Intelligent Classifier for WBC Physiology Assignment Based on Active Contour Model

Sammar Jaafar Ismail*

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Abstract

White blood cell (WBC) plays an important role inside human body, because it is acting as the body defense mechanism against infection and cellular injury. Segmentation in biomedical imaging often the starting point for other process. In this paper an Intelligent classifier has been used to classify the normal and abnormal WBC, this model built using MATLAB 7 package. The output from active contour model (ACM) will be the input to the intelligent classifier . The accuracy of classification is about 90% according to American Heart Association (AHA) to evaluate procedures for diagnose in biomedical applications. The approach provide a robust and accurate results.

Keywords: Active contour, Image segmentation, WBC, Pattern classification.

بناء نموذج لمصنف ذكي استنادا الى فسلجة خلايا الدم البيض باستخدام تقنية المنحني الفعال

الخلاصة

ان الخلايا البيضاء في جسم الإنسان تعتبر من الأجهزة الدفاعية عند إصابة الإنسان بالإمراض او الجروح. تعد تقنية التقطيع المستخدمة في الصور الطبية مفتاحا للعديد من التطبيقات الطبية. تم في هذا البحث استخدام نموذج التصنيف الذكي لتصنيف كريات الدم البيض السليمة و المريضة وتم استخدام الحقيبة البرمجية MATLAB 7 لبناء البرنامج. إن الخرج من عملية المنحني الفعال (ACM) سوف يكون الدخل للمصنف الذكي. لقد أظهرت النتائج دقة بمقدار 90% استنادا إلى مواصفات الجمعية الأمريكية للقلب لتقييم عملية التشخيص في التطبيقات الطبية. وتعبر هذه النتيجة عن ثبات و دقة النموذج.

1. Introduction

Recently biomedical science that deals with modern health care striving to provide cost effective point of care diagnoses and personalized treatment. One of the general task of image segmentation in biomedical applications, is to split the image into several parts like objects [1,2,3,4]. Generalsegmentation lgorithms are classified in to six classes,

* Electromechanical Engineering Department, University of Technology/Baghdad

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2412-0758/University of Technology-Iraq, Baghdad, Iraq

thresholding, region based, edge based, graph based, classification based and deformable models. These techniques usually work on either separate pixels or local imaging patch, and they are very sensitive to noise and gap in boundaries [1,2,5,6].

The active contour model (ACM) has been developed to handle these problems [7,8]. Many applications which consist of: detection of coronary boarder, surgery simulation, surgical planning, measuring tumor classification of blood cell, studying brain development etc.

Intelligent system underlie what is called soft computing, the precision and certainty carry a cost [9]. The principle partners in such consortium are fuzzy logic, neural network, genetic algorithm and paradigms. Soft computing and their hybrid with other techniques in general used to enhance artificial intelligent techniques (AIT) and incorporation human expert knowledge in computing process [9].

In this paper one of the soft computing techniques (artificial neural network- multi layer perception) used with active contour model to build an intelligent classifier model to distinguish the normal and abnormal WBC. By using the American Heart Association (AHA) recommendation have been employed to evaluate procedures for diagnoses the WBC type.

2. Active Contour Model:

Kass et. al., have proposed the active contour algorithm (snake), as attempt to detect edge and segment it [7].

The basic idea is that, parameterized curve is drawn outside or inside the object that is to be segmented. This curve or contour is attracted to or pushed away from certain feature of the object in the image [10].

The total energy of an active with parametric representation v(s) = (x(s),y(s)) , can be written as follows:

$$E_{total} = \int_0^1 E(v(s))ds \quad \ldots(1)$$

$$= \int \_0\text{^}1 \text{▒} \; [\![E\_int\,(v(s)) + E\_ext\,(v(s))ds]\!] \quad \ldots(2)$$

In this equation, (s) is the parameterization $\in [0,1]$, E_{total} is the total energy, E_{int} is the internal energy. The internal energy is giving by:

$E_{int} = E_{cont} + E_{curv}$

$$= \propto (s) \left|\frac{dv}{ds}\right|^2 + \beta(s) \left|\frac{d^2v}{ds^2}\right|^2 \quad \ldots(3)$$

where E_{cont} is the contained energy which ensures that the parameterization points remain equidistant from each other. E_{curv} is the curvature energy which maintains the rigidity of the snake (the higher rigidity lead to the smother curve).

