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Automated Method for Detection of Sickle Cell Disease

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ABSTRACT: This paper deals with the detection of sickle cell disease in human body using Image Processing and Deep Learning. Sickle cell disease is a hereditary blood cell disorder. Normally, the flexible, round red blood cells move easily through blood vessels while sickle red blood cells are shaped like sickles or crescent moons. The existing method detects sickle cell disease using Hemoglobin Electrophoresis, Prenatal Diagnosis and Chronic Biopsy. The proposed method makes use of techniques of image processing and overcomes the disadvantages of manual method of sickle cell diagnosis. The blood sample of humans is taken and the image is preprocessed followed by segmentation of the cells and finally fed as input to classification. It emphasizes elaborate analysis of proper diagnosis with accuratedetection.

KEYWORDS: Preprocessing, Neural Networks, Bounding box, Connected Components, Deep Learning.

I. INTRODUCTION

Sickle Cell disease is generally caused when the haemoglobin content of the RBCs is reduced and as a result the oxygen consuming capacity of the cells are also reduced. Thus the RBCs deform to a cylindrical sickle shaped cells. These cells when large in number block the flow of blood in the blood vessels and cause pain. In severe cases they may also cause stroke. Thus diagnosis and detection of this disease is an important process. Currently, several manual and laboratory methods are used like Haemoglobin electrophoresis, chronic biopsy but all these methods are not time efficient and their accuracy gets reduced when blood transfusion is done within 3 months. The alternative method we suggest is based on image processing. In this method we collect the images of blood samples and process them to detect if sickle cells are present. Deep Neural Networks are also used for effective classification of Sickle Cells and Normal Cells.

II. METHODOLOGY

The microscopic images of blood cell samples undergo various processes such as Preprocessing, Segmentation and finally subjected for Classification. The Schematic Diagram of this process is shown:

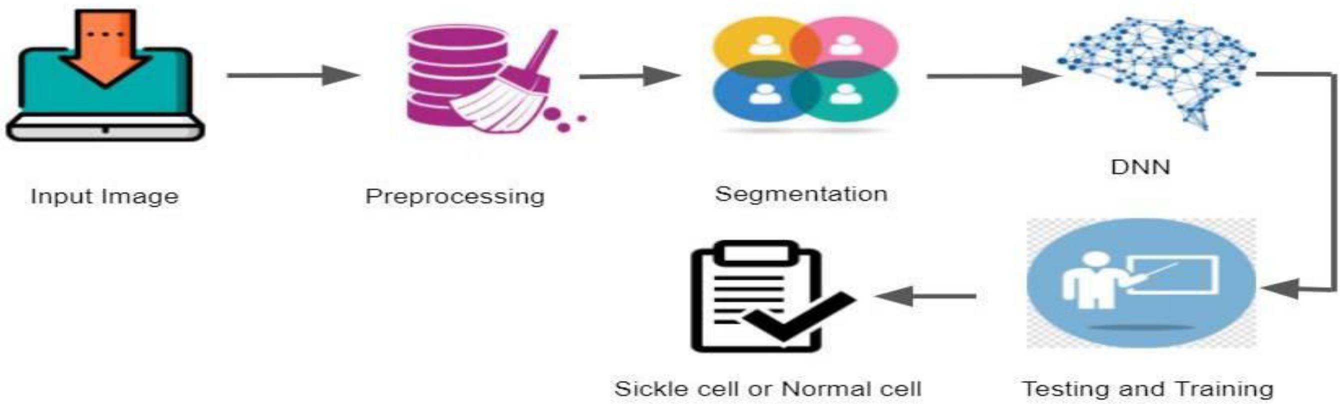

Figure 1: Schematic Representation of Sickle cell Detection

Pre-processing

Pre-processing is the process done before any further analysis of the image is done in order to improve the quality of the image so that analysis becomes easier. In this project we have suggested three steps in pre-processing in order to obtain the image for segmentation and classification process. The steps involved are:

1. Gray scale conversion.
2. Enhancement using Histogram Adaptive equalization method.
3. Binarization using Otsu's method.

1. Gray Scale Conversion

In gray scale conversion, the RGB image is converted to a gray scale image. There are generally two methods to obtain a gray scaled image which are average method and weighted method. In Average method the weights of all the three colours red, blue and green are equal and thus the image obtained is not clear. Thus we use weighted method in which the weights of the colours are in the order green >red>blue as our eyes sensitivity to these colours are also same. Thus to obtain the gray scale image we use the formula as, 0.2989*R+0.5870*G+0.1140*B.

