Short Communication

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Extracting, Recognizing, and Counting White Blood Cells from Microscopic Images by Using Complex-valued Neural Networks

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ABSTRACT

In this paper a method related to extracting white blood cells (WBCs) from blood microscopic images and recognizing them and counting each kind of WBCs is presented. In medical science diagnosis by check the number of WBCs and compared with normal number of them is a new challenge and in this context has been discussed it. After reviewing the methods of extracting WBCs from hematology images, because of high applicability of artificial neural networks (ANNs) in classification we decided to use this effective method to classify WBCs, and because of high speed and stable convergence of complex-valued neural networks (CVNNs) compare to the real one, we used them to classification purpose. In the method that will be introduced, first the white blood cells are extracted by RGB color system's help. In continuance, by using the features of each kind of globules and their color scheme, a normalized feature vector is extracted, and for classifying, it is sent to a complex-valued back-propagation neural network. And at last, the results are sent to the output in the shape of the quantity of each of white blood cells. Despite the low quality of the used images, our method has high accuracy in extracting and recognizing WBCs by CVNNs, and because of this, certainly its result on high quality images will be acceptable. Learning time of complex-valued neural networks, that are used here, was significantly less than real-valued neural networks.

Key words: *Color system and feature vector, complex-valued neural networks, white blood cell*

INTRODUCTION

One of the today's challenges in medical science is recognizing diseases by recognizing and counting white blood cells. White blood cells are divided into two main groups (Granulocytes and A granulocytes) and five final groups (Neutrophils, Eosinophils, and Basophiles belong to the first whole group and Lymphocytes and Monocytes belong to the second whole group).

Existence of red blood cells with high quantity beside white blood cells makes the recognizing difficult. And the variety of white blood cells (in size and type) increases this difficulty.[1]

In Figure 1 all kinds of white blood cells and their classification are shown. The proportion of each one of white blood cells in a healthy and mature person is in this way; Neutrophils: 58.5%, Eosinophils: 3%, Basophiles: 0.5%, Lymphocytes: 34% and Monocytes: 4%. Changes in each one of these globules' quantity can indicate to specific diseases which their on-time and careful reorganization can have a special effect on their perfect conquer.[1]

In this article we try to introduce a plenary method, which proceed to extract, recognize and count the white blood cells in blood microscopic images with various qualities of color and resolution by complex-valued neural networks' helps.

In the second section of this article, previous related works has been presented. In third section, globule extracting by using the RGB color system[3] will be explained. And in fourth section, feature extracting and recognizing has been presented after introducing complex-valued back-propagation. And we do the scientific conclusions and the real implementation by using Matlab software.

RELATED WORKS

WBCs are recognized by automatic machines; for example, cell counter and other method based on electro-chemical methods or electro-physical based on laser methods, electric resistance and etc. on the blood instance by high cost.[4] Among these, the methods "Watershed",[5] "Gabor filter",[6] "Active contours"[7] and "Gradient vector flow",[8] etc. are also usable methods which are explained briefly in continuous.

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In the method based on watershed algorithm, first one image for demarcation is prepared by distance function. Then we segment the picture by using above algorithm and a recursive Post Processing procedure. In the method which uses the Gabor filter, one Gabor filter bank is designed for distinguishing the border between WBCs and RBCs which their tissue is deferent from each other. In this bank, because of non-existence of dominant direction in the globules' tissue, the used direction is more than the usual quantity and they are few versus frequency's quantity because the image's dimensions are small. Also, is proposed one method for determining the first place of the curve in "Active Contour" method by using the nucleus's information. In this method, we use a version of "Active Contour" which is based on the image's gradient and has suitable results.

