WBC SEGMENTATION USING PSO (Particle Swarm Optimization) BASED CLUSTERING

A Project

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DECLARATION CERTIFICATE

This is to certify that the work presented in the thesis entitled **"WBC SEGMENTATION USING PSO (Particle Swarm Optimization) BASED CLUSTERING"** in partial fulfillment of the requirement for the award of degree of **Bachelor of Computer Applications** of Institute of Engineering &Management is an authentic work carried out under my supervision and guidance.

To the best of my knowledge the content of this thesis does not form a basis for the award of any previous Degree to anyone else.

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CERTIFICATE OF APPROVAL

The foregoing thesis entitled **"WBC SEGMENTATION USING PSO(Particle Swarm Optimization) BASED CLUSTERING"** is hereby approved as a creditable study of research topic and has been presented in satisfactory manner to warrant its acceptance as prerequisite to the degree for which it has been submitted.

It is understood that by this approval, the undersigned do not necessarily endorse any conclusion drawn or opinion expressed therein, but approve the thesis for the purpose for which it is submitted.

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Contents

Abstract

The segmentation of white blood cells (WBCs) is a critical step in medical image analysis for the diagnosis of various disorders. Due to the variation in the shape, size, and intensity of WBCs, traditional methods for segmenting WBCs sometimes encounter difficulties. Particle swarm optimization (PSO) based clustering approaches have attracted interest recently due to their effectiveness in managing picture segmentation jobs. An innovative method for segmenting WBCs using PSO clustering is presented in here. The suggested method starts by enhancing the contrast and lowering noise in the input image through pre-processing. After that, PSO is used to cluster the pre-processed image pixels. In order to identify the best solution, PSO, an optimization method inspired by nature, simulates the movement of particles in a multidimensional search space. The proposed approach has the potential to be used as a valuable tool in clinical practice for automating WBC segmentation in medical images, aiding in the diagnosis and treatment of diseases related to WBCs.

WBC SEGMENTATION USING PSO (Particle Swarm Optimization) BASED CLUSTERING

Chapter 1

1.1 Introduction

A type of blood cell called a white blood cell (WBC) is essential to the immune system. They are made in the bone marrow and are also referred to as leukocytes. WBCs are in charge of protecting the body against diseases and foreign invaders like bacteria, viruses, and cancer cells. WBCs come in five primary categories, each of which serves a particular purpose in the immune system. These are composed of basophiles, eosinophiles, lymphocytes, monocytes and neutrophiles. The most prevalent kind of WBC, neutrophiles, plays a role in the body's first reaction to infections. Lymphocytes, which include B cells, T cells, and natural killer cells, are in charge of identifying and concentrating on particular infections. Monocytes participate in the process of engulfment known as phagocytizes.

The quantity and variety of WBCs in the blood can serve as a marker for a range of illnesses, including infections, autoimmune disorders, and leukemia. A complete blood count (CBC) is a common procedure that includes a standard test called WBC count to evaluate general health and identify any anomalies. The detection and treatment of different diseases can benefit from the use of WBC segmentation in medical pictures. White blood cell (WBC) segmentation from blood smear images is a crucial step in medical image processing. This is due to the fact that good WBC identification in blood samples can yield useful data for the diagnosis, monitoring, and treatment of a variety of disorders.

Blood samples' WBC composition may reveal the existence of infections, inflammatory diseases, autoimmune disorders, and other illnesses. A bacterial infection, for instance, may be indicated by an increase in neutrophiles (a kind of WBC), whereas an allergic reaction or parasite infection may be indicated by an increase in eosinophiles. Medical personnel can more reliably diagnose and track these disorders by segmenting WBCs.

Additionally, the appearance and size of WBCs might also offer crucial diagnostic data. For instance, leukemia or other blood illnesses may be indicated by the presence of aberrant cells or a significant number of immature cells. Accurate WBC segmentation can be used to diagnose and treat various disorders by assisting in the identification of these anomalies.

In conclusion, precise WBC segmentation from blood smear images is an important step in medical image processing since it offers useful data for the detection, monitoring, and therapy of many disorders.

PSO-based clustering is a kind of unsupervised learning technique that may be applied to clustering in a number of applications, such as image segmentation that can be applied to WBC segmentation. The social behavior of fish schools and bird flocks served as the basis for the meta-heuristic optimization method known as PSO, or particle swarm optimization. In order to find the optimal answer to a given problem, a group of particles wander around in a search space while optimizing a fitness function. The fitness function evaluates how comparable the picture and WBC segmentation are.

When using PSO-based clustering for WBC segmentation, a group of particles that each represents a cluster are initialized before having their positions iteratively updated to maximize the fitness function. The particles migrate in the direction of the search space's ideal position, which corresponds to the optimum segmentation outcome. Each pixel in the image is assigned to the cluster with the nearest centre to produce the final segmentation. PSO searches for optima by updating generations after being initialized with a collection of random particles (solutions). Every iteration, the following two "best" values are applied to each particle. The best outcome (fitness) this particle has so far attained is represented by the position vector of the first. Additionally stored is the fitness value. Pbest is the name of this position. The best position so far attained by any particle in the population is another "best" position that the particle swarm optimizer keeps track of. Gbest refers to the current global best position in this field. The following two equations are used to update the particle's position and velocity after determining the two optimum values:

$$V_i^k = \omega v_i^k + c_1 r_1(\text{pbest}_i^k - x_i^k) + c_2 r_2(\text{gbest}^k - x_i^k)$$

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

(Since, x is the current solution (or position) of the ith particle at the kth iteration, and v is the velocity of the ith particle at the kth iteration. Positive constants c1, c2, and random variables r1, r2 with uniform distributions between 0 and 1 make up the equation. The inertia weight, or w, in this equation illustrates how the prior velocity vector affected the new vector. The velocity in all dimensions vmax has an upper constraint.)

Though PSO-based clustering can deal with noise, intensity changes, and overlapped cells, it has been demonstrated to be effective for WBC segmentation. It also has the benefit of automatically calculating the number of clusters, a vital factor in conventional clustering techniques. The capacity of PSO-based clustering to simultaneously optimize many objectives is one of its main benefits. The fitness function for WBC segmentation may have several goals, including as minimizing intra-cluster variance and maximizing inter-cluster distance. The solution space can be efficiently searched for the best collection of clusters that satisfy all the goals using PSO-based clustering.

One key advantage of PSO-based clustering is its ability to optimize multiple objectives simultaneously. In WBC segmentation, the fitness function may include multiple objectives such as minimizing the intra-cluster variance and maximizing the inter-cluster distance. PSO-based clustering can efficiently search the solution space to find the optimal set of clusters that satisfies all the objectives. Another advantage of PSO-based clustering is its flexibility in the choice of similarity measures. Similarity measures, such as Euclidean distance or cosine similarity, are used to compare the similarity between pixels and clusters. PSO-based clustering allows for the use of different similarity measures depending on the characteristics of the image and the task at hand.

