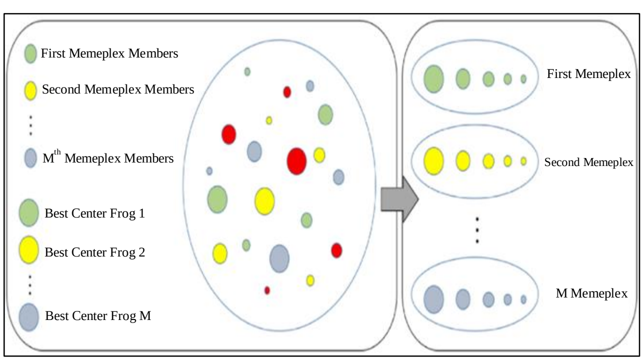

Fig. 1 Procedure of the Shuffled Frog Leaping Algorithm (SFLA)

4.3. Firefly Algorithm

Yang originally created the Firefly Algorithm (FA) in 2007 (Yang, 2008, 2009). It was based on the behavior and flashing patterns of fireflies. Yang created the firefly algorithm in 2008 by animating the distinctive behaviors of fireflies. It is categorized as swarm-intelligent, metaheuristic, and nature-inspired [5]. In actuality, the population of fireflies exhibits distinctive luminescent flashing behaviors to serve as a means of communication, partner attraction, and predator warning. Drawing inspiration from those activities, Yang developed this strategy based on the supposition that all fireflies are unisexual, meaning that each has the ability to attract other fireflies and that an individual's attractiveness is directly correlated with their light level.

4.3.1. Distance and Attractiveness

The fluctuation in light intensity, or the attractiveness between nearby fireflies, is the main factor determining the efficiency of the FA. Two major challenges in FA are light intensity variation and attractiveness formulation [10]. For the sake of simplicity, it is believed that a firefly's brightness, which is always associated with the objective function, determines how attractive it is [11]. Procedure for Initialization of the Firefly Algorithm,

- Attractiveness and Distancing.
- Create the next generation.
- Termination of iterative computing.

4.3.2. FA's Numerical Expression

The initialization of a swarm of fireflies, each of which determines the intensity of its flashing light, is the first of the FA's primary phases. The firefly with the lower light intensity will go towards the one with the greater light intensity throughout the pairwise comparison loop [11]. The attractiveness determines the movement distance. The newly arrived firefly is assessed and adjusted for light intensity after migrating. The makespan, which is a measure of how well a schedule works, may be computed using the following formula, where Ck is the job k's completion time.

$$\text{Minimize: } C_{max} = \max(C_1, C_2, C_3, \ldots\ldots C_k \tag{4}$$

Calculation of Distance, Attractiveness and movement,

$$r_y = \|X_i - X_j\| = \sqrt{\textstyle\sum_{k-1}^{d} (x_{i,k} - x_{j,k})^2} \tag{5}$$

4.4. Modification in Firefly Algorithm

The modified firefly is an algorithm that can dynamically form the clusters without mentioning the 'k' value and, at the same time, can produce clusters with quality better than the k-means. As the firefly algorithm forms the clusters using the absorption coefficient, this paper focuses on finding an appropriate absorption coefficient. Find the mean/median of the entire population. Find the points that are far away from the mean/median by using the standard deviation, which acts as the absorption coefficient. Now, whatever could not be absorbed by the initial cluster goes for the next iteration, and the process repeats till all data points are clustered. By this, the major disadvantage of ‘k’ means, which is finding the value of k is overcome, and the cluster quality is also higher than k-means.

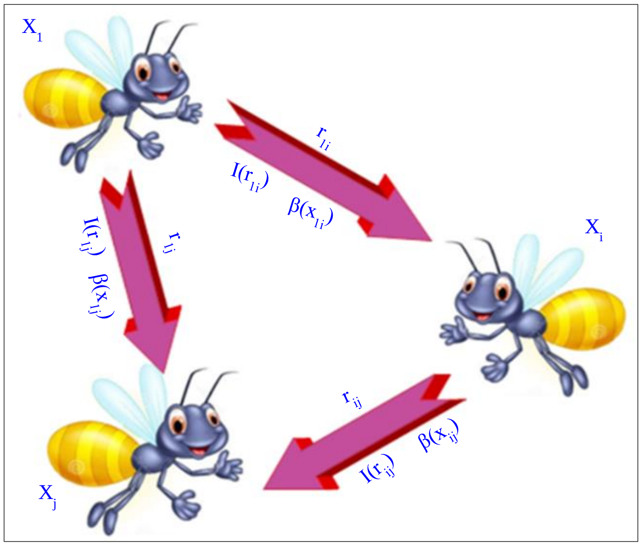

Fig. 2 Firefly algorithm

4.5. Spider Monkey Algorithm

The list of swarm intelligence-based optimisation methods includes the more recent addition of the Spider Monkey Optimisation (SMO) algorithm Bonabeau, E., Bansal, J.C, et al. [19]. Euclidean distances between possible solutions serve as the foundation for the updated equations. The technique has been widely used to address challenging optimisation issues.

Dhar, J.& Arora, S [21] designed and optimised a fuzzy rule foundation using the Spider Monkey Optimisation Algorithm (SMO). In IEEE-14, 30 and 33 test bus systems, Sharma et al. [24] apply SMO to address the optimal capacitor placement and sizing problem with the correct allocation of 3 and 5 capacitors. The explanations of each of these SMO phases follow:

Step 1: Initialization: A uniformly distributed random solution U (0,1) serves as the initial solution in SMO. In this case, the centroid value represents the solution. The first answer is displayed as,

$$C_{xy} = C_{miny} + U(0,1) \times (C_{maxx} - C_{minx}) \quad (6)$$

The maximum and lower boundaries are shown by C_{maxx} and C_{min}, whereas C represents the starting solution.