2. Enhancement

The process of improving the quality of an image is known as enhancement. It is done for sharpening, removing noise from an image and brightening, which are then used for extracting the key features.

Histogram Equalization

Histogram of an image is nothing but the graphical representation of the gray level of an image. That is histogram gives information of how often a particular gray level has been occurred in an image. We know the range of gray level is from 0 to 255, when we consider a dark image, the histogram of such image lies close to the gray level of 255. Whereas for a light image, the histogram will lie close to 0 and for image with medium contrast the histogram will lie in the midrange between 0 and 255. Therefore, in order to improve the quality of an image we need to obtain a flat profile of the histogram. Histogram equalization technique helps in obtaining the flat profile of the gray levels in an image. The following table and matrices show the computation of histogram equalization technique.Consider the gray levels of an input image.The table below shows the gray level of input image and the number of pixels corresponding to that gray level.

4	4	4	4	4
3	4	5	4	3
3	5	5	5	3
3	4	5	4	3
4	4	4	4	4

Figure 2: Gray level of an image

GRAY LEVELS	0	1	2	3	4	5	6	7
NO. OF PIXELS	0	0	0	6	14	5	0	0

Table 1: Gray Level and its frequency

6	6	6	6	6
2	6	7	6	2
2	7	7	7	2
2	6	7	6	2
6	6	6	6	6

Figure 3: Adaptive Histogram Equalized Image

GRAY LEVEL	NO. OF PIXELS(nk)	PDF= nk/sum	CDF (sk)	CDF*7	HISTOGRAM EQUALIZATION LEVELS
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	6	6/25=0.24	0.24	1.68	2
4	14	14/25=0.56	0.8	5.6	6
5	5	5/25=0.2	1.0	7	7
6	0	0	1.0	7	7
7	0	0	1.0	7	7

Table 2: Histogram Equalization Table

Equalization method for the values in the above matrix is calculated by taking into account the probability distribution function followed by cumulative distribution function and the histogram equalization levels. Then the gray scale values get replaced by the equalized values thus enhancing the image suitable for further processing.

3. Binarization

In binarization, the enhanced gray scale image is converted in to binary (black and white) image (i.e) the image would consist of black and white pixels.Otsu's method has a formula $(\sigma B)^2 = WbWf(\mu b - \mu f)^2$ to identify the optimum threshold intensity where Wf, Wb represent the weights of foreground and background pixels followed by µb, µf representing the means of the background and foreground weights respectively. The values Wb, Wf, µb, µf have separate formulae as shown here: Wb = (No. of pixels lesser than threshold) / (total no.of pixels); Wf = (No. of pixels greater than threshold) / (total no.of pixels); µb = (height of gray level < threshold level in histogram * gray value) / (Total pixel values < threshold) and vice versa for µf. The gray values lesser than the threshold assumed are termed as background pixels whereas the gray levels equal to or greater than threshold assumed are termed as foreground pixels. In Otsu's method, initially a threshold value is assumed and the weights and mean of foreground and background pixels are calculated and the variance $(\sigma B)^2$ is obtained by substituting their values in the formula. This process is repeated by assuming each gray level appearing in the enhanced input image as threshold and consequently the greatest threshold is taken as the optimum threshold value. Thus this method leads to efficient binary conversion of enhanced gray scale image. This is explained further by considering the image matrix as shown below.

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0	1	2	1	0	0
0	3	4	4	1	0
2	4	5	5	4	0
1	4	5	5	4	1
0	3	4	4	3	1
0	2	3	3	2	0

Figure 4: Gray level Image

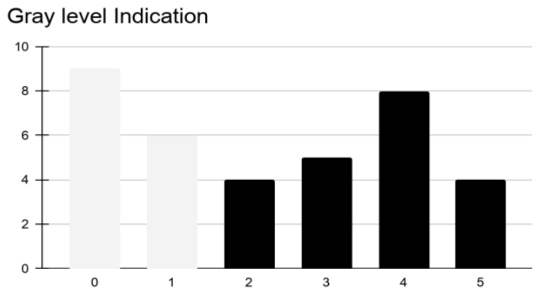

Figure 5: Graphical Representation of Threshold Image

Assume the threshold to be 2 and the following graph is obtained.The process is repeated for each gray level value and the corresponding optimum threshold table is shown.