The weight factor for the elasticity is constant ($\propto$), the higher value of this constant is more the contour points will be

drawn towards each other. The weight factor for the curvature is the constant (β), the higher value of this constant produce many contour points, this will appear as a part of rigid rods.

Both internal energies of the snake are depending on the distance between consecutive points for this reason it is necessary to calculate the difference between two points.

The external energy is usually taken to be gradient magnitude of the image.

$$E_{ext} = -\gamma|\nabla G_\delta(x,y) \times I(x,y)|^2 \ldots(4)$$

In this section, $\nabla G_\delta(x,y)$ is the Gaussian Kernel with scale γ which convolves with image I(x,y). γ is a constant represents the weight factor for the image energy that attracts by the image features [6, 10, 11].

3. Terminology and standard measurements:

The American Heart Association (AHA) recommended the use of four measurements to evaluate procedures for diagnose in biomedical applications. These measurements are useful in other area of diagnoses as well as be used in evaluating most diagnoses system.

$$(TPF) = TP \times 100/TP + FN \quad \ldots(5)$$

$$(TNF) = TN \times 100/TN + FP \quad \ldots(6)$$

$$PA = TPF \times P(D) + TNF \times (1 - P(D)) \quad \ldots(7)$$

$$PV = \frac{TPF \times P(D)}{TNF \times (P(D) + (100 - TNF) \times (1 - P(D))} \quad \ldots(8)$$

Where TP is the true positive, FN is the false negative, TN is the true negative FP is the false positive, TPF is the true positive fraction (sensitivity), TNF is the true negative fraction (specificity), PA is the predictive accuracy, PV is the predictive value and P(D) is the priori probability.

$$FPF = 1 - TNF \quad \ldots(9)$$

$$FNF = 1 - TPF \quad \ldots(10)$$

Where FPF false positive fraction probability healthy patient be incorrectly diagnosed and FNF false negative fraction is the probability that a patient who is suffering from diseases will incorrectly diagnosed as health [9].

4. The Proposed Model:

The proposed model divided in to three stages: Processing the input image stage, ACM stage, and intelligent selection (classification) stage. The three stages operate together to classify the normal and abnormal (sick) cells, as shown in Fig. (1)

Processing the input image stage contains two enhancement procedures which manipulate the input images. These procedures help the ACM to detect the WBC correctly from the microscope image. First procedure, convert all input images to gray scale images (0-255), where 0 is black and 255 is white. Second

procedure, normalizing the gray scale images to reduce the variability between the images. The image size is 64 × 64 pixel.

Twenty one different type of WBC where used to cover the research (10 normal cells and 11 abnormal cells), as shown in Fig. (2).

The ACM stage, received the input manipulate image then selecting some points on the image around the target cell. These points represent the initial values of the active contour to detect the boundaries of the target cell. The values of $\propto, \beta, and\ \gamma$ adjusted as shown in table (1).

The intelligent selection (classification) stage is represented by artificial neural network using multilayer perceptron (MLP) algorithm. The construction of the network contains three layers (input layer, hidden layer and output layer). The network was learned by a training set represent the types of the WBC. The learning rate and momentum are the most important parameters in the (MLP) algorithm. The learning rate varied during the learning process while the momentum value adjusted at (0.9).

The input layer consist of (82) neurons. The input vector contains the boundary pixel of the target WBC from the ACM stage as shown in Fig. (7-a). The hidden layer contains (30) neurons were selected by try and error procedure. The try and error procedure stopped when the network learned to satisfy the desire output. The output layer consists of (1) neuron, which is also represent the output of the model. The output vector contains the number of the WBC type as classified in table (2). The model classify the patterns as normal or abnormal as well as the name of the cell type

Fig.(3) shows the flow chart of the proposed model. The model was built using MATLAB 7.

5. Results and discussions:

The ACM progress sequence to get the boundary pixels for acute lymphatic leukemia cell type (abnormal) and for Monocyte cell type (normal) is shown in Figs.(4-a), (4-b), (4-c) and Figs. (5-a), (5-b), (5-c) respectively.