In practice, we implement the methods like Gram-Schmidt is for apportioning the nuclear areas (which the result of implementing this method on a hematology image, is an image which has the most amount of light in desirable areas, means the WBC's nucleus areas, and the less amount of light in other areas.), Deformable algorithms (snake algorithm) for segmentation Cytoplasmic areas, and comparative algorithm for finding the best primary contour for the snake algorithm, and by artificial neural networks and Support Vector Machine (SVM) is obtained precision between 90% and 96%.[9,10]

In using the method Granulometry on the based diameter of the recognized parts in image and omitting the not needed parts,[11] if other parts change because of disease access and similar things there is possibility for errors. The best acquired conclusion up until now belonged to the "Active Contour" method, and the quickest one belonged to the "Watershed" method.[4]

GLOBULES EXTRACTION

Here, we extract the addresses from blood's microscopic images which WBCs exist there. In the reviews done on these images, the difference of color and size among WBCs and other blood cells was in the way that seems by using these features we can separate the WBCs from other cells. In Figure 2, there is a microscopic image which has 5 white blood cells of Neutrophil kind.

In this method, first we change image's size to a determined size, then we use the point that "in blood's images, white blood cells in the blue part have noticeable differences with the other cells" and we peruse all of image's pixels values, and if the value of each spot's blue color is more than a constant number, we make some changes in it by using equation (1).

$$x1(kk,jj,3)=abs(x(kk,jj,3)) \quad (1)$$

In above equation x (kk, jj,3) are the pixels of the first image's blue color page, $x1$ (kk, jj,3) are the pixels of blue color page of the acquired image of changes in first image's pixels. The result of implementing the above transformation on Figure 2 is shown in Figure 3.

Then we average values of three color planes of all points of new image (*Thresholding*), and we put 1 for the pixels which their average of their three colors is less than the average value plus a constant, and we put 0 for the other pixels. Output image is shown in Figure 4.

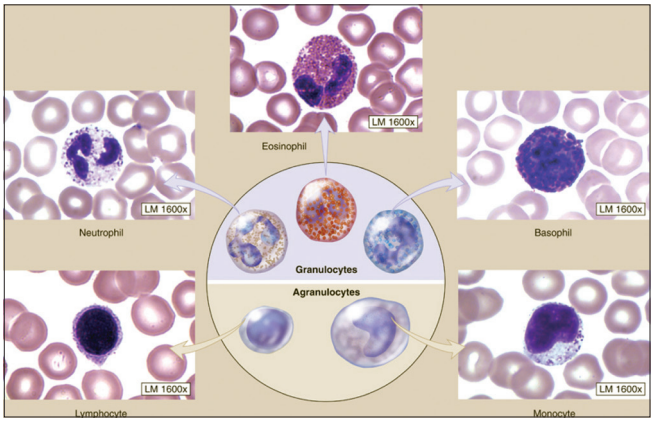

Figure 1: The picture of all kinds of white blood cells and their groups [2]

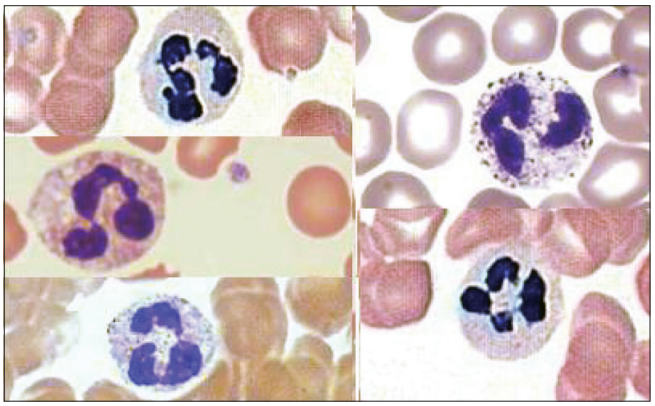

Figure 2: Blood microscopic image with 5 Neutrophils which is combined of some images with different qualities