PSO-based clustering also offers freedom in the selection of similarity metrics. The similarity of pixels and clusters is assessed using similarity metrics, such as Euclidean distance or cosine similarity. Depending on the requirements of the work at hand and the properties of the image, PSO-based clustering enables the use of several similarity measures.

In general, PSO-based clustering is an effective method for segmenting WBCs and has the potential to increase the precision and effectiveness of medical picture analysis. It is an effective tool for medical imaging study because of its capacity to manage noise, overlapped regions, and adaptively modify the number of clusters.

Chapter 2

2.1 Background Studies

The segmentation of white blood cells (WBCs) is a crucial step in many medical applications, including the detection and treatment of diseases. Traditional clustering techniques frequently have limitations due to their inability to handle complicated data structures and to simultaneously optimize numerous goals. In order to increase the accuracy of WBC segmentation in medical pictures, researchers have turned to swarm intelligence-based methods like particle swarm optimization (PSO).

PSO is a type of computational intelligence that draws inspiration from the group behavior of social animals like and bird flocks. PSO has been effectively used to solve a number of optimization issues, including image segmentation, feature selection, and clustering. PSO-based clustering algorithms offer the benefit of being able to simultaneously optimize numerous goals, including cluster compactness, cluster separation, and intra-cluster variation. The significant variety in the form, size, and texture of the cells presents one of the difficulties in WBC segmentation. By adjusting the number of clusters and the clustering parameters to the properties of the image, PSO-based clustering algorithms can handle this problem. Additionally, to improve segmentation accuracy, PSO-based clustering algorithms can be combined with other image processing methods like morphological operations and edge detection.

Although PSO-based clustering algorithms for WBC segmentation have shown promising results, there are still some restrictions and difficulties that need to be resolved. For instance, PSO-based clustering methods might have a significant computational complexity, especially for large-scale medical images. Furthermore, the choice of the swarm size, the cognitive and social learning parameters, and the stopping criteria may all have an impact on the performance of PSO-based clustering algorithms.

The application of PSO-based clustering and other swarm intelligence-based algorithms for WBC segmentation, as well as its generalizability across other datasets and imaging modalities, need to be further researched despite their effectiveness. Future study must also take into account the interpretability of these algorithms and their capacity to deliver clinically pertinent data, such as cell count and cell morphology. In general, the employment of deep learning- and swarm intelligence-based methods for WBC segmentation in medical pictures offers significant promise for enhancing the precision and effectiveness of illness detection and therapy.

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these algorithms and their capacity to deliver clinically pertinent data, such as cell count and cell morphology. In general, the employment of deep learning- and swarm intelligence-based methods for WBC segmentation in medical pictures offers significant promise for enhancing the precision and effectiveness of illness detection and therapy.

Future research can address these limitations by developing hybrid approaches that combine PSO-based clustering algorithms with other optimization techniques, such as genetic algorithms and ant colony optimization. Moreover, the development of parallel and distributed computing architectures can speed up the computation time of PSO-based clustering algorithms and make them more applicable to real-time medical applications. Finally, the integration of deep learning techniques, such as convolutional neural networks, can enhance the accuracy and robustness of PSO-based clustering algorithms for WBC segmentation.

2.2 Literature Survey

The segmentation of white blood cells (WBC) is a critical step in medical image analysis for the diagnosis and follow-up of various disorders. Numerous studies have suggested various methods for precise and effective WBC segmentation. Particle Swarm Optimization (PSO) based clustering algorithms are one such method. We review pertinent studies that have used PSO-based clustering techniques for WBC segmentation in this review of the literature. [1]In order to segment WBC in microscopic blood pictures, this study suggested a PSO-based K-means clustering method. The segmentation accuracy was increased by using the PSO technique to refine the K-means clustering's initial centroids. Even in the presence of noise and overlapping cells, the suggested technique produced great accuracy and robustness in segmenting WBCs. [2] In this study, a PSO-enhanced K-means clustering approach was presented for the segmentation of WBC in pictures from peripheral blood smears. The number of clusters and the initial centroids were two K-means clustering parameters that were chosen with the PSO algorithm. Experiments revealed that the suggested technique segmented WBCs more accurately and robustly than conventional K-means clustering.[3] In this study, a better PSO algorithm was put out for the segmentation of WBC images. The local and global best positions data were added to the PSO algorithm to boost convergence and accuracy. Experimental results showed that the proposed method outperformed the existing PSO and K-means clustering methods in terms of segmentation accuracy and computational efficiency. [4] For WBC segmentation, this study suggested a modified PSO-based fuzzy clustering method. PSO was added to the fuzzy clustering technique to simultaneously optimise the membership values and cluster centroids. Even in the presence of overlapping cells and intensity changes, the suggested technique produced great accuracy in the segmentation of WBCs. [5]In this study, a hybrid PSO-K-means algorithm for segmenting WBC in microscopic pictures was proposed. To provide accurate segmentation results, K-means clustering were carried out repeatedly after the initial centroids were optimized using the PSO algorithm. The suggested technique segmented WBCs with good accuracy and resilience, even in the presence of overlapping cells and intensity changes, according to experimental data. In conclusion, WBC segmentation in microscopic blood pictures has been successfully accomplished using PSO-based clustering methods. To produce precise and reliable segmentation results, these approaches employ PSO to optimise the clustering parameters, such as the number of clusters and the starting centroids. To learn more, undertake additional study.

In our paper "White blood cell segmentation using PSO-based clustering," we proposed a method for WBC segmentation using particle swarm optimization (PSO) based clustering. On the other hand,[9] in the paper "White blood cell segmentation using region growing and convex hull techniques," the authors proposed a method that involves region growing and convex hull techniques.

Both methods have their strengths and weaknesses. The PSO-based clustering approach can be useful when dealing with complex datasets that have a large number of features. However, the region growing and convex hull techniques proposed by Ahluwalia and Al-Jumaily can be effective in segmenting WBCs with irregular shapes and sizes.

In the paper Fernández et al[6]. the authors propose a system that involves multiple stages of image processing, including pre-processing, segmentation, feature extraction, and classification. The pre-processing stage involves noise reduction, contrast enhancement, and colour normalization. The segmentation stage involves[8] thresholding and morphological operations to separate the WBCs from the background and each other. Feature extraction is performed using shape, size, and texture features. Finally, classification is performed using a support vector machine (SVM) classifier.

