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An Efficient Method for Detection of Red Blood Cells in Digital Images in Sickle Cell Anaemia Diagnosis

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***Abstract*—With sickle cell anemia, erythrocytes break down so early changing their shape which blocks blood flow through the blood vessels. This paper introduces a unique algorithm for the detection and classification of sickle cells and normal red blood cells present in digital images of blood smear samples. Detection of sickle cell is based on image morphology of an erythrocyte, analyzing its shape, size and curvature. A circumference adjustment algorithm is used to impose appropriate circles over the normal cell with best fit. The ellipse fitting algorithm is used to locate sickle cells present in a digital image of the blood smear sample. Cells present in clusters are also detected and classified efficiently. This paper demonstrates a simple and an efficient method of classification of detected cells with exact number of cell count..**

Keywords—Erythrocytes, Sickle cell morphology, Curvature calculation, Region properties, Circumference adjustment algorithm, Ellipse fitting algorithm.

I. INTRODUCTION

Many blood disorders cause a change in the form and structure of erythrocytes. Sickle Cell anemia is a genetically transmitted blood disorder that requires medical diagnosis and frequent blood tests for the treatment of a patient. By using a morphological image processing tool, we can extract image components useful in the representation and description of image shape, boundaries, skeletons, convex hull, etc. In this research, we have detected and classified two different types of red blood cells in the case of sickle cell anemic patient by using image morphological operations.

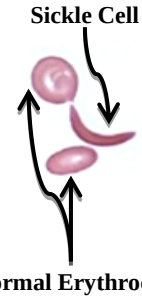

Fig.1. Deformation in Erythrocytes

Erythrocytes look like biconcave discs. They carry Oxygen and Carbon Dioxide to and from the tissues of our body. A person suffering from Sickle Cell Anemia does not able to produce enough healthy cells in the body. Unhealthy erythrocytes have a deficiency to carry enough Oxygen, which loses its original shape and starts becoming crescent-shaped. Such cells have inability to flow through small blood vessels smoothly causing blockage, pain and infection [1]. Patients suffering from sickle cell anemia have to go through frequent blood tests before treatment.

At present, a diagnosis and estimation of Sickle cells in blood smear samples is done by visual assessment using a microscope. Morphological change in Red blood cells plays a vital role in the treatment of an anemic patient. We used digital image processing approach for the detection of sickle cells present in blood smear samples. An algorithm is applied to a digital image once we get it from USB-connected digital microscope to the computer system. Maintaining records of a patient in the form of digital microscopic images becomes easier. This approach gives an efficient result which adds some help in further treatment of Sickle cell anemic patient.

In previous studies, T. S. Chy and M. A. Rahaman [2] used a morphological image processing tool for preprocessing of images, and then Support Vector Machine (SVM) is used for classification into three categories, but this method is ineffective in cell cluster areas. Kothari [3] et al. semiautomatic method is used which requires human interaction in an initial stage for locating the point of interest. Then a k-means algorithm is used for the detection of cells. In another study, P. Rakshita [4] et al. used Weiner and Sobel filter for detecting edges of objects. Region properties are used for pre-processing. Detection is based on matric calculation. In this paper, overlapping cells are not considered while obtaining results. Metric value for normal cells are nearly equal to one whereas for sickle cells it is about half, according to this accuracy is calculated which is nearly equal to 95.8 %. But for overlapped objects, both metric conditions reflect false result. Xiangzhi Bai [5], et al, “Splitting touching cells based on concave points and ellipse fitting,” proposed a method that finds concave points of contour then divides objects into segments, giving result as a single cell with the best fitted ellipse. Many other ellipse fitting techniques have been proposed for different applications like subway tunnel deformation using residual p-norm minimum an adaptive threshold selection method [6], eccentricity, and Root Mean Square Error (RMSE) calculation [7]. In this paper, an image processing algorithm is applied on digital microscopic red blood cell images for detecting Sickle cell anemia which does not require any

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human interaction once image acquisition is done. Also overlapped normal erythrocytes can be visualized efficiently by applying this image processing technique.

Normal blood cell is biconcave disk-shaped. For locating normal cells a circumference adjustment algorithm is used. The best fit is chosen for round-shaped cells by using regionprops in MATLAB. For locating sickle cells in a given image, an ellipse fitting algorithm is used.