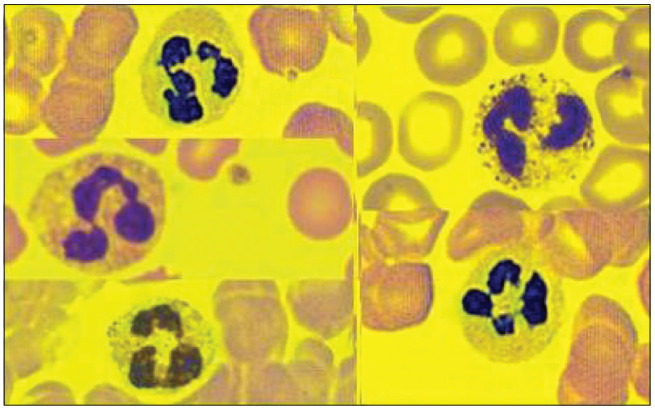

Figure 3: The output image of equation (1)

Every color we can see is compose of three colors (Red, Green and Blue) and change in each of them will change whole view of the color we can see. For example in Figure 5 we see changes in each color of an image.

Finally, the acquired white coherent spots from previous section which their values is more than a determined value, indicates a white blood cell. The result of noticing this issue is shown in Figure 6.

The noticeable point here is, as we know that the WBCs mainly divided into two groups (Granulocyte and Agranulocyte), but noticing the less quality of existing images, recognizing this feature is almost impossible, and we classify them in section 4 without regard to this feature.

EXTRACTING FEATURE AND RECOGNIZING BY COMPLEX-VALUED BACK-PROPAGATION NEURAL NETWORK

Extracting Feature

In this section we put the extracted WBC from the image in the center of one square with a side equal to the size of acquired square to the basic square which is here 100 × 100. Then, we blacken the background spots which is here those out-of-edge spots (we assign 0 to them) and we whiten the spots which are in the image (we assign 1 to them).

Edge's spots and radial lines

Here we get the ratio of surrounded spots in image's edges to the whole square's spots and we name it "a", and also we attained the all edge's spots number and name it "b". We drew some lines in the radial form from the square's centre, which is now so close to the gravity centre of object. We drew these until they interrupt the edge at spots, we save the strike spots' coordinates (and if they don't bop the edge, the square's extreme spots) in a vector. And then we save the distance between strike spots and the centre in another vector and then we normalize it (r). We arrange the normal acquired vector in the ascendant way name it "R". The number of the drawn radial lines and also normalizing expanse is related to the system resources and also to the needed delicacy.

Concentric squares

After doing all above stages and extracting the selected square which its size has been determined, we draw some concentric squares from that center (in the way that each square's side is just two pixels bigger than the previous square) until they interrupt the image's edges in some spots. And this time we put the spots' number in order from the first circle to the last circle in a vector and then we name the vector "C".

Color's real histogram

Here instead of using image's gray level histogram, we use the histogram which is emanated from all three color sheet in the RGB color system. Its result is a vector which by dividing each color level's range to 3 parts we get 27 elements for the histogram, which every level of them are shown in Table 1. These 27 elements will be saved in