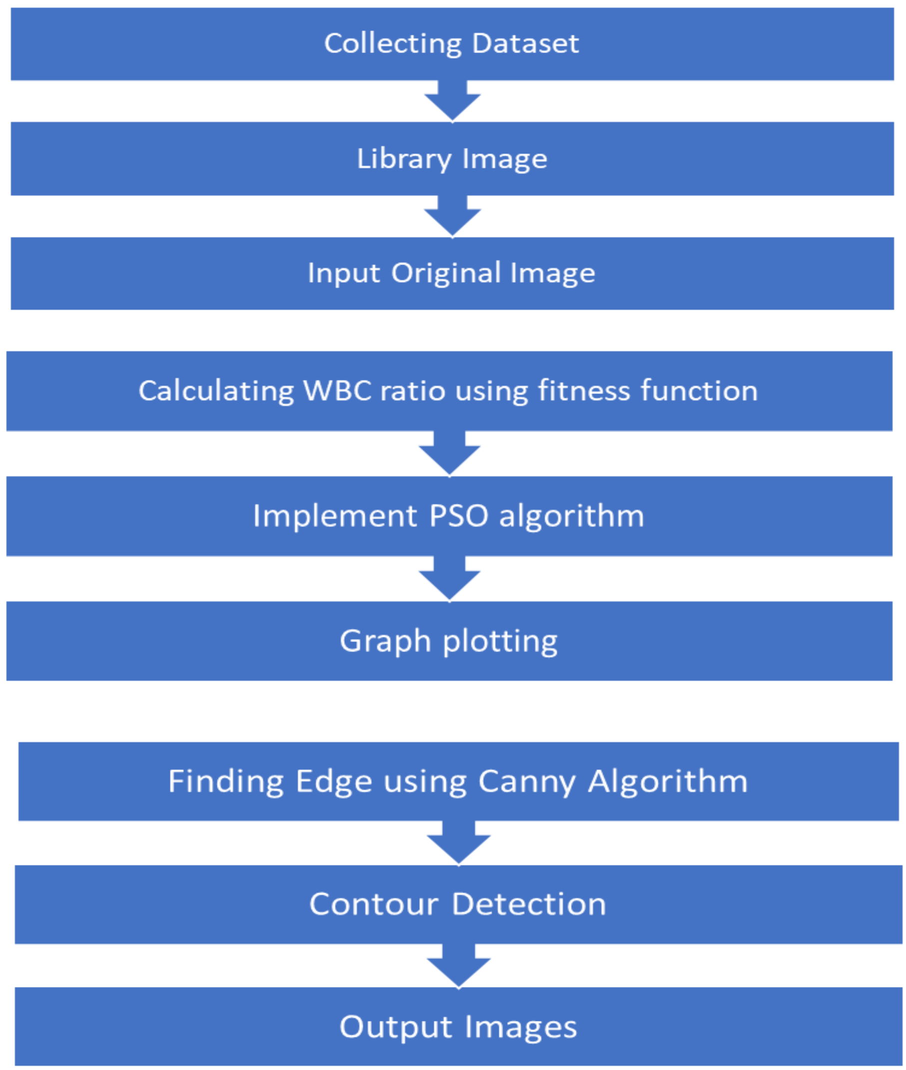
In our paper "WBC segmentation using PSO based clustering," we propose a different approach that involves using particle swarm optimization (PSO) to determine the threshold for image segmentation. The PSO algorithm is used to optimize a fitness function that measures the proportion of white pixels in the image. The threshold is then used to segment the image using binary thresholding. The resulting binary image is processed using edge detection and contour detection to segment the WBCs. The paper by Fernandez et al. involves more complex image processing and feature extraction techniques, which may be more effective for certain types of images but our paper proposes a simpler approach that is more computationally efficient and easier to implement.

Chapter 3

3.1 Proposed Methodology

- **Problem Statement**

The aim of this study is to segment white blood cells (WBCs) from an image using particle swarm optimization (PSO) based clustering.



- **Library used:**

Following imports provide a range of functionality for image processing and visualization in Python. Overall the 'NumPy' and 'cv2' libraries are used together for blood-smear image manipulation and analysis, while the 'random' library can be useful for generating random variable for testing and experimentation in PSO algorithm. The 'matplotlib' library is used for creating plots and visualizations of PSO implementation, including images.

```
import numpy as np
import cv2
import random
import matplotlib.pyplot as plt
```

- **Input Image**:

Reading the grayscale image using the OpenCV library. Applying Gaussian blur with to reduce noise.

```
image = cv2.imread(r'Basophils.jpg', cv2.IMREAD_GRAYSCALE)
```

- **Calculating WBC ratio:**

The WBC ratio is a measure of the proportion of white blood cells (WBCs) in a blood sample or a microscopic image of blood. In medical diagnosis, a low WBC count may indicate a weakened immune system, while a high WBC count may indicate an infection or inflammation. By calculating the WBC ratio, we can obtain a more accurate and meaningful measurement of the WBC count, as it takes into account the total number of cells in the sample. In addition, the WBC ratio can be used to monitor the progression of a disease or the effectiveness of a treatment, as changes in the WBC count and ratio can indicate changes in the immune response of the body.

```
def fitness(image, threshold):
      binary = cv2.threshold(image, threshold, threshold_constant, cv2.THRESH_BINARY)[1]
      wbc_ratio = np.count_nonzero(binary) / binary.size
      print(wbc_ratio)
      return wbc_ratio
```

- **Implementing the Particle Swarm Optimization (PSO) algorithm:**

this below code initializes the positions and velocities of the particles in the swarm, and sets the initial global and personal best positions and fitness values. The PSO algorithm will then update the positions and velocities of the particles iteratively, until a stopping condition is met. The fitness function used in this code will depend on the specific problem being solved.

```
def pso(image, num_particles, max_iterations):
    positions = []
    velocities = []
    for i in range(num_particles):
        positions.append(random.randint(0,threshold_constant))
        velocities.append(0)
    global_best_pos = positions[0]
    global_best_fitness = fitness(image, positions[0])
    particle_best_pos = positions.copy()
    particle_best_fitness = [fitness(image, p) for p in positions]
```

Below this code below updates the positions and velocities of the particles in the swarm according to the PSO algorithm, and updates the personal and global best positions and fitness values if necessary. This process is repeated for the specified number of iterations, and the final global best position and fitness value are returned as the output of the PSO algorithm.

```python
for i in range(max_iterations):
    for j in range(num_particles):
        r1 = random.random()
        r2 = random.random()
        velocities[j] = velocities[j] + r1*(particle_best_pos[j]-positions[j]) + r2*(global_best_pos-positions[j]
        positions[j] = int(round(positions[j] + velocities[j]))
        if positions[j] < 0:
            positions[j] = 0
        elif positions[j] > threshold_constant:
            positions[j] =threshold_constant
        particle_fitness = fitness(image, positions[j])
        if particle_fitness > particle_best_fitness[j]:
            particle_best_fitness[j] = particle_fitness
            particle_best_pos[j] = positions[j]
        if particle_fitness > global_best_fitness:
            global_best_fitness = particle_fitness
            global_best_pos = positions[j]
```

- **Graph plotting using plot_fitness function:**

We used this function to plot the fitness values of an optimization algorithm against the iteration number, where fitness is defined as the proportion of white pixels in an image. In general, when the algorithm iterates, the fitness values rise, which shows that the segmentation performance is strengthening. The plot can aid in our comprehension of the algorithm's performance and rate of convergence to a successful solution. While a sluggish increase in fitness values could mean that the algorithm has hit a local optimum and needs to be tweaked or further optimised, a quick increase in fitness values suggests that the system is making substantial progress. In order to evaluate the effectiveness of the algorithm and spot any problems or patterns, it may be helpful to use this function to visualise how the fitness values vary over time while the algorithm iterates.

```python
def plot_fitness(fitness_values):
    plt.plot(range(len(fitness_values)), fitness_values)
    plt.xlabel('Iteration')
    plt.ylabel('Fitness (Proportion of white pixels)')
    plt.show()
```