Step 2: Fitness Calculation: Each solution’s quality is assessed in relation to the fitness function. It assesses the monkey’s fitness using precision in recognition.

$$\text{Fitness} = \text{Max Accuracy} \quad (7)$$

Step 3: Updation: SMO is used to update each solution following the fitness computation. The steps for updating are described below.

Phase of the Local Leader: In this phase, every spider monkey chooses its new position based on the knowledge of its particular leader and peers. The equation is used to solve the spider monkey’s new condition.

$$C_{newxy} = C_{xy} + U(0,1) \times \left(LL_{yz} - C_{xy}\right) + U(-1,1) \times (C_{rx} - C_{xy}) \quad (8)$$

LLyz is the local leader, while Crx is the randomly chosen solution r≠x.

Phase of the Global Leader: Every spider monkey revives the ambience of the social gathering of individuals and global leaders.

$$C_{newxy} = C_{xy} + U(0,1) \times \left(GL_x - C_{xy}\right) + U(-1,1) \times (C_{rx} - C_{xy}) \quad (9)$$

When the global leader’s position is GLx, the spider monkeys update their position according to the probability value. The fitness value is used to calculate this probability. The formula for calculating this probability (Pr) is using (10),

$$P_r = \frac{\text{Fitness}_x}{\sum_{x=1}^{N} \text{Fitness}_x} \quad (10)$$

Phase of Learning for Global Leaders: The individual chosen as the global leader is the fit spider monkey. The size of the surrounding best solution’s limit is increased by one if the condition is not renewed.

Local Leader Learning Phase: The group member who is the most physically fit is chosen to be the local leader. The size of the surrounding best solution’s limit is increased by one if the condition is not renewed.

Phase of Decision-Making for Global Leaders: If the total number of individual leaders exceeds the limit for individual leaders, then the positions of all individuals will either be updated randomly or in accordance with the information provided by both general leaders and individual leaders.

$$C_{newxy} = C_{xy} + U(0,1) \times \left(GL_x - C_{xy}\right) + U(-1,1) \times (C_{rx} - LL_{xy}) \quad (11)$$

The spider monkey position is updated using the Equation (11) above.

Local Leader Decision Phase: At this stage, individuals are split up into smaller groups with a very small number if the general limit number is higher than the overall leader limit. The neighborhood leader limit is now in place in order to choose the meeting leader who is closest to each meeting. The global leader will then compile all of the meetings into one special meeting if the general leader's position is not renewed.

Termination: Until the ideal centroid value is discovered, the previously mentioned processes continue. The procedure is stopped if the ideal centroid value is reached. The procedure of recognition employs the centroid value that was found to be best. The suggested work introduces a fresh distance measure for recognition. First, determine how similar each cluster's feature is to its ideal centroid value. The feature is recognized if the cluster has the smallest distance; otherwise, it is not. The distance measure is displayed in the equation below.

$$\text{Fitness} = \min \sum_{j=1}^{M} \sum_{i=1}^{N} D(f_i - c_j)\, D(f_i - c_j) = \|f_i - c_j\| \tag{12}$$

Where the distance measurement between the cluster center cj and the feature fi is displayed by D(fi-cj).

4.6. Modification in Spider Monkey Optimization

Modified spider monkey, Previous research is applied to the facial images. The advanced PCA is used to reduce the facial features and identify the key features of the face. Based on the identified features, images are randomly clustered. The centroid of the cluster is found, and the distance of each face w.r.t centroid is estimated. The quality of each image is used as the criterion for moving in and out of the clusters. The quality of the clusters formed is 20% much higher than the k-means algorithm.

5. Implementation of Modified Algorithm for Image Segmentation

The above 3 modified algorithms are used for the image segmentation task. Various types of color and black-and-white images were used. The following architecture explains the task. By briefing the above architecture, the images are pre-processed by resizing, smoothening and applying a noise-filtering process. From that processed image, the key features are extracted. These features are used for segmenting the images. The extracted features are passed through the three modified algorithms for segmentation. The metrics of these three algorithms are further used to recommend the best algorithm for the given image.