Initializing the ACM by selecting some points (seeding) is shown in Fig.(4-a) and Fig.(5-a). The ACM selection of the target cell boundary is shown in Fig.(4-b) and Fig.(5-b). The blue arc view of the internal and external energy distribution to capture the cell is shown in Fig.(4-c) and Fig.(5-c).

After training the twenty one WBC types to the network, validation process which is a random subset from the whole training set of data used to cheek the network validity. Validation data that applied to

the proposed model classified all correctly

Among 10 tested data, 8 images classified correctly and 2 images have un accurate results. These un accurate results may be due to noise edge in the image. As a compression, choosing a Neutrophil cell type (normal) Fig.(6-a) and Fig.(6-b) shows the distinguished cell and undistinguished cell respectively.

The term of training data, validation data and test data have a special meaning of artificial neural network (measuring its rigidity).

The two examples where selected from the training set. The boundaries of acute myeloid leukemia and lymphatic leukemia types of WBC respectively shows in Fig.(7-a) and Fig.(8-a).

These two examples were distorted by changing the pixels location randomly as shown in Fig.(7-b) and Fig.(8-b).

Fig.(7-c) and Fig.(8-c) shows the correct and distorted pattern together.

The model was able to classify the distorted pattern correctly. The test checks the reliability of the network.

Table (3) shows the input values to measurement and evaluate procedures for diagnose depending on the AHA.

Table (4) shows TPF sensitivity, TNF specificity, PA accuracy and PV the predication value of positive. These results show how the model correctly and accurately operates. The 90% accuracy of the model gives a very good result. The accuracy is one of the most important properties of registration methods. The predictive value of the correct diagnoses value gives an idea about the correct diagnoses.

6. Conclusions

In this paper an intelligent classifier to diagnoses normal and abnormal WBC have been used. Choosing the input within a certain aspect (like tissue shape, size, texture and density), and using ACM (one of the image processing methods to select certain parts from maps) support the classifier to give a 90% accuracy. Increasing the efficiency of the artificial neural network by combining it with other techniques. The proposed model satisfies a desired requirement and gives a very good performance.

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Table (1) input value to AHA measurements and evaluation.

α	β	γ
0.05	1	1

Table (2) Classificationof output vector

Pattern No.	Name of WBC type
Normal	
1	**Neutrophil)**
2	**Eosinophil**
3	**Bosophil**
4	**Lymphocyte**
5	**Monocyte**
6	**Hyper segmented**
7	**Atyplcal lymphocyte**
8	**Blast cell**
9	**Plasma cell**
10	**Normoblast**
Abnormal	
11	**Lymphatic Leukemia**
12	**Myleocytic Leukemia**
13	**Erythro Leukemia**
14	**Megakayocitic**
15	**Eosmophilic**
16	**Plasma cell**
17	**Monocytic**
18	**Myelomonocytic**
19	**Undifferentialted**
20	**Lymphoblastic**
21	**Myeloblastic**

Table (3) input value to AHA.

FN	*TP*	*TN*	*FP*	*P(D)*
2	*9*	*8*	*2*	*0.428*

Table (4) The AHA values for evaluation.