- **Finding Average fitness value:** we have to calculate the average fitness for a range of values defined as significant_range by taking a subset of fitness_values. Finally, the average fitness is printed to the console using an f-string.Using these values we can compare result between different images.

```
import numpy as np
significant_range = range(200, 400)
significant_fitness = fitness_values[significant_range]
avg_fitness = np.mean(significant_fitness)
print(f"Average fitness for significant changes area: {avg_fitness}")
```

- ## Edge Detection using Canny Algorithm:

Firstly, we tried Sobel and Prewitt operator to proceed further but we faced some problems like –low accuracy,localization and false detection.But Canny Edge detection algorithm have low error rate,high accuracy and parameterized.It gives us better performance. The Canny algorithm works by first smoothing the image using a Gaussian filter, then computing the gradient magnitude and orientation.

The gradient magnitude formula is used to compute the strength of the edges in the image. It is given by:

G(x,y) = sqrt(Gx^2 + Gy^2)

(where Gx and Gy are the x and y derivatives of the image, respectively and finally applying non-maximum suppression and hysteresis thresholding to obtain the final edges)

```
edge = cv2.Canny((cv2.convertScaleAbs(img_blur,25,2)),100,100)
```

- ## Contour detection:

This function is used to perform automated WBC detection and segmentation in an input image using a PSO algorithm, edge detection, and contour detection. The function also draws bounding boxes around the detected WBCs for visualization purposes.

```
def contours():
    marked= pso(image, 10, 5)
    img_blur = cv2.GaussianBlur(marked, (5,5), 0)
    edge = cv2.Canny((cv2.convertScaleAbs(img_blur,25,2)),100,100)
    contours, hierarchy = cv2.findContours(edge,cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NONE)
    cv2.drawContours(marked, contours, -1, (0, 0, 255), 2)
    plot_fitness(marked)
    for i, cnt in enumerate(contours):
        x,y,w,h = cv2.boundingRect(cnt)
        cv2.rectangle(marked,(x,y),(x+w,y+h), (0,0,255), 2)
```

In summary, this methodology section described the key methods and techniques used in this project to achieve the objectives. The project utilized PSO algorithm, canny edge detection, contours detection, plotting graph for visualization. While implementing the methodology, some challenges were encountered, such as this code is specifically designed to detect white blood cells in microscopy images. Therefore, it may not be suitable for detecting other types of cells or objects in different types of images. Overall, the methodology used in this project is successful to detect WBCs, as described in the next section.

Chapter 4

4.1 Experimental Dataset

- Platform used: Python
- IDE used: Spyder & Visual Code
- Designing tools used: PSO-based Clustering
- Dataset used:

Dataset*: https://raabindata.com/free-data/

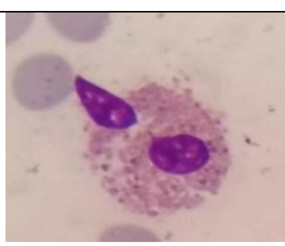
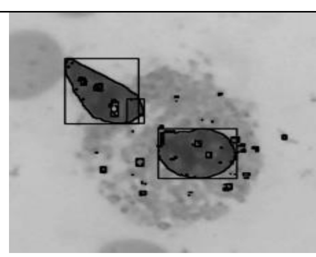
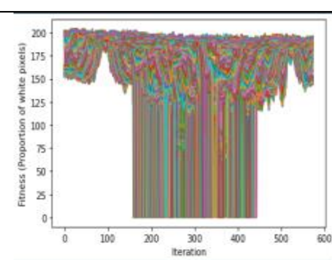
Dataset#: https://drive.google.com/drive/folders/1XGDf0P--G8fbTEV5vLdmr1kZIGckFVFG

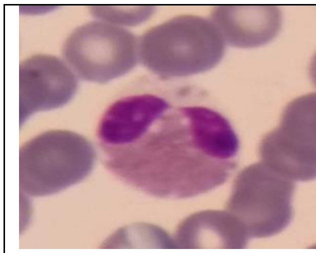
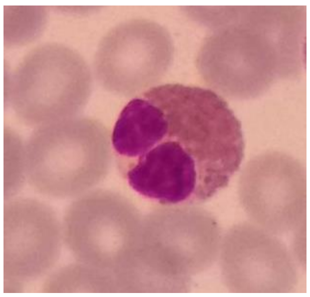
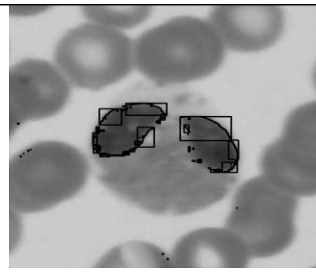
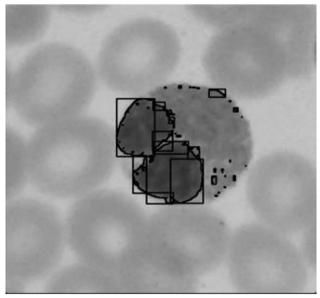
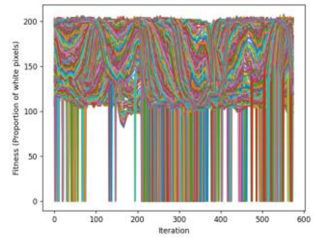
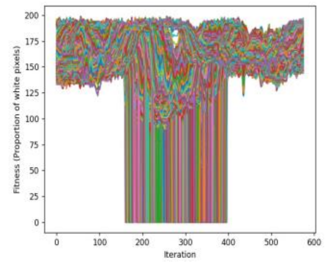
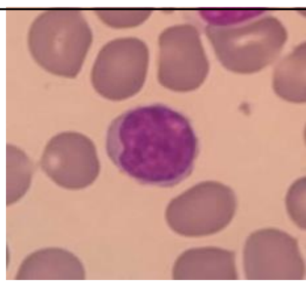
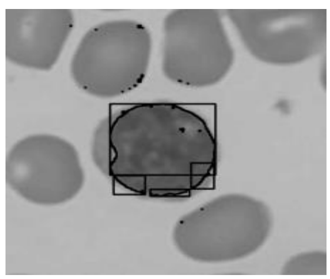
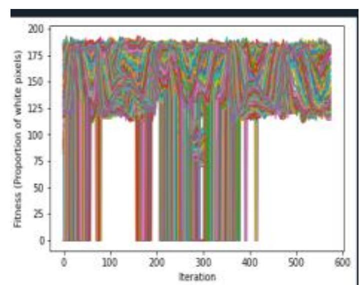
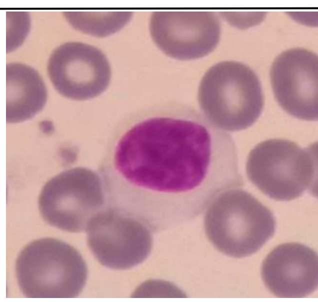
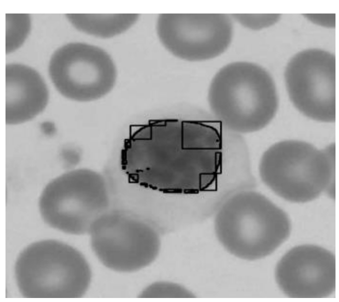
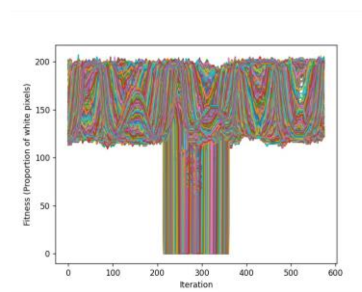
Two different datasets used in this study are Raabin-WBC Dataset , IEEEDataPort WBC Dataset. These datasets are discussed in the next sections, and are compared in Table 4 and Table 5. Also, Table 1 and Table 3 shows some sample images of these two datasets.