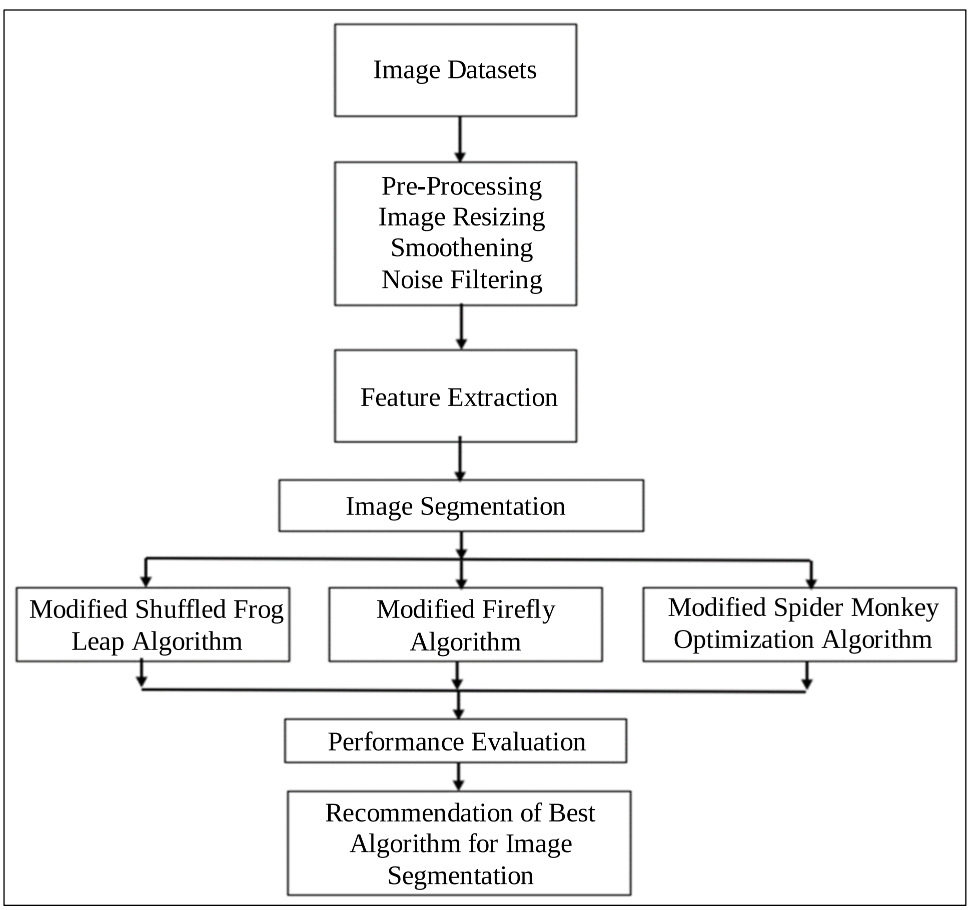

Fig. 3 Overall architecture

6. Results and Discussion

The open surfaces dataset and the standard Berkeley Segmentation Dataset (BSDS) were used to evaluate the suggested recommender engine on the coloured and grayscale photos of insects, animals, faces, and scenery. The best method was identified for each dataset category based on the recommendations, and it was further validated by running several identical photos through the system.

When the algorithms were applied to gray scale and coloured images, their behavior differed significantly. The recommender engine ranks the algorithms based on how well the segmented images are produced. Segmentation's quality was assessed using:

1. SSIM
2. FSIM
3. Time taken for segmenting the image

The behavior of proposed algorithms on grayscale images: It is clear from Figure 4 that, in comparison to the other 2 methods, the modified Firefly algorithm performs significantly better for the grayscale animal photos. Even while the modified Spider Monkey algorithm and the modified Shuffled Frog Leap algorithm can segment animal images, it has been found that the segmentations' FSIM quality is very low, making them inappropriate for use with animal datasets.

Figure 5 shows that the modified Shuffled Frog leap method performs best for face photos. Compared to the segmented animal image, the final segmented image is of higher quality. Even though the other two algorithms can segment data rather well, they need a lot more time than the modified shuffled frog leap. In comparison to the other two algorithms, the Modified Spider Monkey method processes face photos with the lowest quality in the longest amount of time.

It has been found that grayscale insect photos yield the greatest results when using the modified Spider monkey algorithm. The updated Spider Monkey technique produces segmented images with significantly higher SSIM and FSIM quality despite the fact that all three algorithms require almost the same amount of time. The Modified Firefly algorithm performs the worst with grayscale bug photos.

When compared to other datasets, the total time consumed by all three techniques is excessive. The modified Shuffled Frog Leap method produces segmented images with considerably higher quality, but the modified Firefly algorithm produces segmented images faster.

However, the images produced by the updated Firefly algorithm have too poor of quality. Thus, the recommender chooses the modified Shuffled Frog Leap method as the best choice for gray scale scenery photographs, taking into account the fact that the suggested work seeks to identify the optimal solution in all feasible ways.

For gray scale textured images, the modified Spider monkey performs best in terms of both time and image quality, while the modified Shuffled Frog leap performs worst in terms of both time and image quality.

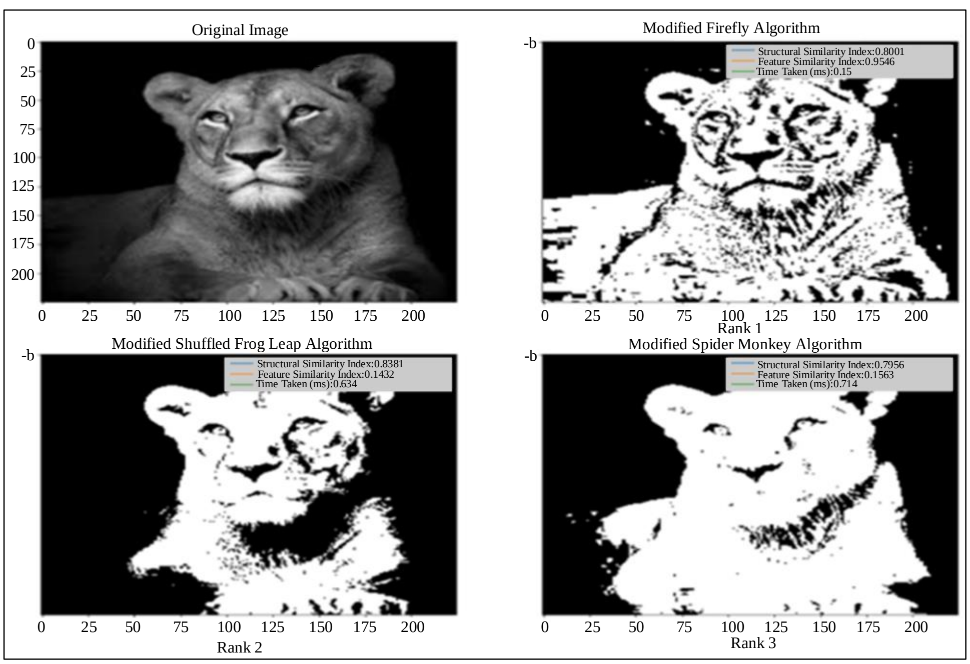

Fig. 4 Ranking of algorithm for animal images (B&W images)