II. MATERIALS AND METHODS

Following steps are followed for detection and Classification of erythrocytes into two categories as shown in Fig. 2.

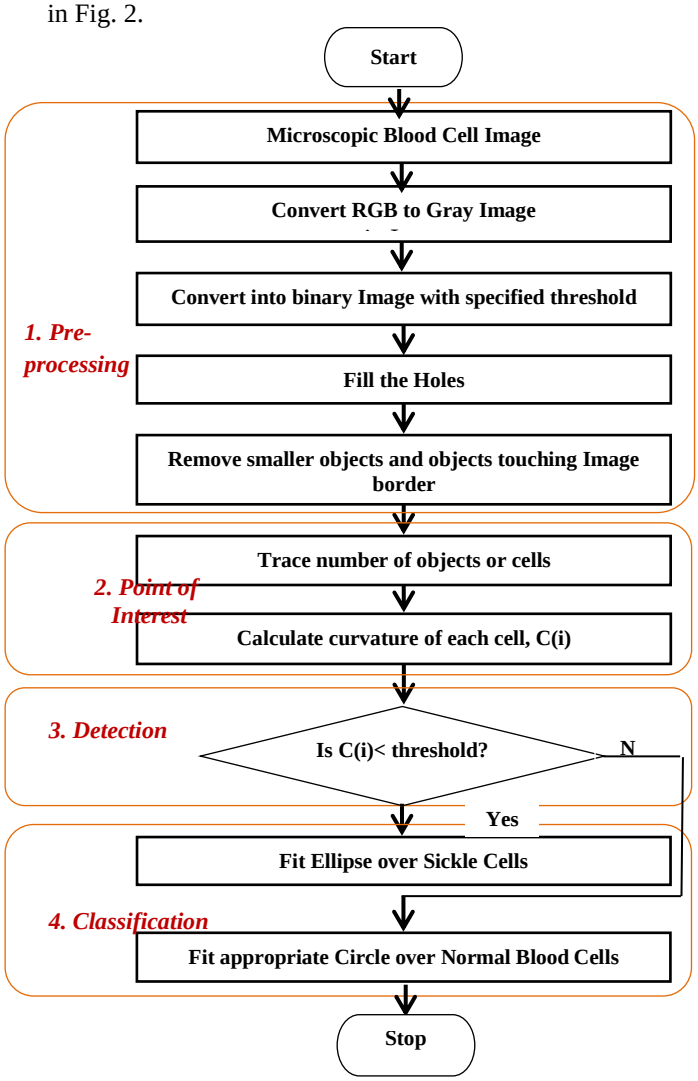

Fig.2. Algorithm for detection and classification of erythrocytes

Digital microscopic images were obtained by connecting the computer system to the digital microscope. They were captured with 1000X magnification. The acquired image is in pale yellow due to immersion oil used during the magnification process under the microscope. Fig. 3 shows the original digital microscopic image.

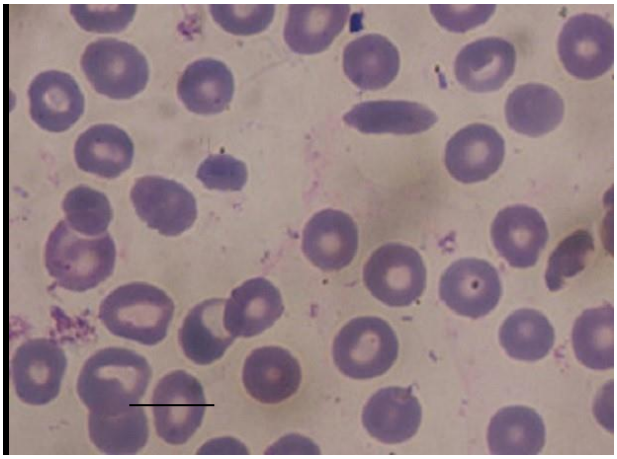

Fig.3. Digital Microscopic Image

A. *Pre-processing*

After getting a digital image, it is converted into a gray scale image. Then it is converted into a binary image with the specified level of 0.708 as shown in fig. 4.