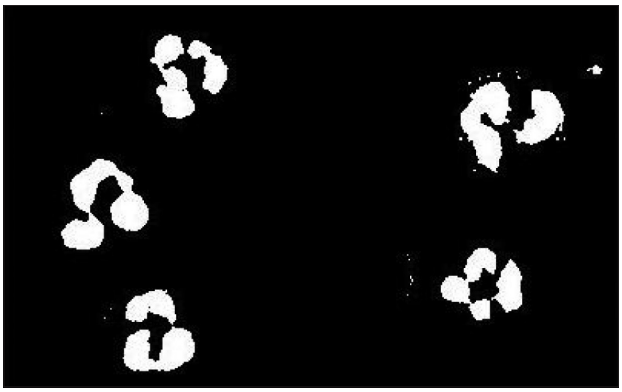

Figure 4: Thresholding image

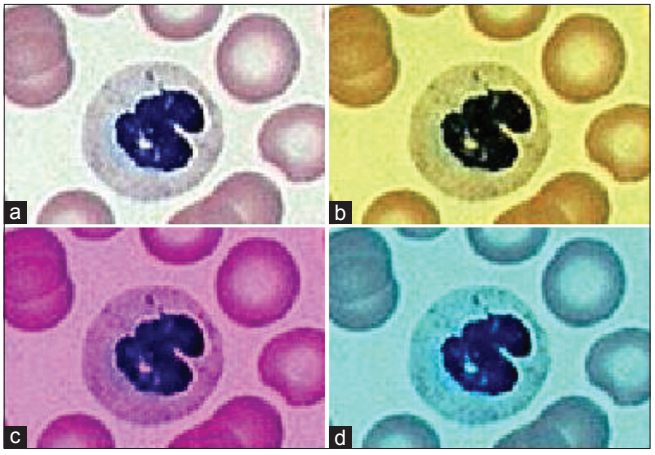

Figure 5: Effect of change in each channel of an image; (a) Original image; (b) Original image with Blue channel minus 100 (c) Original image with Green channel minus 100, and (d) Original image with Red channel minus 100

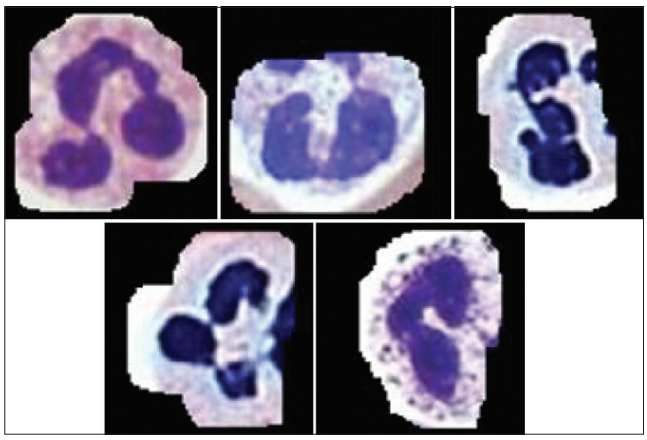

Figure 6: The extracted white blood cells from Figure 2

a vector and they are demonstrator for possible colored levels for this histogram. After extracting the histogram, we normalize it (by natural logarithm) and save it in another vector, equation (2), which is shown in the Figure 7 and after arranging in the ascendant layout (because of the color conversion which we mention above, we arrange the histogram in order to have less effective color conversion in the main object), we name it "H", equation (3). The histogram's levels value is determined noticing the system's resources and the needed delicacy.

$$h=rgbhist(fig) \quad (2)$$

$$H=sorted(h) \quad (3)$$

In above equations h is real color histogram and H is sorted of h.

We set all above vectors in a vector and after natural logarithm; we normalize them as equations (4).

$$S0=[H,R,C,a,b]$$

$$S1=log(S0+1)$$

$$S=S1/max(S1) \quad (4)$$

In above equations S0 is extracted feature vector, S1 is output of natural logarithm of S0 and S is normalized S1.

Recognition by Complex-valued Back-ProPagation and Counting

Introduction to complex-valued back-propagation

Complex-valued Back-ProPagation is a multi layer artificial neural network, which the three-layer kind of it (with 1 hidden layer and 1 output unit) has been shown in Figure 8, that instead of use of real value, it uses complex valued for input, output, weights or some of them or all of them and use complex values for activation function.

In every neuron from the network after achieving that neuron's net input for output making we should use an activation function. One high usage of activation functions in artificial neural network that we use in complex-valued neural network is tangent-hyperbolic (tanh), shown at Figure 9. We use this activation function here. Naturally we learn network by real-imaginary activation function type of tanh (discrete type of CVBP), we explain it in (5).

$$f_{(R\_I)}(u)=f_R(u)+if_I(u) \quad (5)$$

Where f_{R_I} is real-imaginary activation function (f_R is real part of activation function and f_γ is imaginary part of activation function) and u is input vector to function.