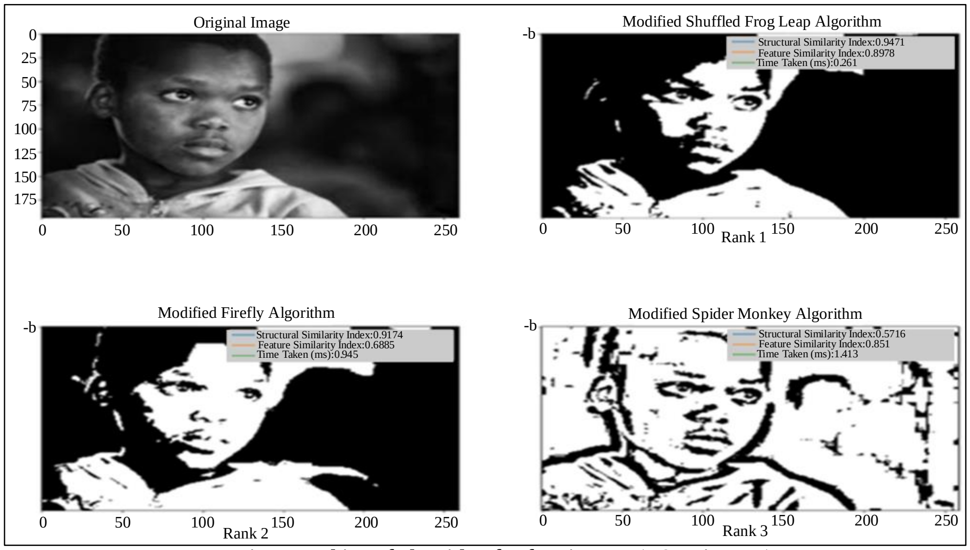

Fig. 5 Ranking of algorithm for face images (B&W images)

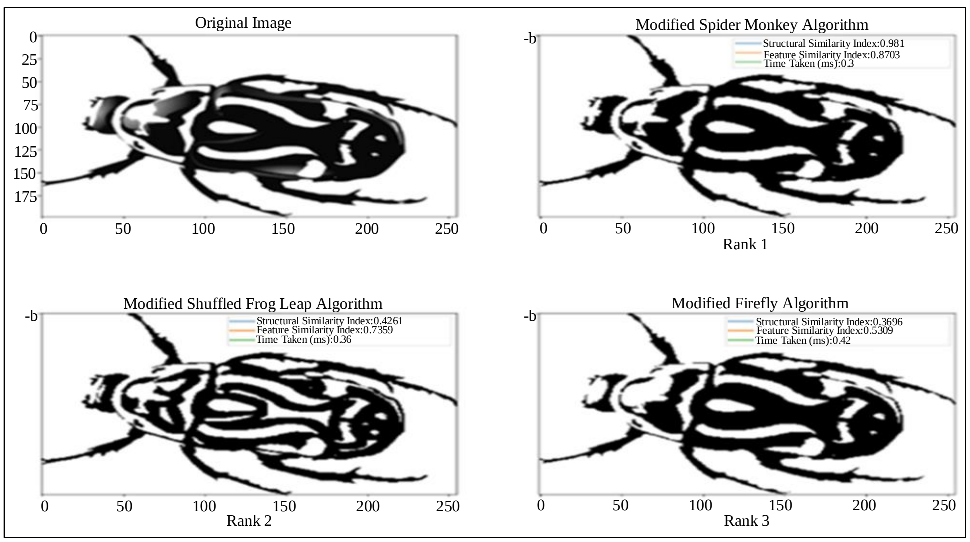

Fig. 6 Ranking of algorithm for insect images (B&W images)

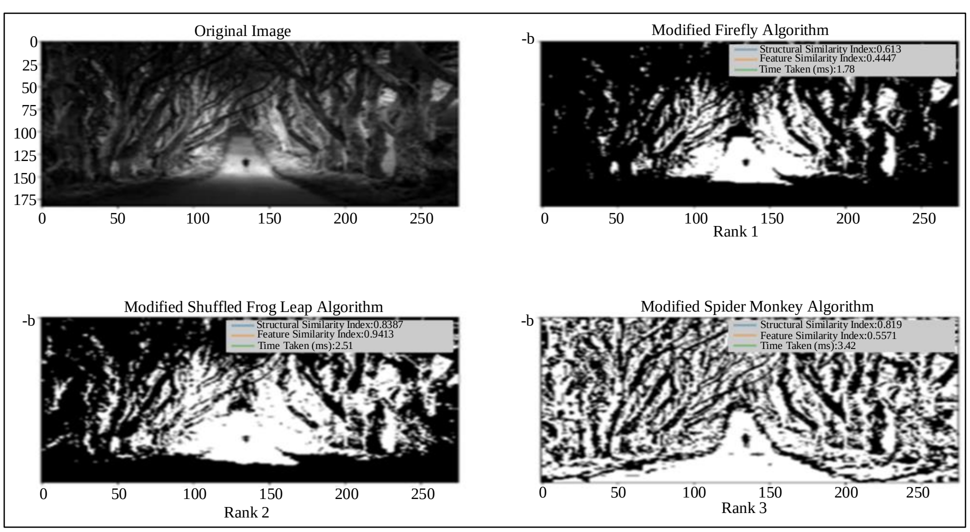

Fig. 7 Ranking of algorithm for scenery images (B&W images)