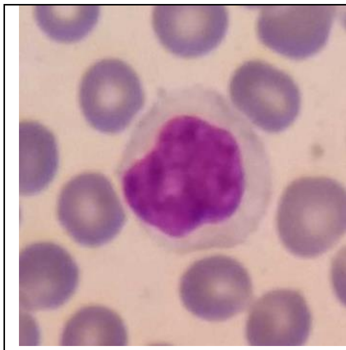
Chapter 5

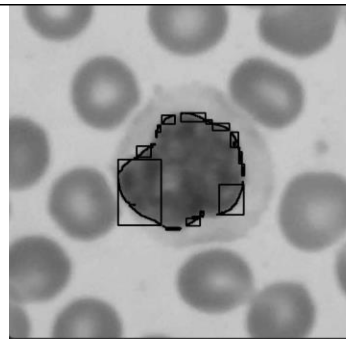
5.1 Result and Discussions

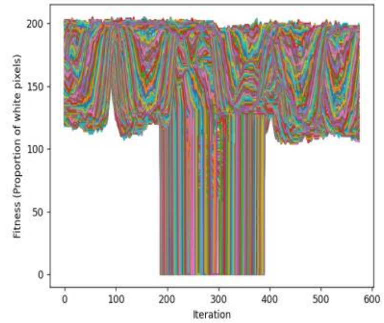
The WBC segmentation algorithm was applied to the test set, and the evaluation metrics were calculated. By using this proposed method we can segment all 5 types WBCs. These graphs can provide insights into how the fitness values change over the course of the PSO algorithm. Ideally, we would like to see the fitness values increase over time, indicating that the PSO algorithm is converging towards a good threshold value. In following graphs the x-axis represents the number of iterations, and the y-axis represents the fitness value at each iteration. This graph can be used to visualize how the fitness value changes over the course of the particle swarm optimization (PSO) algorithm. Output images shows segmented WBCs-

Original image	**Output Image**	**Iteration-Fitness graph**
 Eosinophil 1		

 Eosinophil 2  Eosinophil 3	 	 
 Lymphocyte 1		
 Lymphocyte 2		







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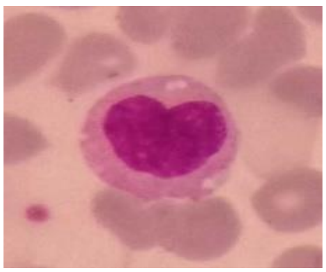

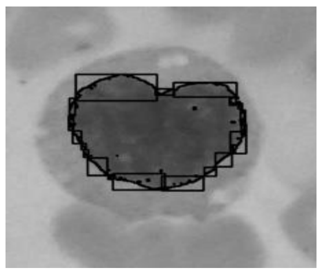

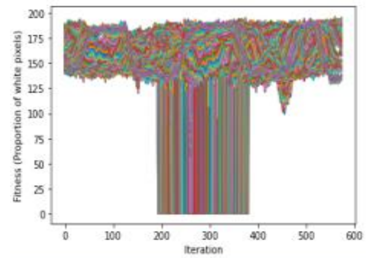

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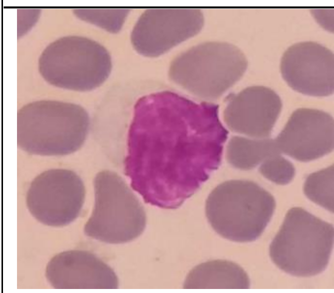

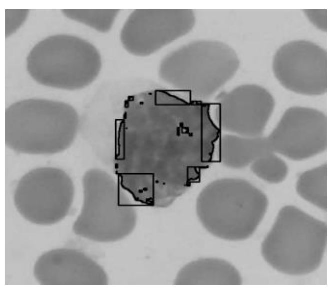

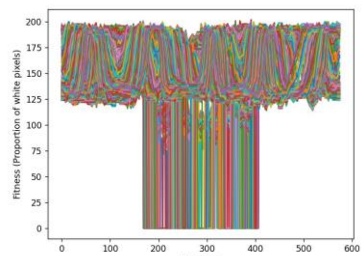

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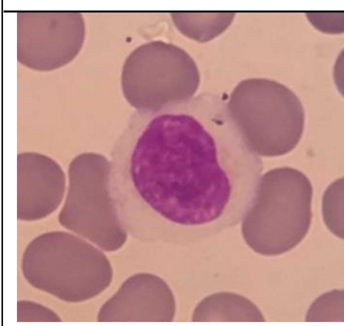