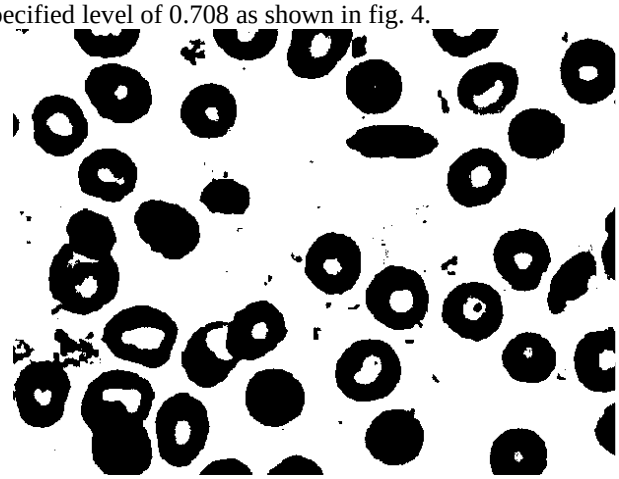

Fig. 4. Binary image

As the erythrocytes are biconcave, holes were created at the inner portion of cells. These holes are nothing but background pixels which must be filled first with object color.

Many objects are touching the borders of image. Applying algorithm to such objects may give false results. All such objects are cleared which are touching image border. All other objects are also suppressed which are comparatively lighter and smaller than the size of normal erythrocytes. The final image after applying preprocessing algorithm is shown in fig. 5.

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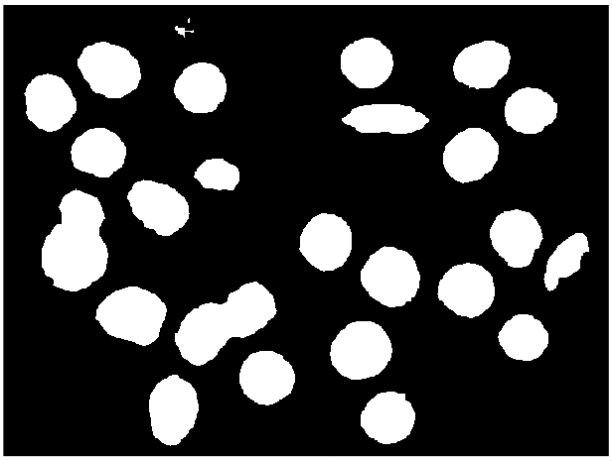

Fig.5. Erosion of an Image

B. *Points of Interest*

Morphological change in normal erythrocyte takes place which distorts the disk like shape of erythrocyte into an elongated nonsymmetrical shape. Our point of interest is in its shape. A normal erythrocyte looks like a circular object having almost equal radii from the center. Due to the change in curvature of an erythrocytes, there is a noticable change in the value of slope calculated for normal erythrocyte and sickle cell. Hence finding a slope of every object present in the image is key point, based on which further detection and classification are done.

C. *Detection*

A preprocessed binary image containing number of 2-D objects has to be labeled before applying the detection algorithm.

Center and axis lengths are determined by using regionprops for calculating the crescent shape of the labeled object. Formula (1) is used to calculate the curvature of every object by taking a ratio of Major Axis length to the difference between Major and Minor Axis lengths, according to which we can classify an object into two categories.

$$C(i)=\frac{\text{Major axis length}}{\text{Major axis length}-\text{Minor axis Length}} \quad \text{- - - - - - - (1)}$$

After calculating curvature,C(i) for every object present in a binary image, the threshold value is decided by taking many experimental results into account. If an object is circular, its value of C(i) will be more than the threshold value. If erythrocyte lost its circular shape, object in the binary image tends to be linear, hence its C(i) will be less than the threshold value.

D. *Classification*

After detecting whether an object is elongated or circular, one of the following algorithms is applied for final classification.

a. Ellipse Fitting Algorithm

If an object has a curvature value less than the threshold value, it gives a result as a sickle cell, as it has lost its circular shape and became more linear. In every sample, the orientation of the detected elliptical object might be different. By using 'Orientation' property, the first alignment of every elongated object is predicted. Then ellipse is drawn over an elongated object with the best fit by using the following equations 2 and 3.

$$x = Xc + a * \cos(t) * \cos\phi - b * \sin(t) * \sin\phi \text{ --(2)}$$
$$y = Yc + a * \cos(t) * \sin\phi + b * \sin(t) * \cos\phi \text{ --(3)}$$

Where,

Xc and Yc=Centroid of an elongated object along major and minor axis respectively.

a=Length across the major axis of elongated object

b= Length across minor axis of elongated object

x and y returns 2-D plot values which draws an ellipse with the best fit for sickle cells present in a sample.