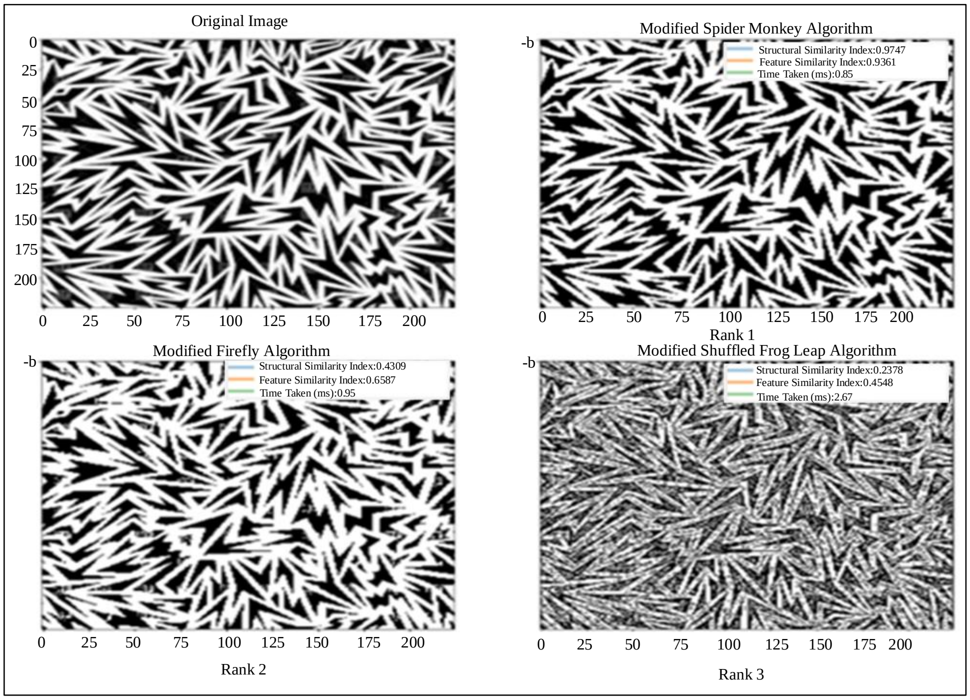

Fig. 8 Ranking of algorithm for texture images (B&W images)

Modified Firefly algorithms often take the least amount of time to segment animal photos in gray scale, whereas modified Spider Monkey algorithms produce the best segmentation quality in textured images. Comparably, the modified Shuffled Frog algorithm produces the worst segmentations, and the modified Spider Monkey algorithm takes the longest to segment the scene photos. The way suggested algorithms behave with coloured images: The best-quality segmented images are produced in the shortest amount of time using a modified Firefly algorithm. The segmented images produced by the other 2 algorithms are of much lower quality, even though they likewise require less computing time.

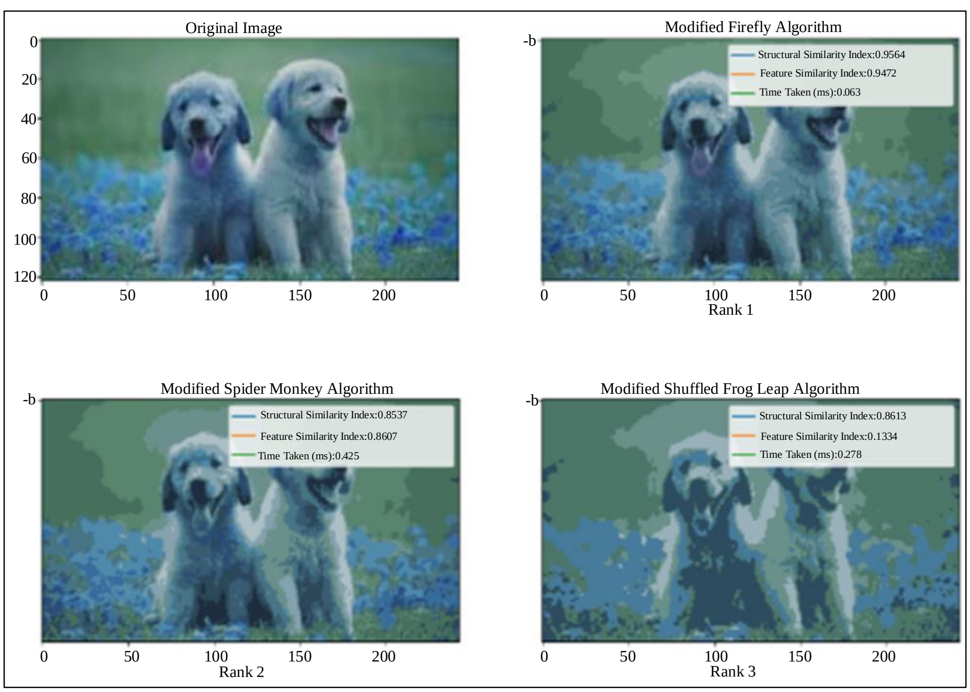

Fig. 9 Ranking of algorithms for animal images (color images)