It	0	1	2	3	4	5
Wb	0	0.25	0.42	0.53	0.67	0.89
Mb	0	0	0.40	0.74	1.21	1.91
Wf	1	0.75	0.58	0.47	0.33	0.11
Mf	2.25	3	3.57	3.94	4.33	5
(σB)^2	0	1.69	2.44	2.56	2.17	0.95

Table 3: Otsu's Optimum Threshold Table

Here approximating the value 2.56, we get 3 as the optimum threshold. Gray values < 3 become 0 and >3 become 1.

0	1	2	1	0	0
0	3	4	4	1	0
2	4	5	5	4	0
1	4	5	5	4	1
0	3	4	4	3	1
0	2	3	3	2	0

→

0	0	0	0	0	0
0	1	1	1	0	0
0	1	1	1	1	0
0	1	1	1	1	0
0	1	1	1	1	0
0	0	1	1	0	0

Figure 6: Conversion representing the gray level enhanced image and resultant binary image.

The image obtained in the above method is further subjected to segmentation to obtain the sickle cells in order to detect the presence of it.

Segmentation

Segmentation is the process of portioning or dividing the image into several parts in order to obtain the desired object. This process is also done to differentiate the boundaries and obtain the required image for classification. The first step in segmentation is to fill in the holes present in the images. Holes are part of whites present in the black or part of blacks present in the white. In this process the boundaries are fixed and then the holes inside the boundaries are filled using morphological reconstruction by obtaining the regional maxima and minima.

Bounding box

A bounding box is process of forming rectangle for the necessary objects by passing X-width, Y-width, X-corner and Y-corner parameters. Semi-lunarity factor is calculated from the extracted major axis and minor axis features. Semi-lunarity factor is the ratio of major axis to the difference between major axis and minor axis. If a particular cell has a semi-lunarity factor less than 1.7 then those cells will be bounded by the rectangular boxes which is then separated from other cells. Compared to other image processing methods, this method can reduce costs and increase the efficiency of segmentation. After this process, the segmented image undergoes erosion, dilation, opening and closing based on the connected components and label matrix to obtain the final images in the result section.

Classification

Deep Neural Network

Artificial neural networks (ANNs) are made up of nodal layers which are an input layer, a output layer and one or more hidden layers. The number of hidden layers can be selected based on the data set used. Artificial neural network with more than one hidden layer is known as Deep Neural Network. Each node present in the network connect with the other layer of nodes. Each of them has a weight and bias value. Depending on this, if the signal present is above the threshold level, then the signal will be passed on in the network. This is the process in the neural network.

Algorithms

1. Back Propagation Algorithm

For the training process in Deep Neural Network back propagation is the base algorithm for obtaining any other algorithm that is used in the project. The main aim of back propagation algorithm is to reduce the error in the training process. The steps are:The weights and biases of the neural network are assumed to have any value between 0 and 1.Using the assumed values and input, the output of the network is obtained in forward propagation.The error is found between the predicted value got in the first step and the actual output to be obtained is, Error = $\frac{1}{2}$(predicted value-actual value)^2.To reduce the error we use gradient descent method to update the parameters i.e., weights. The updated weight is obtained by, New weight = Old weight – gradient*learning rate, where gradient is the gradient of total error with respect to the respective weight to be updated. Similarly all the weights are updated from backward direction to the input.After the weight is updated the error is again calculated and found that error is reduced. After several such steps the error is reduced to the minimal level of nearly zero.

2. Conjugate Gradient Propagation Algorithm

To improve computation speed we use this algorithm. In this algorithm along with gradient of the total error we also use direction gradient to update the parameters as,$w(i+1)=w(i)+d(i).\eta(i)$, $d(i+1)=g(i+1)+d(i)\cdot\gamma(i)$; g→ gradient ; d → training direction; γ→ conjugate parameter(generally negative of the gradient).Thus using similar steps as in that of back propagation algorithm we obtain reduced error for the training process with higher computation speed.

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3. Resilient Back Propagation Algorithm

Resilient back propagation algorithm follows back propagation algorithm with few changes. The general back propagation algorithm takes more time to train the neural network as it needs large number of iterations to make the error value zero. This is overcome by the resilient back propagation algorithm thus making the training method faster and leading to earlier results. Resilient back propagation algorithm makes the learning rate adaptable to the weight values as required. The Back propagation algorithm fixes the learning rate as constant throughout the entire training process and its values ranges between 0 and 1. In back propagation algorithm, since the learning rate is fixed irrespective of the weight values the updated weight values will oscillate around the optimum weights thus making the process slower by not leading to the zero error value. This is changed in resilient back propagation algorithm by the following steps: When the current weight value and the updated weight value are of same signs, then the learning rate is increased and the weight is further updated by propagating in forward direction. If they are of different signs, then in the previous step the learning rate is changed accordingly. This overcomes the blurred adapting method of learning rate thus increasing the training speed.