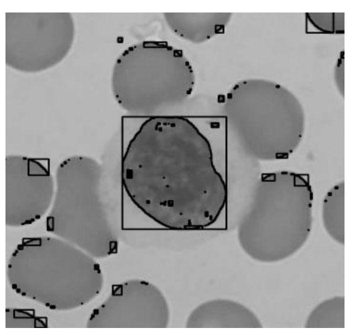

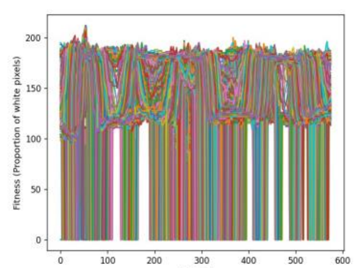

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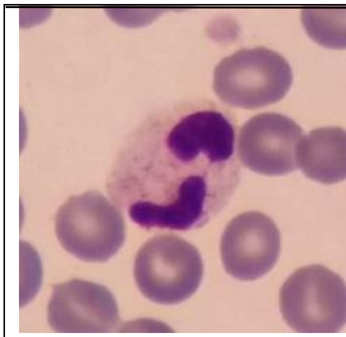
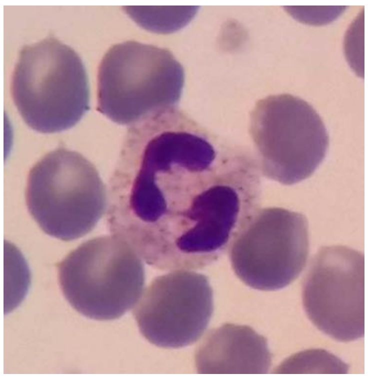
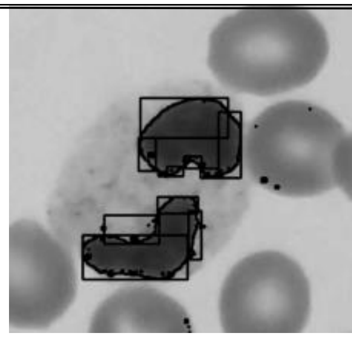
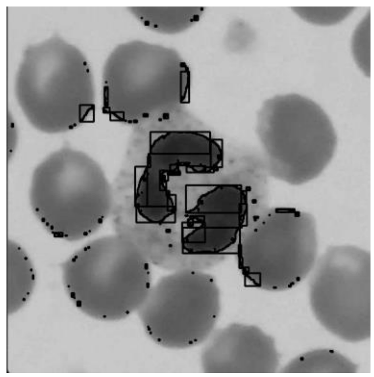
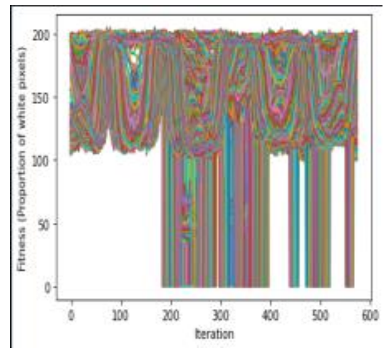
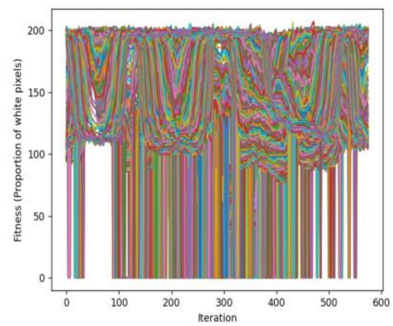
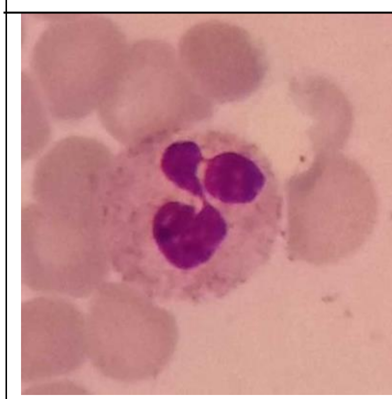
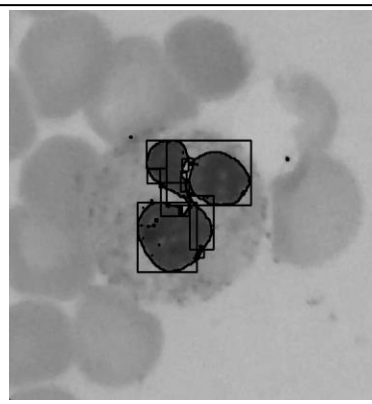
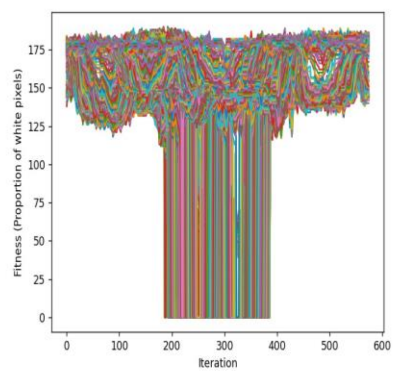
 Neutrophil 1  Neutrophil 2	 	 
 Neutrophil 3		

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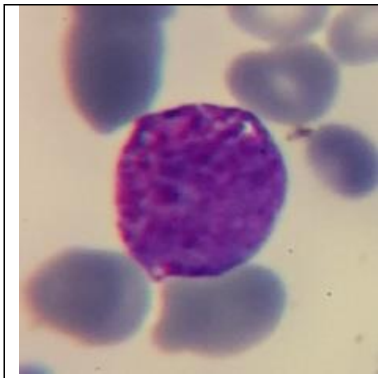
<td>

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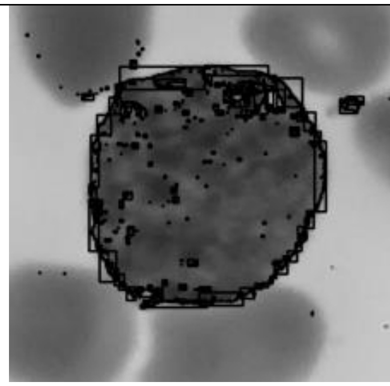
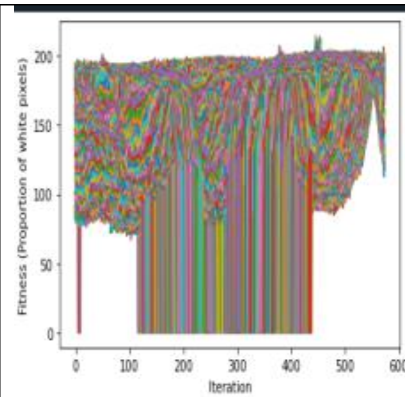
<td></td>
<td>
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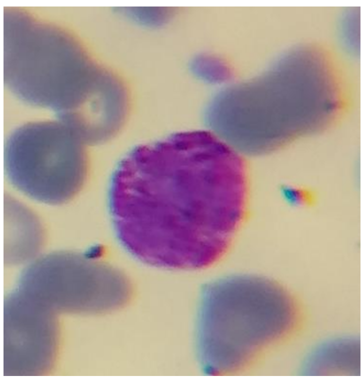
<td>

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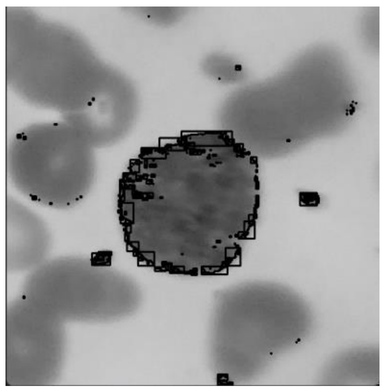
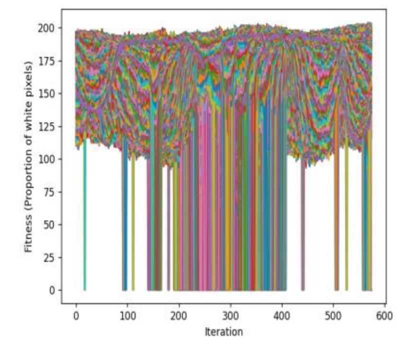
<td></td>
<td>
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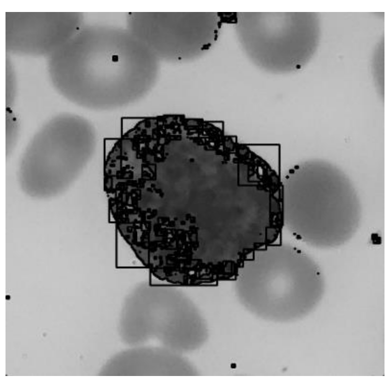
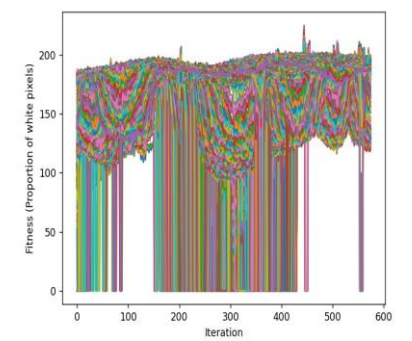
<td></td>
<td>
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Table-1