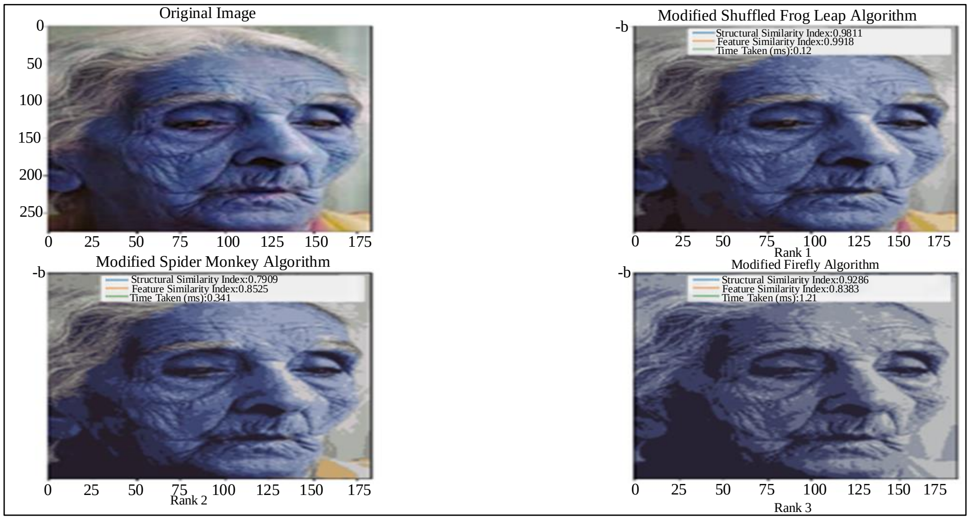

Fig. 10 Ranking of algorithms for face images (color images)

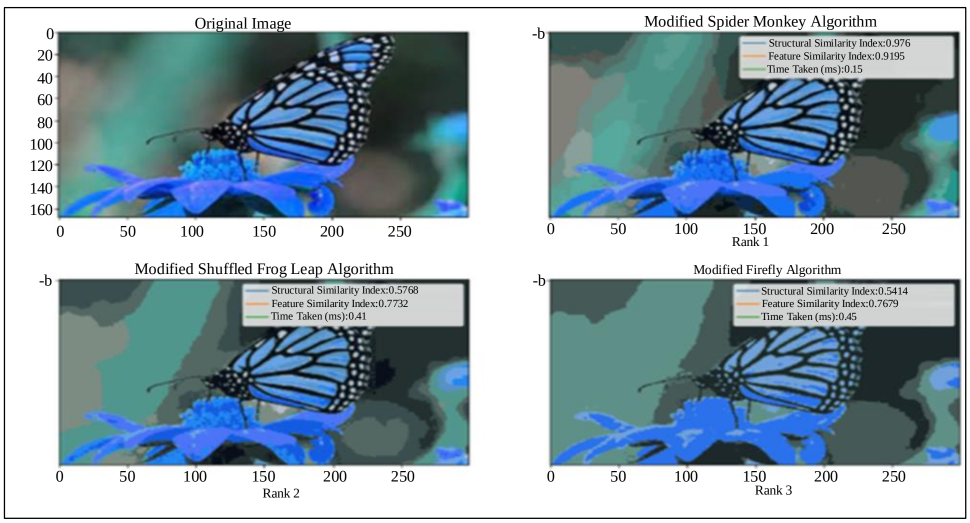

Fig. 11 Ranking of algorithms for insect images (color images)

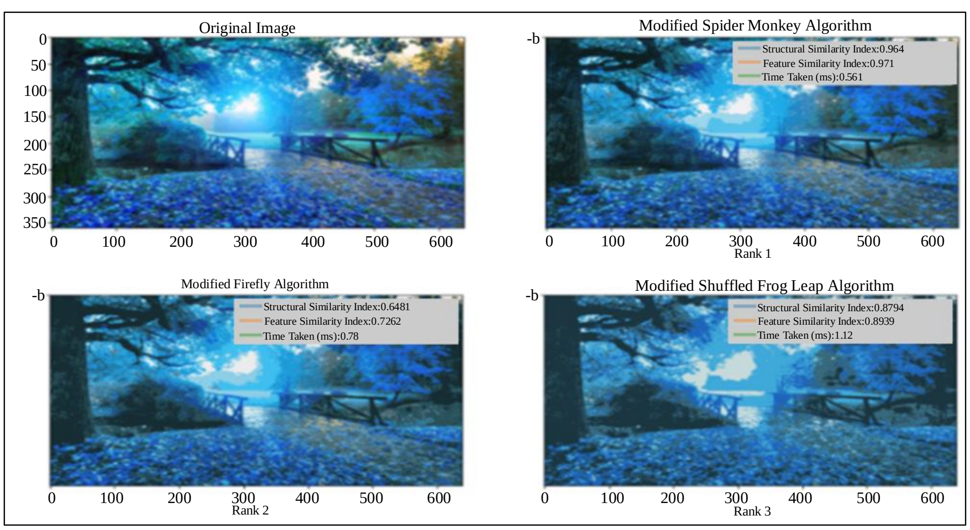

Fig. 12 Ranking of algorithms for scenery images (color images)

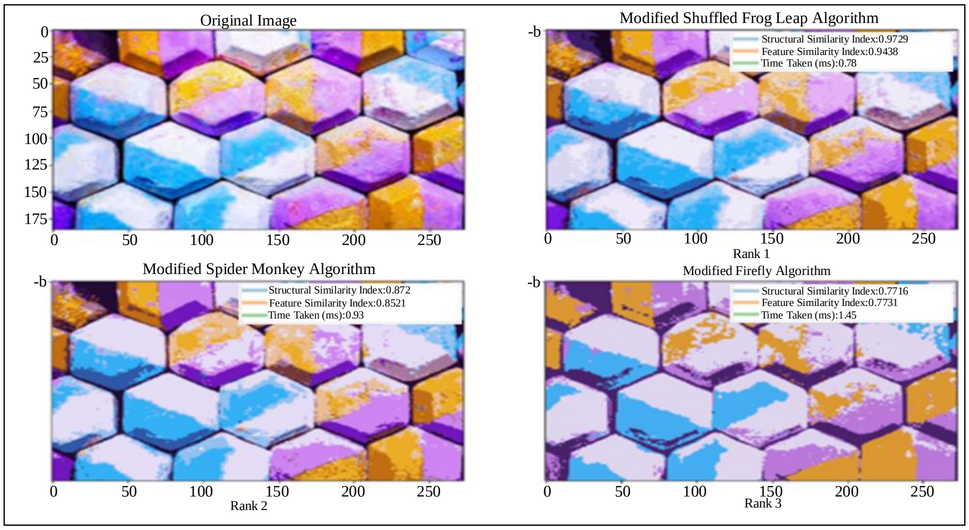

Fig. 13 Ranking of algorithms for textured images (color images)

The performance of the above algorithms for the segmentation of given images is listed below.