III. EXPERIMENTAL RESULTS

The output obtained when images with sickle and without sickle cells undergo the process in MATLAB is as follows. The accuracy of the proposed method is around 96%.

Images with Sickle cell

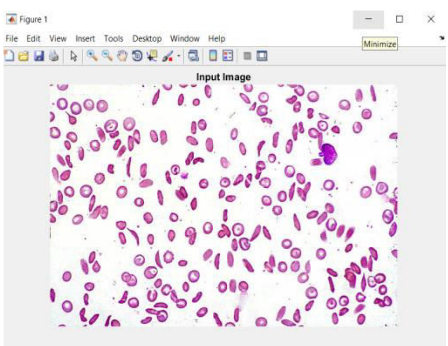

Figure 7: Input image

Images without Sickle Cell

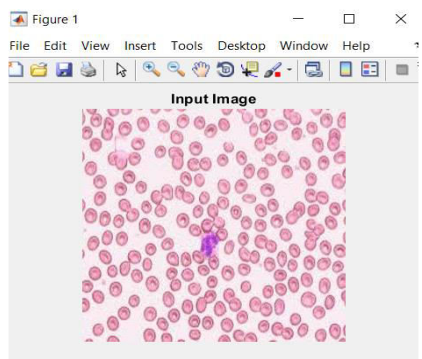

Figure 8: Input image

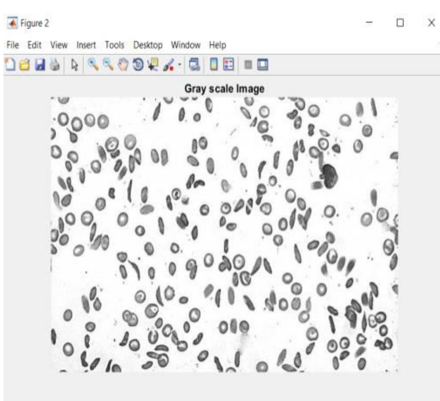

Figure 9: Gray Scale Image

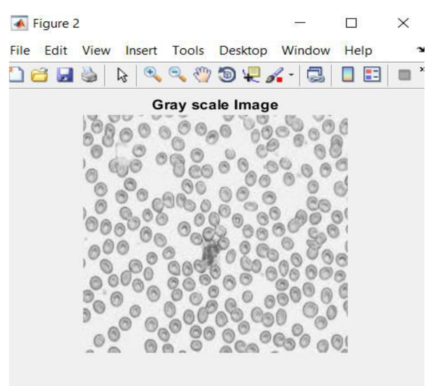

Figure 10: Gray Scale Image

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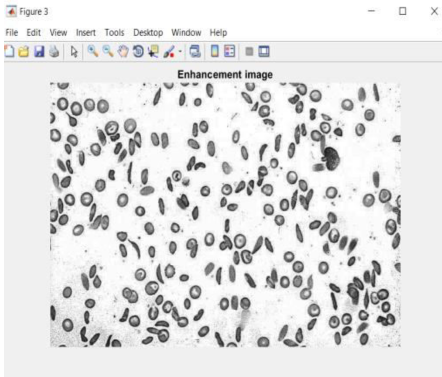