TPF	TNF	PA	PV
81.81%	80%	90%	80.76%

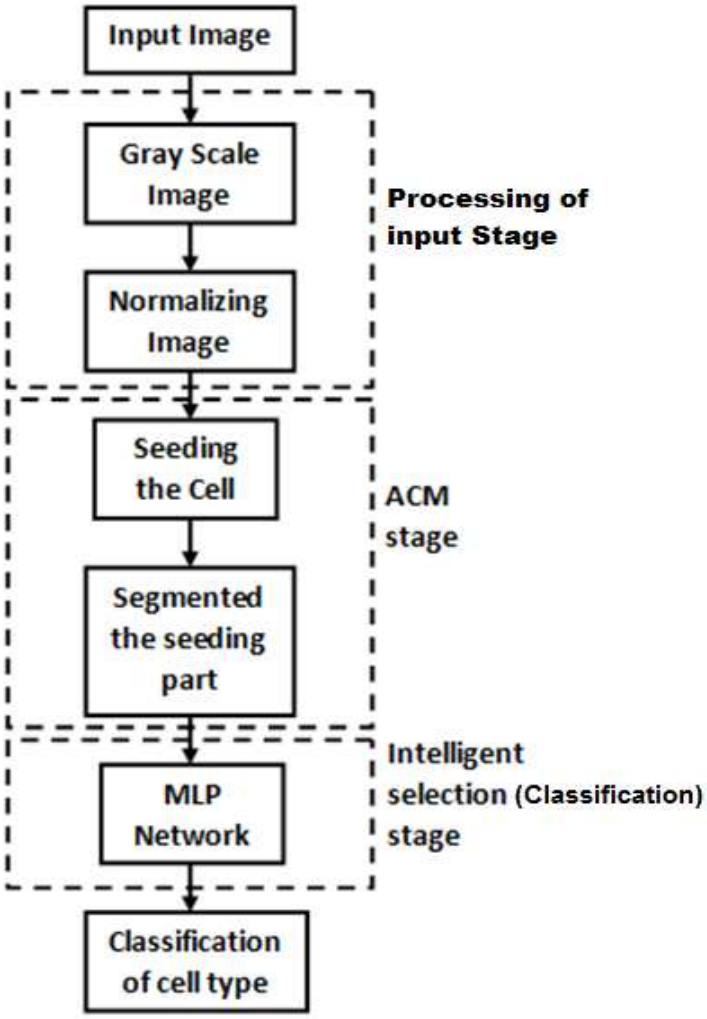


Figure (1) shows the three stages of the proposed model

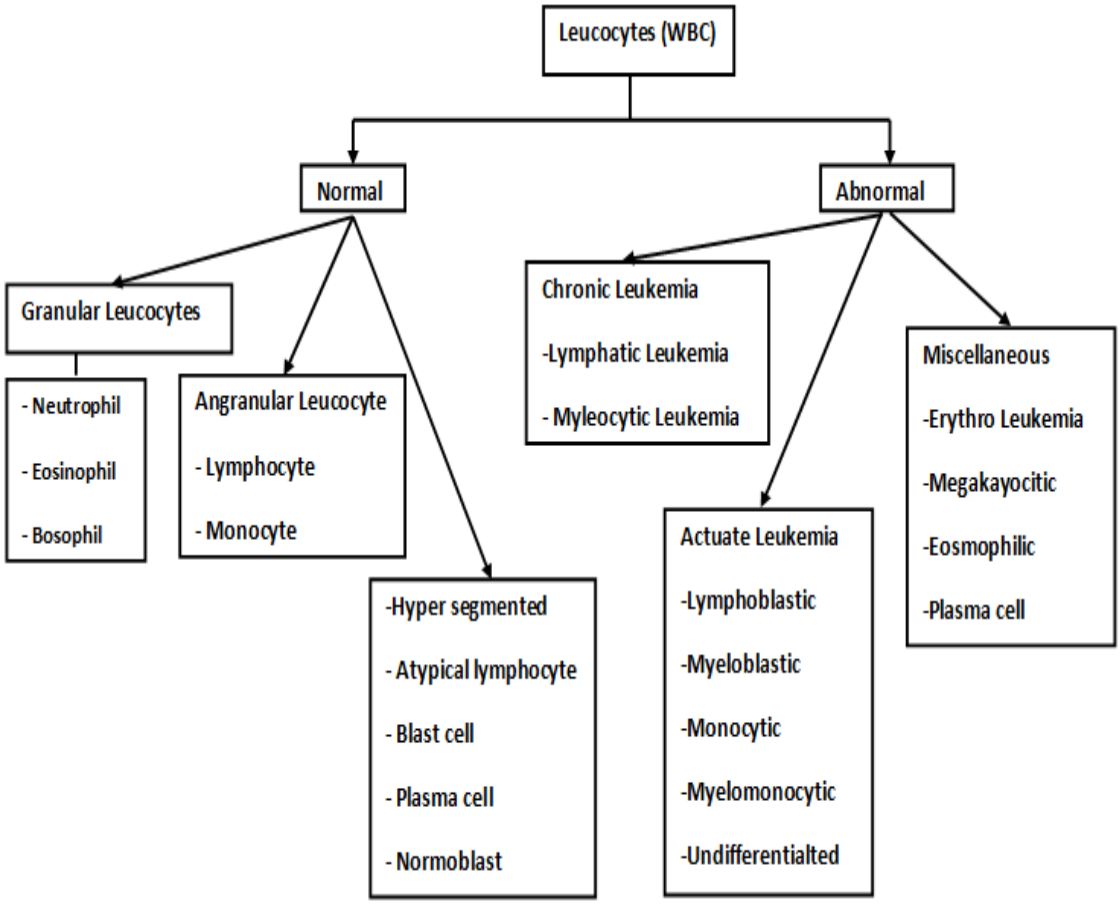