(Table-1 shows segmented images and iteration-fitness graph of five types of WBCs **from Dataset*-**Raabin-WBC datasets**)**

Types of WBC	Number of WBC	Average Fitness Value for 0-200 iteration	Average Fitness Value for 200-400 iteration
Neutrophils	20	179.73	149.19
Eosinophils	19	183.47	150.03
Basophils	21	138.91	126.78
Monocytes	19	155.55	138.35
Lymphocyte	20	162.26	160.94

Table -2

(Table-2 shows average fitness value and range of iteration of five types of WBCs on basis of numerous images of each type cell from dataset*-Raabin-WBC datasets .)

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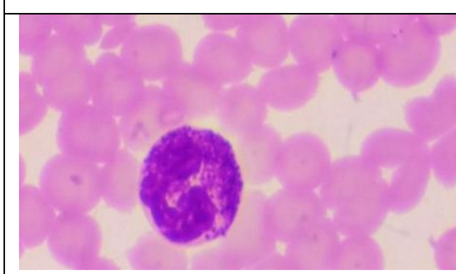
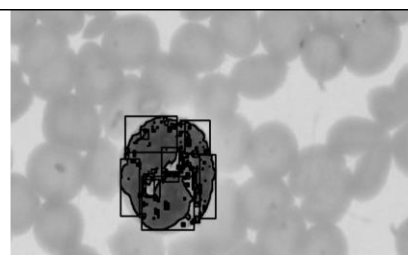
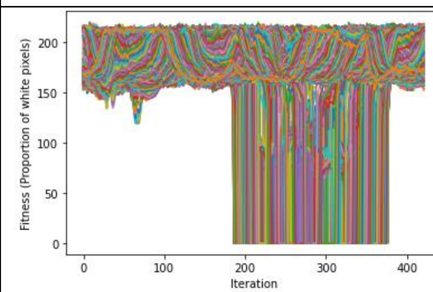
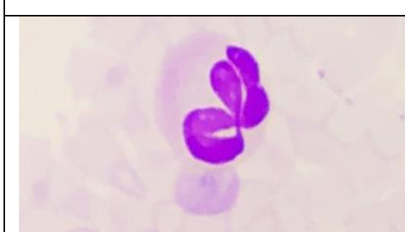
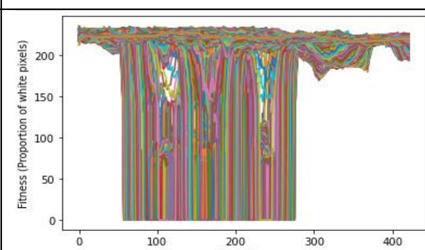
<tr><td>
Basophils 1</td><td></td><td></td></tr>
<tr><td>
Neutrophils 1</td><td></td><td></td></tr>
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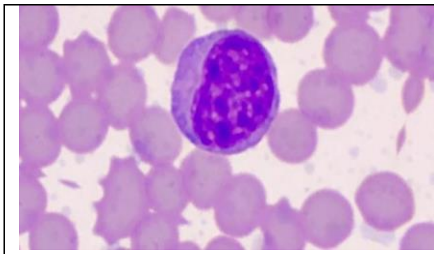

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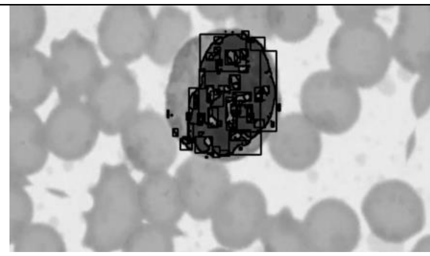

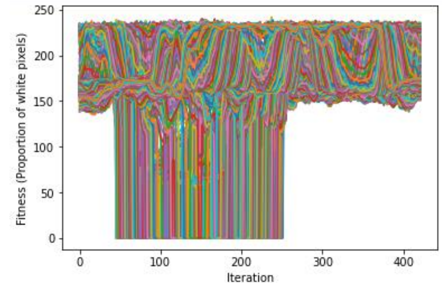

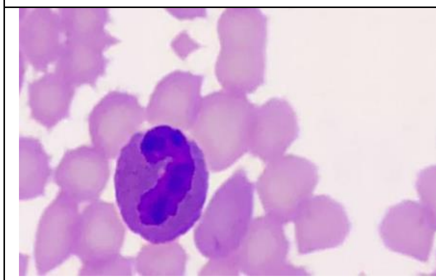

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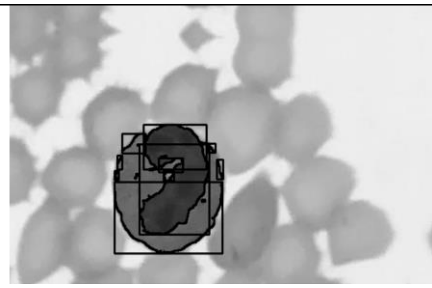

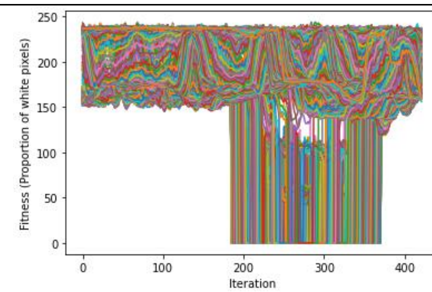

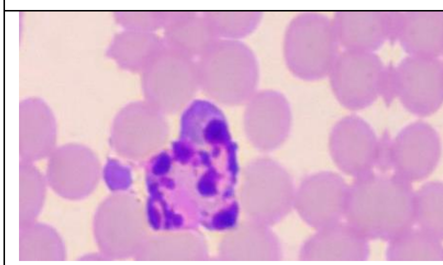

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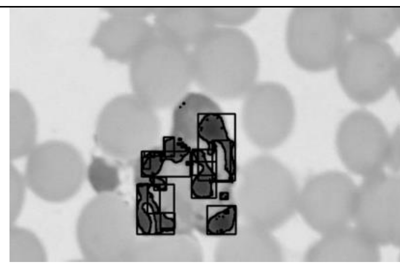