Table 1. Performance metrics of Modified Spider Monkey Algorithm on color images

Modified Spider Monkey Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.15	0.976	0.9195
Animals	0.425	0.8537	0.8607
Face	0.341	0.7909	0.8525
Scenery	0.561	0.964	0.971
Textures	0.93	0.872	0.8521

Table 2. Performance metrics of Modified Shuffled Frog Leap Algorithm on color images

Modified Shuffled Frog Leap Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.41	0.5768	0.7732
Animals	0.278	0.8613	0.1334
Face	0.12	0.9811	0.9918
Scenery	1.12	0.8794	0.8939
Textures	0.78	0.9729	0.9438

Table 3. Performance metrics of Modified Firefly Algorithm on color images

Modified Firefly Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.45	0.5414	0.7679
Animals	0.063	0.9564	0.9472
Face	1.21	0.9286	0.8383
Scenery	0.78	0.6481	0.7262
Textures	1.45	0.7716	0.7731

Table 4. Performance metrics of Modified Spider Monkey Algorithm on B&W images

Modified Spider Monkey Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.3	0.981	0.8703
Animals	0.714	0.7956	0.1563
Face	1.413	0.5716	0.851
Scenery	3.42	0.819	0.5571
Textures	0.85	0.9747	0.9361

Table 5. Performance metrics of Modified Shuffled Frog Leap Algorithm on B&W images

Modified Shuffled Frog Leap Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.36	0.4261	0.7359
Animals	0.634	0.8381	0.1432
Face	0.261	0.9471	0.8978
Scenery	2.51	0.8387	0.9413
Textures	2.67	0.2378	0.4548

Table 6. Performance metrics of Modified Firefly Algorithm on B&W images

Modified Firefly Algorithm			
Image Datasets	**Time**	**SSIM**	**FSIM**
Insect	0.42	0.3696	0.5309
Animals	0.15	0.8001	0.9546
Face	0.945	0.9174	0.6885
Scenery	1.78	0.613	0.4447
Textures	0.95	0.4309	0.6587

The goal of this work is to create a recommendation system that can identify the optimal segmentation algorithm based on the image input.

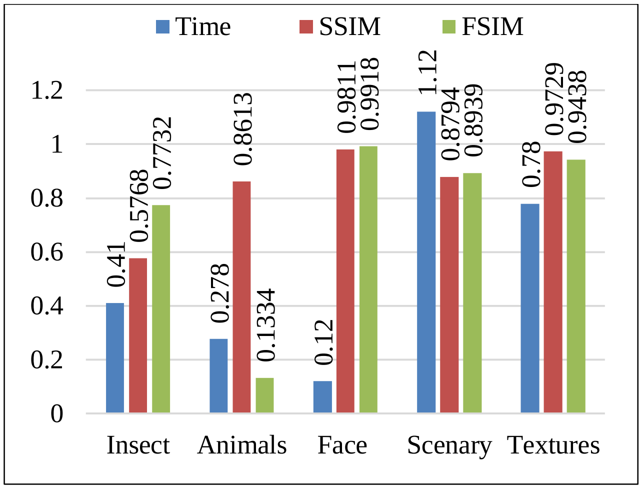

Fig. 14 Performance of Modified Shuffled Frog Leap Algorithm (color images)

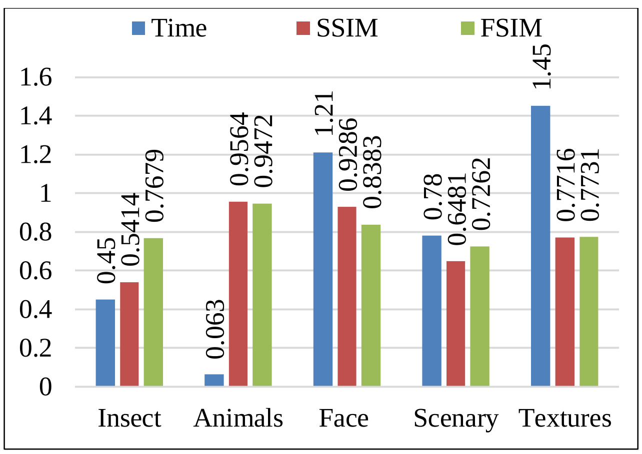

Fig. 15 Performance of Modified Firefly Algorithm (color images)

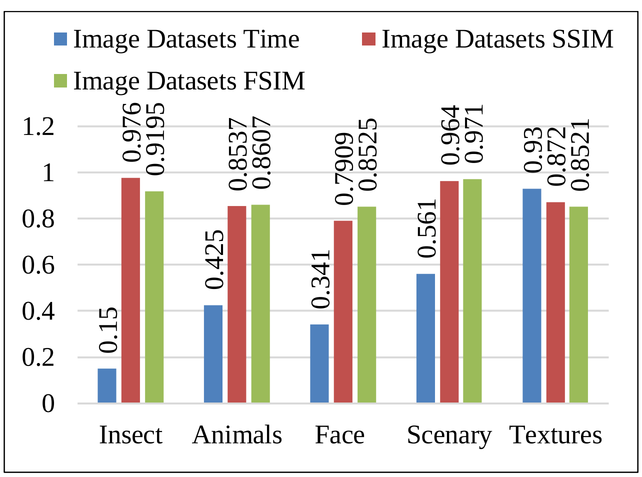

Fig. 16 Performance of Modified Spider Monkey Algorithm (color images)