Figure (2) Shows types of WBC used in the training set

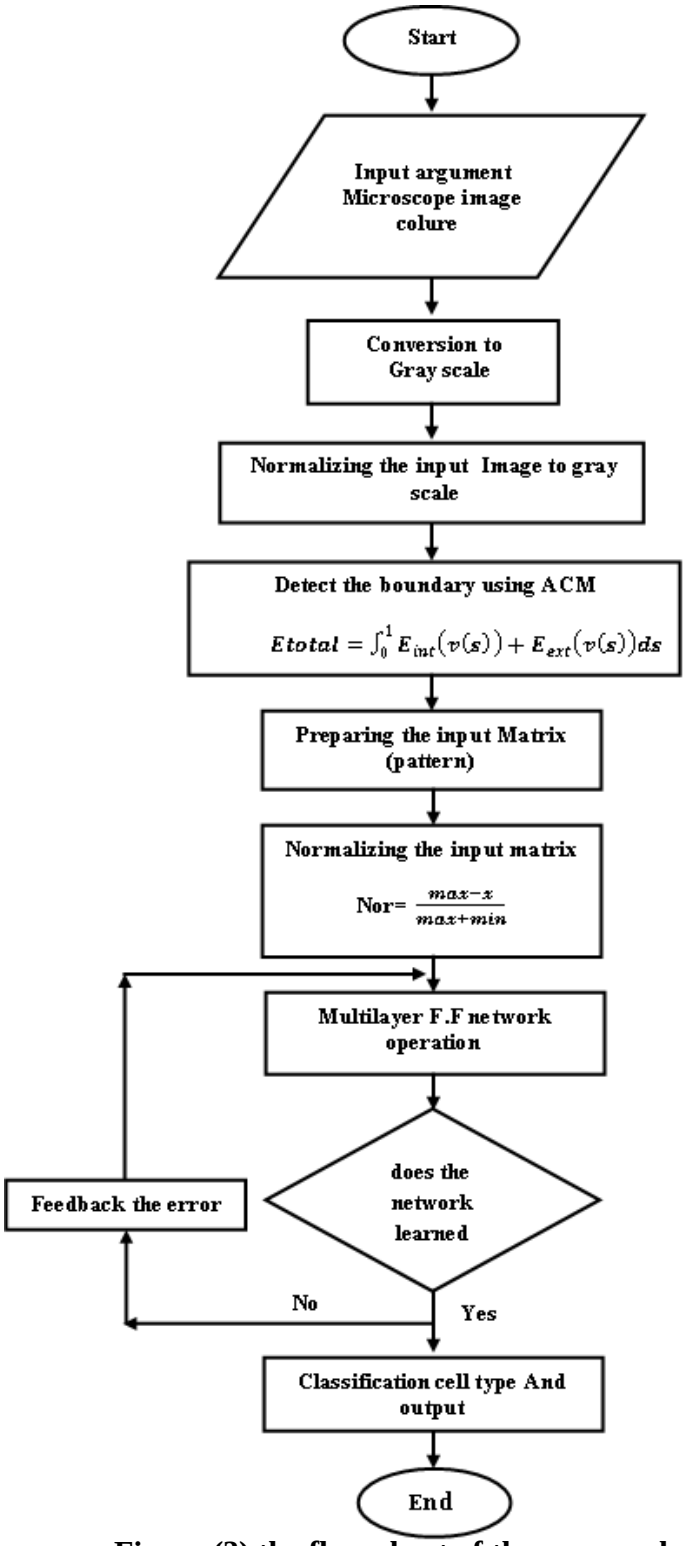
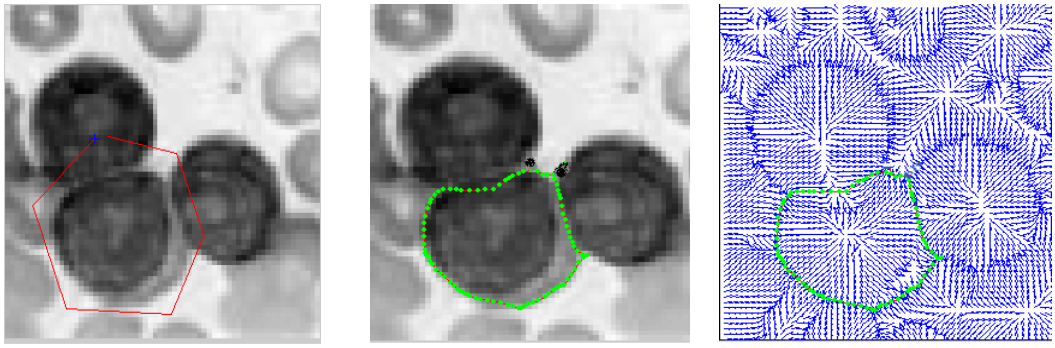