Table 1: Various colored levels for histogram

Blue	Green	Red
0-85	0-85	0-85
86-170	86-170	86-170
171-255	171-255	171-255

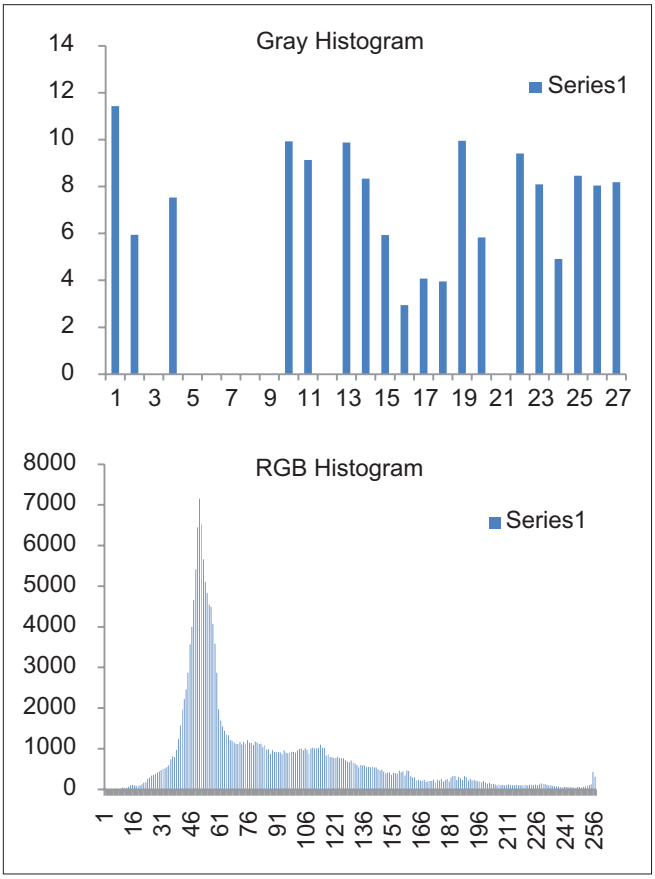

Figure 7: Comparing the gray histogram with the colored one

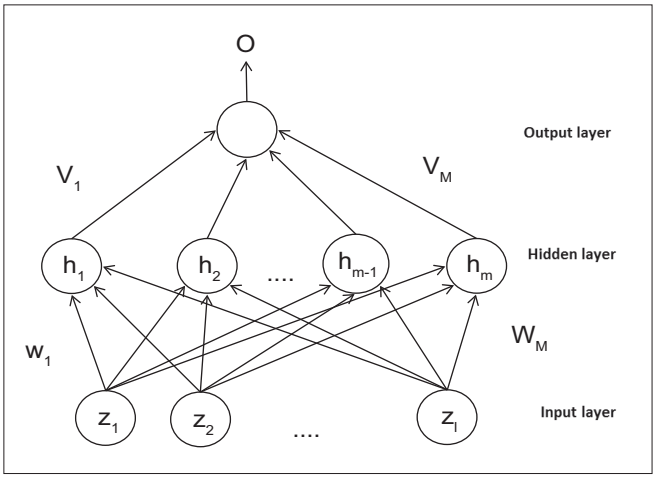

Figure 8: A three layer back-pro pagation, with 1 hidden layer and 1 output layer[12]

We use a CVBP here that has one hidden layer and one output layer, use real values to input and output and use

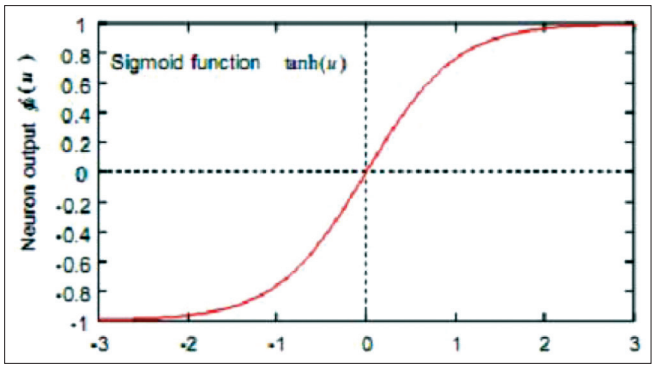

Figure 9: Tanh activation function[13]

complex values to weights and functions. Naturally use of real values to input and output do not dubious totality of problem, because real values are subset of complex values. Net input to hidden layer is vector "S" attained from (4).