Figure 11: Enhanced Image

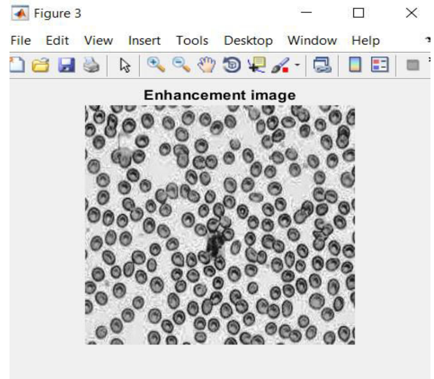

Figure 12: Enhanced Image

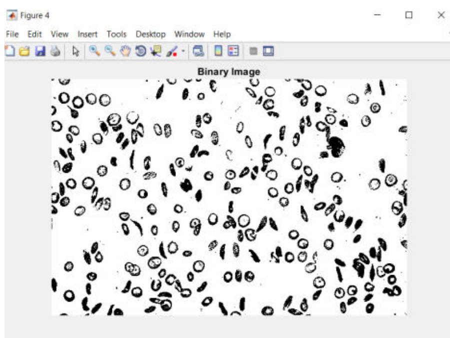

Figure 13: Binary Image

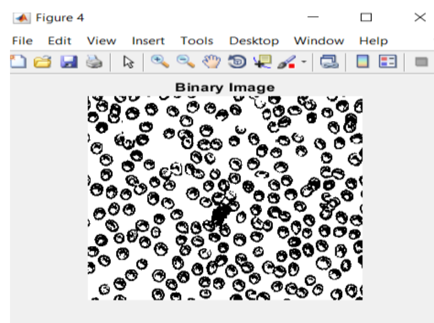

Figure 14: Binary Image

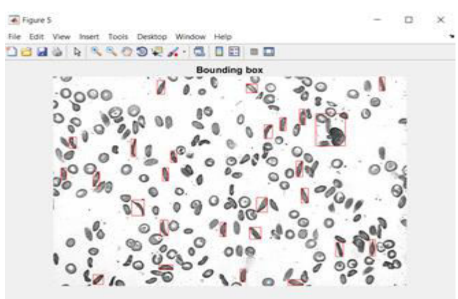

Figure 15: Bounding Box Image

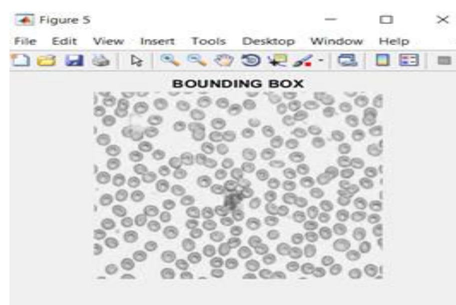

Figure 16: Bounding Box Image

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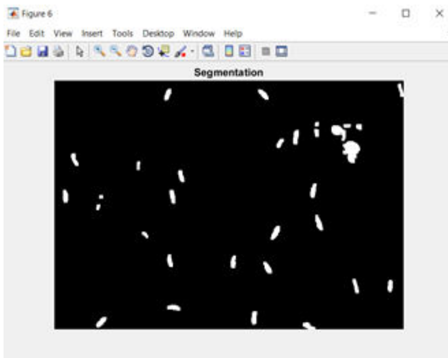

Figure 17: Segmented Image

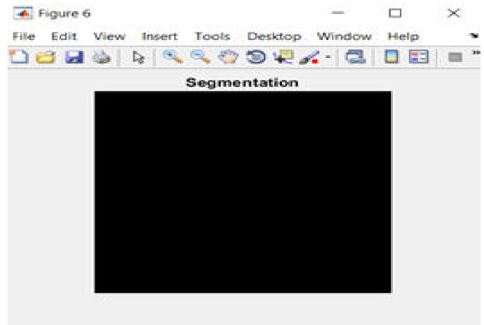

Figure 18: Segmented Image

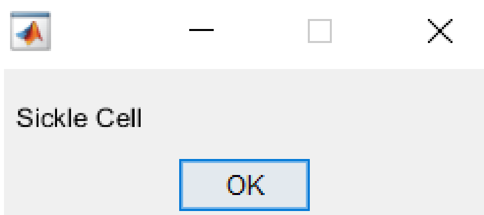

Figure 19: Message box (Final Result)

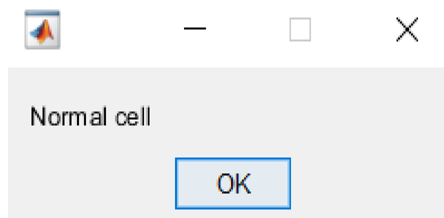

Figure 20: Message box (Final Result)

IV. CONCLUSION

The principle objective of the paper is to provide an automated method using enhancement, segmentation and classification of the images containing RBCs to detect sickle cell disease. This entire process plays an important role in diagnosis of sickle cell disease. The proposed work classifies efficiently using neural network functions. Here the bounding box and the morphological operations lead to the segmented area and position. Finally, the deep neural network classifier is used in order to identify the image as normal cell or sickle cell. It focuses how to handle inherent problems with the segmentation of overlapping cells. This overcomes the manual error, increases the detection speed and efficiency of the result. This may help researchers and clinicians in deciding a particular methodology, best suited for detection and analysis of Sickle celldetection.

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