Figure (3) the flow chart of the proposed model



(a) (b) (c)

Figure (4) The ACM Progress Sequence for Lympathic Leukemia cell type.
(a) The seeding process in ACM (b) Selecting the object by the ACM
(c) Blue arc view diagram

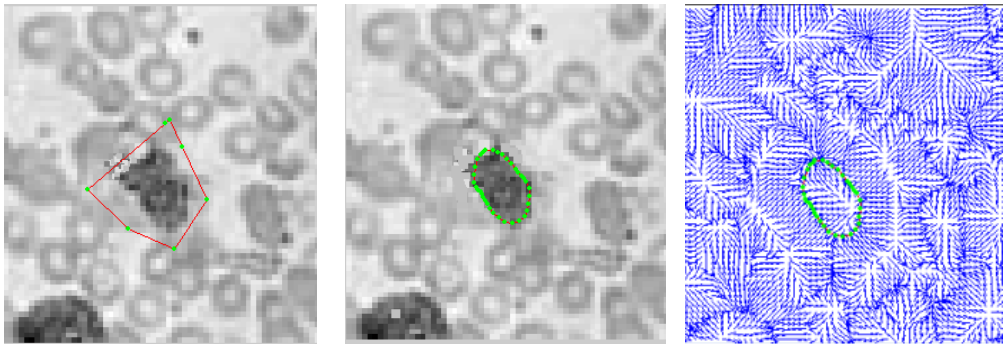
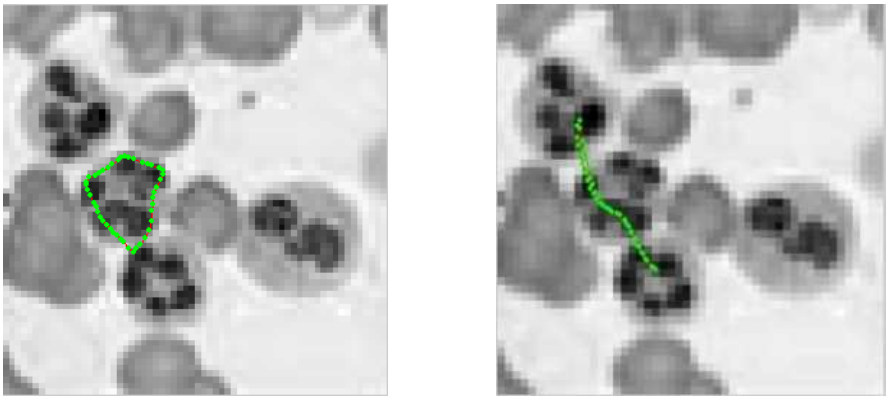
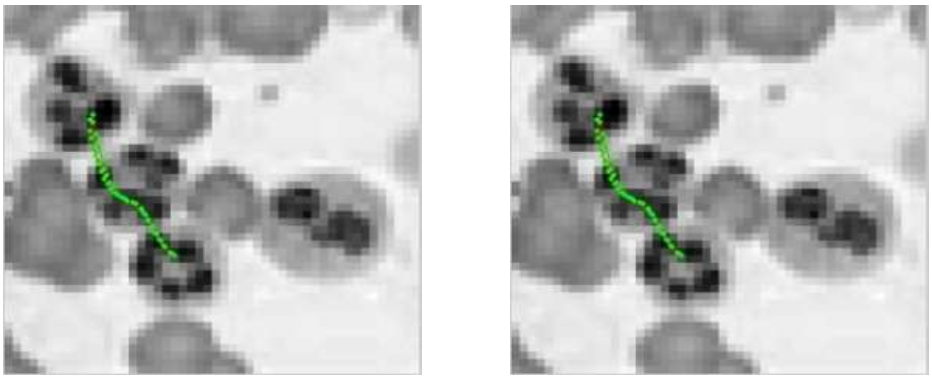