$$U_m = U_m^R + iU_m^I \begin{pmatrix} w_m^R \\ w_m^I \end{pmatrix} \cdot \begin{pmatrix} X \\ Y \end{pmatrix} + \begin{pmatrix} w_m^I \\ w_m^R \end{pmatrix} \cdot \begin{pmatrix} X \\ Y \end{pmatrix} \quad (6)$$

Where U_m is net input, w_m^R is real part of weight, w_m^I is imaginary part of weight from *m-th* unit of hidden layer, X is real part of input vector and Y is imaginary part of input vector. Output of every hidden neuron is attained by (7) equation.

$$H_m = H_m^R + iH_m^I = f\left(U_m^R\right) + if\left(U_m^I\right) \quad (7)$$

Where H_m is output of m, f is activation function. Input of net to the output attained by (8).

$$S = S^R + iS^I = \begin{pmatrix} v^R \\ -v^I \end{pmatrix} \cdot \begin{pmatrix} H^R \\ H^I \end{pmatrix} + i \begin{pmatrix} v^I \\ v^R \end{pmatrix} \cdot \begin{pmatrix} H^R \\ H^I \end{pmatrix} \quad (8)$$

Where **S** is net input to output, V^R is real part of weight, V^I is imaginary part of weight, H^R is real part of output, H^I is imaginary part of output. Output attained by (9).

$$O = O^R + iO^I = g(S^R) + ig(S^I) \quad (9)$$

Where O is output of CVBP, g is activation function. Output error is attained by (10).

$$Dk = \text{real}(Y-T).*(\text{sech}(\text{real}(Y)).^2) + i*\text{imag}(Y-T).*(\text{sech}(\text{imag}(Y)).\hat{}\,2)$$
$$DV = \alpha * Z^* * Dk \quad (10)$$

Where *D*k is error of output unit, *DV* weight change vector for output unit, *Z* is output of hidden layer, *sech(.)^2* (secant-hyperbolic) activation function's derivation, *Y* is temporal output, α is learning rate and *T* is desired output. Hidden layer's error also attained by (11).

$$D_{in} = Dk * W^*$$
$$D_j = \text{real}(D_{in}).*(\text{sech}(\text{real}(z)).^2) + i*\text{imag}(D_{in}).*(\text{sech}(\text{imag}(z)).\hat{}\,2)$$
$$DW = \alpha * in^* * D \quad (11)$$

Where $(.)^*$ is conjugate transpose, *DW* is weight change vector in hidden layer, D_{in} is temporal error vector of output of hidden layer, *D* is hidden layer's error vector, *Z* is output of hidden layer, (.)^a means power by "a" of every member of vector separately and in is input vector.

Using complex-valued back-propagation neural networks for recognizing

Here, the image extracted feature vectors are sent to a two-layer CVBP neural network for classification. The aim groups which are here 5 groups (all kinds of white blood cells) are trained for the determined network and then experimented. In fact, we send vector S, the acquired from previous sections (which is the final vector), to a CVBP neural network for recognizing the group which the image is belonged to (first for training and at last for experimenting).

The images which are used for this system, has just one main part. And after extracting the edge and making the selected square and acquiring the explained vectors in previous sections, we determine each object's group. Here we used 85 image with resolution about 250 × 350, in 5 groups of white blood cells (including: 16 images of Basophils, 12 images of Eosinophils, 23 images of Lymphocytes, 10 images of Monocytes and 24 images of Neutrophils). Using the CVBP which was done in a amount of more than 20000 iterations with 167 elements input vector (equal to the attained vector from equation (4), including the results of colorful histogram, concentric squares, radial lines, edge points number and the proportion of the into-object spots to image's whole spots) and 87 hidden unit and one output. By training several times from the end of network's previous trainings we can train the data perfectly. The question answer of network about Figure 2 is in this way:

In Figure 2, we can see 5 Neutrophils which in the system's answer to the question about it, 4 Neutrophils and 1 Basophil are recognized and counted. This error is because of the image's less quality, and of course this errors are found in this system rarely.