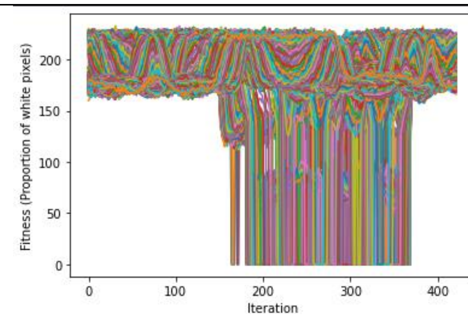

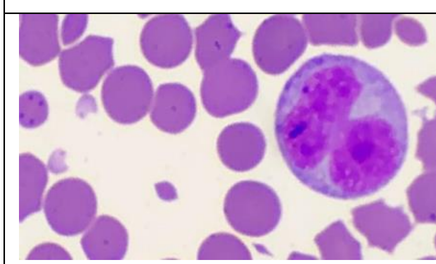

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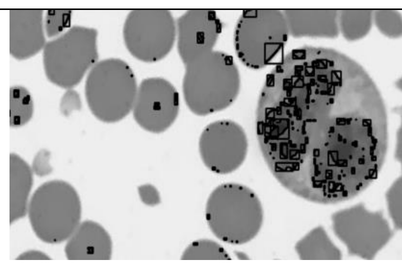

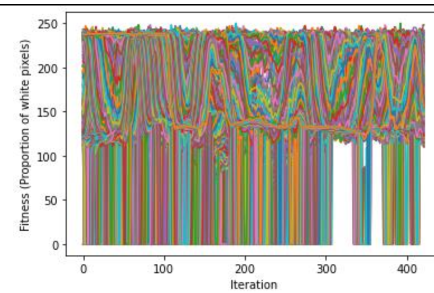

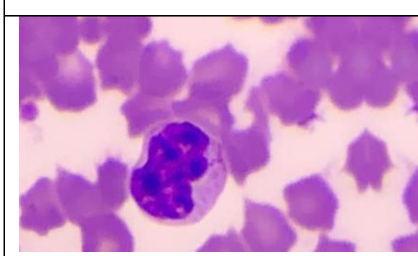

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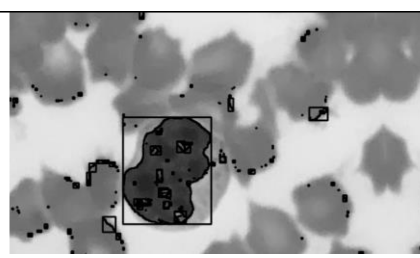
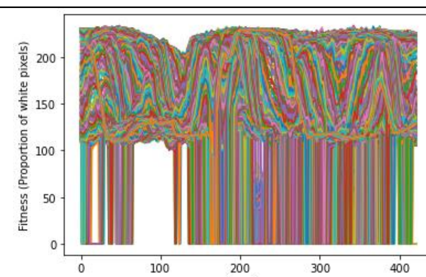




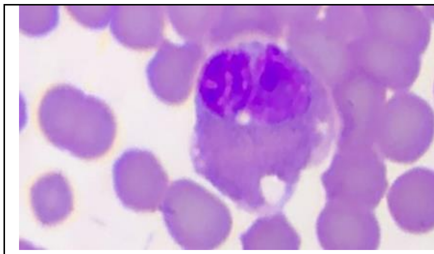
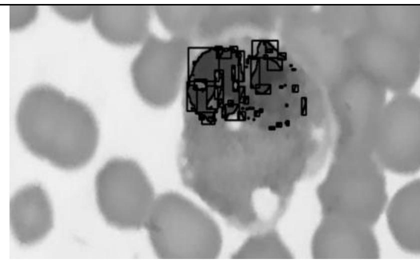
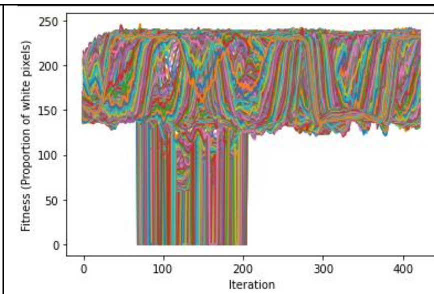
 **Eosinophils 2**		

Table-3

(table-3 shows original images,segmented images and iteration-fitness graph for 4 types WBCs-basophils,neutrophils,monocytes,eosinophils from **Dataset#-**IEEEDataPort)

Types of wbc	Range of iteration value	Average fitness value for Dataset*	Average fitness value for Dataset#
Basophils	0-200	138.9104	177.0811
Neutrophils	0-200	179.3918	207.6713
Monocyte	0-200	155.6995	165.8895
Eosinophils	0-200	183.1430	208.3888

Table-4

(Table-4 shows average fitness value of four types of WBCs from two different dataset for iteration 0-200)

Types of wbc	Range of iteration value	Average fitness value for Dataset*	Average fitness value for Dataset#
Basophils	200-400	126.101	175.884
Neutrophils	200-400	149.593	181.400
Monocyte	200-400	138.825	161.762
Eosinophils	200-400	150.966	178.758

Table-5

(Table-5 shows average fitness value of four types of WBCs from two different dataset for iteration 200-400)

Chapter 6

6.1 Conclusion

In conclusion, White Blood Cell (WBC) segmentation in microscopic pictures using Particle Swarm Optimisation (PSO) based clustering algorithms is a promising study area in medical image processing and computer vision. Comparing with other well-known methodology It can be concluded that our proposed method have following advantages -

Automated threshold selection: This approach automatically selects an optimal threshold value for binarizing the greyscale image, which eliminates step in traditional approaches.

Tunable: The number of particles and the maximum number of iterations can be adjusted to optimize the performance of the PSO algorithm.

High accuracy: PSO has been shown to be effective at finding optimal solutions for a wide range of optimization problems, and in this case, it can lead to high accuracy in segmenting WBCs.

Robustness: The PSO algorithm is designed to handle noisy or complex data, which can be beneficial when dealing with images of varying quality.

We can also conclude that our proposed algorithm successfully works on two different datasets Dataset[*]- Raabin-WBC datasets and Dataset[#]- IEEEDataPort. And we are getting better average fitness values for Dataset[#].

The optimisation capabilities of PSO are used by PSO-based clustering algorithms to automatically select the best clustering parameters, such as the number of clusters, the starting centroids, etc. for WBC segmentation. PSO-based techniques may successfully tackle the difficulties of WBC segmentation, such as cell shape variability, overlapping cells, and picture noise, by adaptively optimising these parameters throughout the clustering phase, leading to enhanced segmentation outcomes.

All things considered, the use of PSO-based clustering algorithms for WBC segmentation shows potential for developing the field of medical image processing and aiding crucial applications, like automated blood cell analysis, disease detection, and treatment monitoring. More study in this field may lead to the creation of more sophisticated and precise WBC segmentation techniques, which would be advantageous to both patients and healthcare professionals in the long run.

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