Figure (5) The ACM Progress Sequence for Monocyte cell type.
(a) The seeding process in ACM (b) Selecting the object by the ACM
(c) Blue arc view diagram

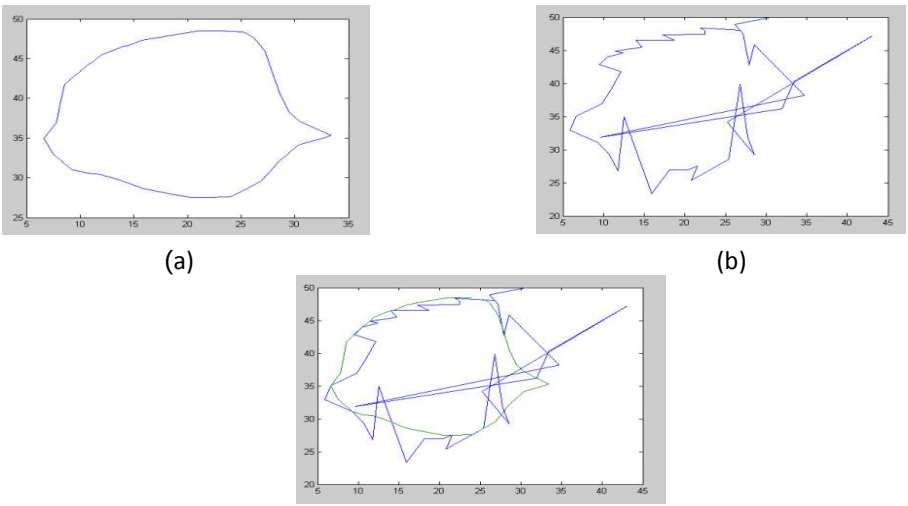


(a) (b)



(a) **(b)**

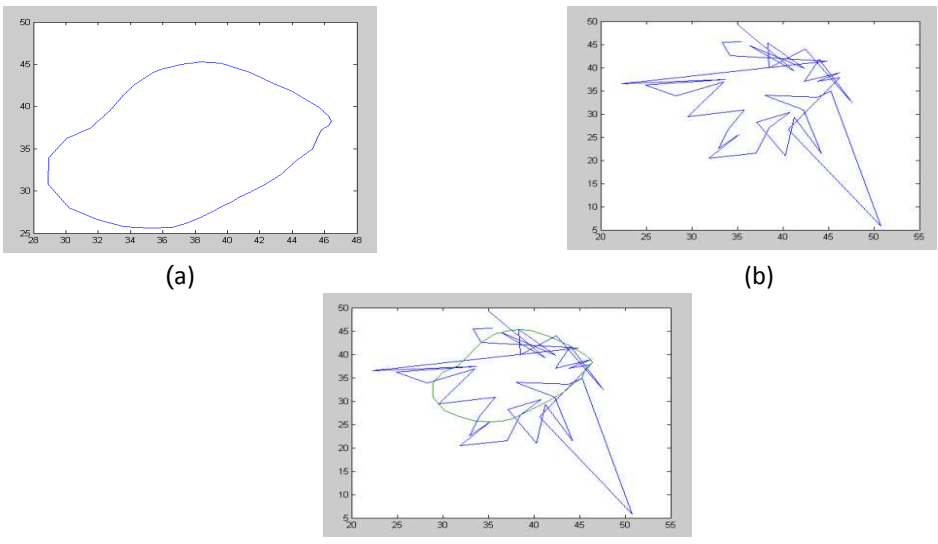
Figure (6) Selecting the Object By The ACM For Neutrophil Cell Type (a) Distinguished Cell By ACM (B)Undistinguished Cell By ACM



(a) (b)

(c)

Figure (7) Shows Acute Myeloid Leukemia Cell Type



(a) (b)

(c)

Figure (8) Shows Acute Lymphatic Leukemia cell type