In this training, we have used 85 images which approximately 25 percent of images, which are 20 images, as the test images, and we have used 60 images, for training. By the method which we explained above, we make the amounts of final output with the error average less than 0.5% near to the desired amounts of output. For example, if the aim is 0.9, the final output will be between 0.895 and 0.905. This is a desirable amount for training the pattern recognition in neural networks.

Table 2: Comparison complex-valued neural networks and real-valued neural networks and summary of result of white blood cells learning to a artificial neural network

Network type	Learning pattern number	Test pattern number	Recognized test pattern number	Learning iteration number	Output precision	Iterration time (second)
Complex	65	20	20	20000	99.3%	0.1
Real	65	20	20	33000	97.5%	0.07

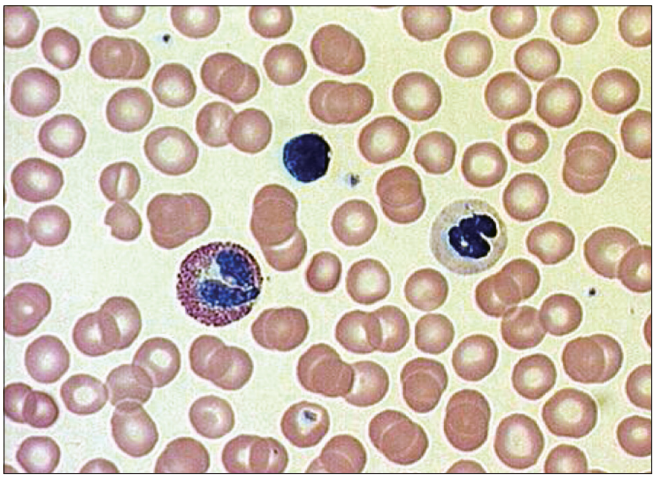

Figure 10: A picture include one Basophile, one Lymphocyte and one Neutrophil

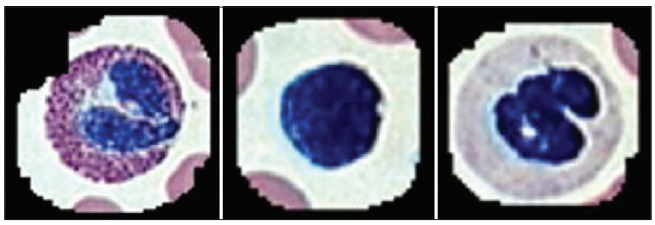

Figure 11: Extracted WBCs from Figure 10

In the Table 2 result of learning extracted WBCs by the CVNN and RVNN have been compared, purpose of "Output value precision percent" at the table is average of all value of 100*(final output-desired output)/ desired output.

As one could see in Table 2, time of per iteration for CVNNs is less than RVNNs and CVNNs can approach desired output values better than RVNNs, but both ANNs have recognized every 20 test patterns.

In Figure 10 three WBCs has been shown, and in Figure 11 extracted WBCs has been shown. As can see in this image there are one Basophile, one Lymphocyte and one Neutrophil, that our system recognized them properly. Some of the images in this paper are available at the State University of New Jersey.[14]

CONCLUSION

In this article, we presented a method on the base of RGB color system for extracting WBCs from microscopic images, which we extract successfully about 98.8 percent of them (Using the above method, it was just one error in extracting WBCs among 85 experiment samples, which was contemplating one red blood cell in the title of as a WBC. This shows the amount of extracting success for these images, equals to 100-(1/85)*100=98.8) by concentrating on the blue part of this colorful system. And by training it to a complex-valued back-propagation network, we extracted each one of 5 white blood cells groups. Finally, we illustrate the number of each type of WBCs as output.

One of the advantages of the method which is used in this article is the possibility of working on variety kinds of blood's microscopic images with different qualities in resolution and color. Which makes this system (with some scrimp changes) usable in many of blood microscopic images collections.

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