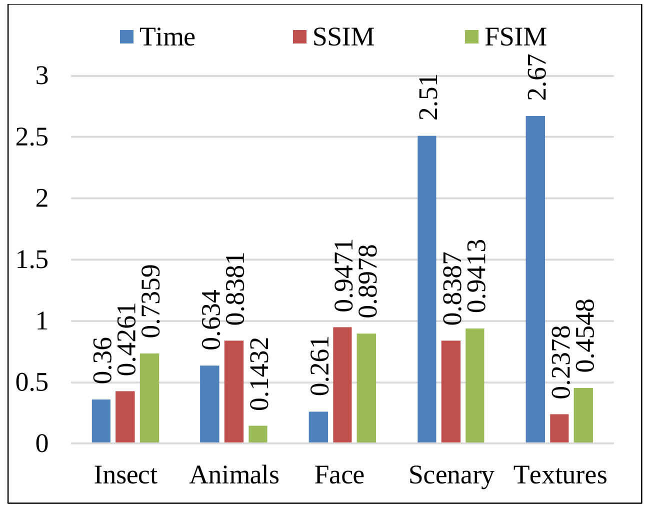

Fig. 17 Performance of Modified Shuffled Frog Leap Algorithm (black & white images)

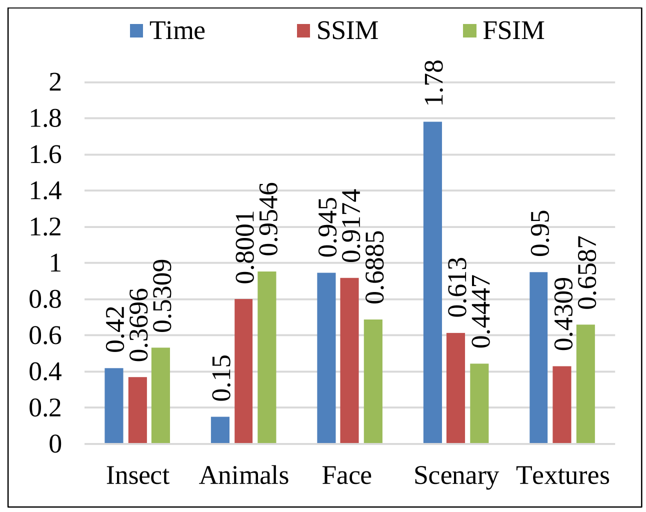

Fig. 18 Performance of Modified Firefly Algorithm (black & white images)

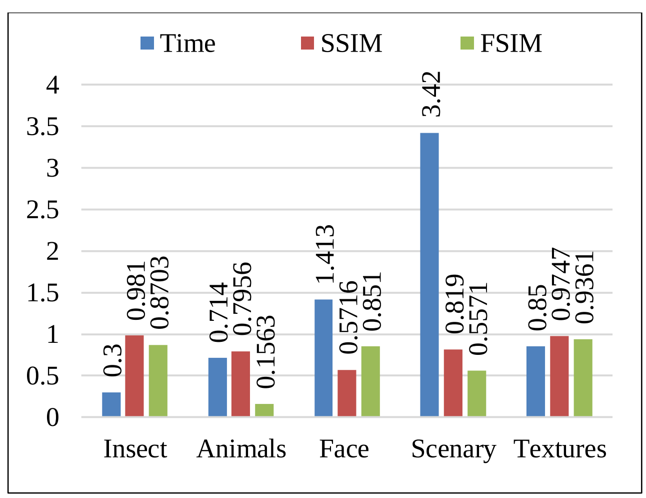

Fig. 19 Performance of Modified Spider Monkey Algorithm (black & white images)

Based on the performance of these modified algorithms it is found that for Insect images, Modified spider monkey gives the best results for the colored images. For Animal images, the modified firefly yields the best results for the colored images, and Face images Modified shuffled frog leap performs well for colored images.

The outcomes demonstrated that, in terms of SSIM, FSIM, and time required, the suggested method is capable of recommending the best segmentation algorithm. It was found that the suggested algorithms required less computing time and were more than 90% efficient for all three modified algorithms.

7. Conclusion

The goal of this work was to create an intelligent recommendation system that could analyze an input image and then suggest the optimal image segmentation algorithm to apply to that image. To train and test this system, two datasets were utilized - the large-scale Open Surfaces dataset with over 20,000 images, and the commonly used Berkeley Segmentation Dataset consisting of 500 benchmark images (BSDS). The recommendation system was exposed during training to a variety of different image segmentation algorithms, ranging from simple methods like thresholding to more complex machine learning-based techniques. Based on analyzing the image features and structure, the trained system predicts which segmentation algorithm will likely perform best on those sets of image inputs. The criteria used to define “best” were segmentation quality, computational efficiency, and time required. Segmentation quality was quantified using two common metrics - Structural Similarity Index (SSIM) and Feature Similarity Index (FSIM). The recommender system learns to pick algorithms that maximize these index scores.

The outcomes showed that across both datasets, the recommendation system was able to reliably pick the optimal algorithm over 90% of the time based on the image inputs.Additionally, the suggested algorithms consistently required lower compute times compared to manually trying out all possible combinations one by one.

Overall, the experiments successfully demonstrated the capability of trained recommendation systems that can automatically shortlist and pick appropriate algorithms instead of manual and exhaustive searching. This can make systems much more efficient, especially when working with large and varied datasets.

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