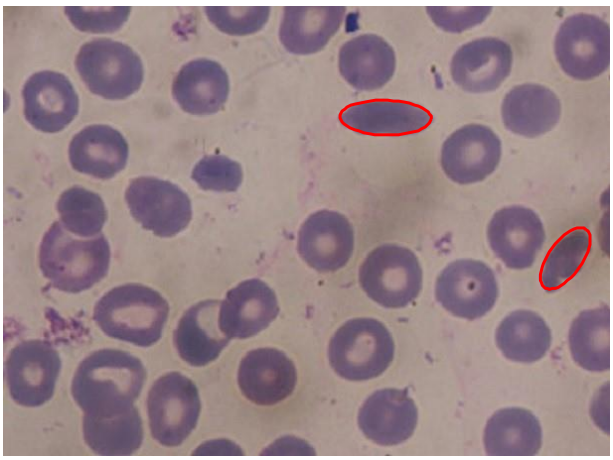

Fig.6. Elongated Object Detection

b. Circumference Adjustment Algorithm

At first, region properties are used to extract useful information to draw circle over normal blood cells. viscircles(centres, radii) draws a circles with specified centres and radii onto the current axes.

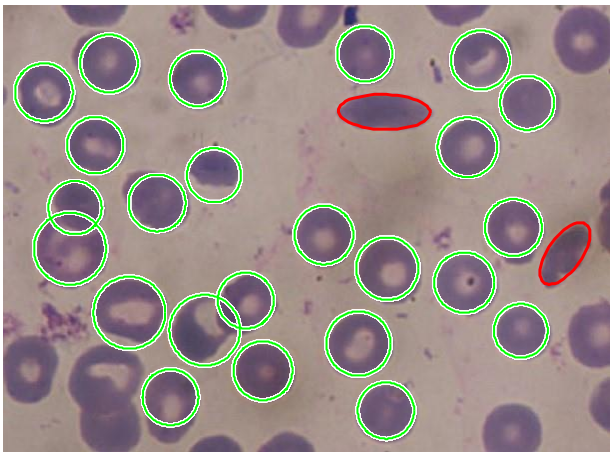

Fig.7. Final Classified Image

III. RESULTS

After detecting and analysing all objects present in an image, we got some parameters for Sample-1 which would be useful for treatment of anaemic patient noted in table 1.

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Table 1. Parameters and values of classified image

Parameter		Value
Normal Cell Estimation	NCE	24
Elongated Cell Estimation	ECE	2
True Positive Rate Normal	TPRN	0.9230
True Positive Rate Elongated	TPRE	0.0769

For a given sample, some objects were neither circular cells nor sickle cells, such objects are left unmarked. These are nothing but white blood cells or broken cell particles. Also counter touching cells were not considered while applying algorithm. Out of all cells, three normal cells were not detected, thus the detection efficiency was 94.11%. True positive rates of normal and elongated cells were calculated by using formula (4) and (5):

$$TPRN = \frac{NCE}{NCE+ECE} \quad \text{----------} (4)$$

$$TPRE = \frac{ECE}{NCE+ECE} \quad \text{----------} (5)$$

Some more results are as shown below:

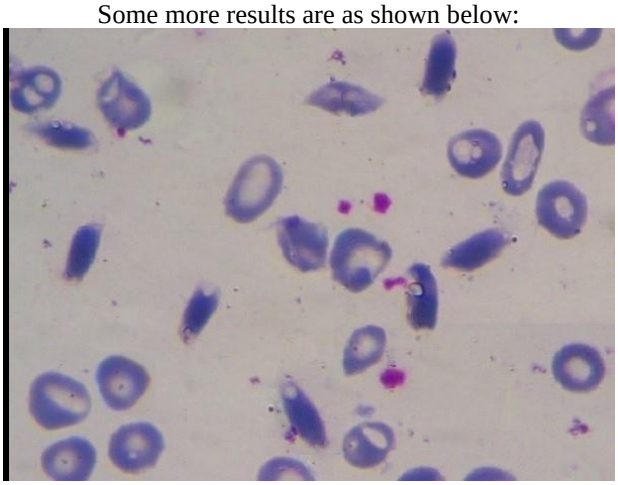

Fig.8. Sample-2 Original Image

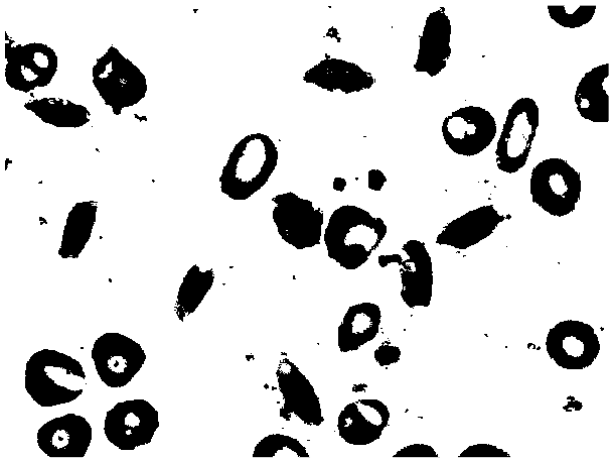

Fig.9. Sample-2 Binary Image

Fig.10. Erosion of Sample-2 Image

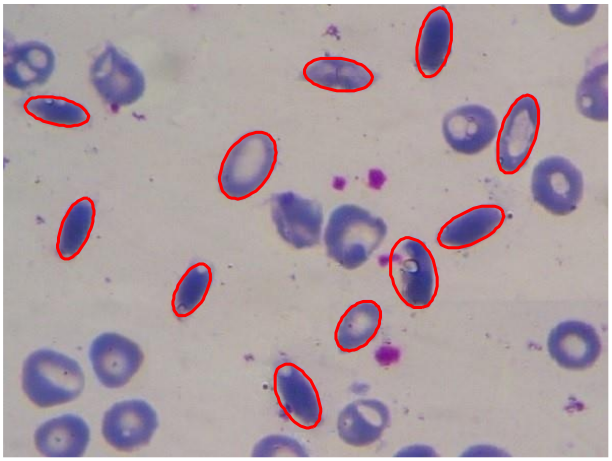

Fig.11. Elongated object detection of Sample-2 image

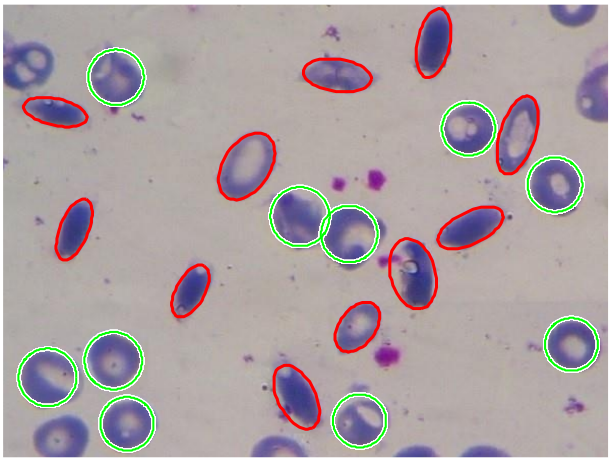

Fig.12. Detection and Classification of Sample-2 Image

Table 2. Calculated parameter values for Sample-2

Parameter		Value
Normal Cell Estimation	NCE	10
Elongated Cell Estimation	ECE	11
True Positive Rate Normal	TPRN	0. 4761
True Positive Rate Elongated	TPRE	0.5238

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IV. DISCUSSION

The Presence of sickle cells present in the blood smear samples depends on the health condition of the patient. TPRN and TPRE range between 0 to 1. More the value of TPRN, the count of Sickle cells present in the digital microscopic image is less which concludes that the patient is less anaemic.

For a critical patient, cell deformation is more which gives more ECE count results in less TPRN can be detected and classified by our method efficiently as shown below images (Sample-3 and Sample-4)

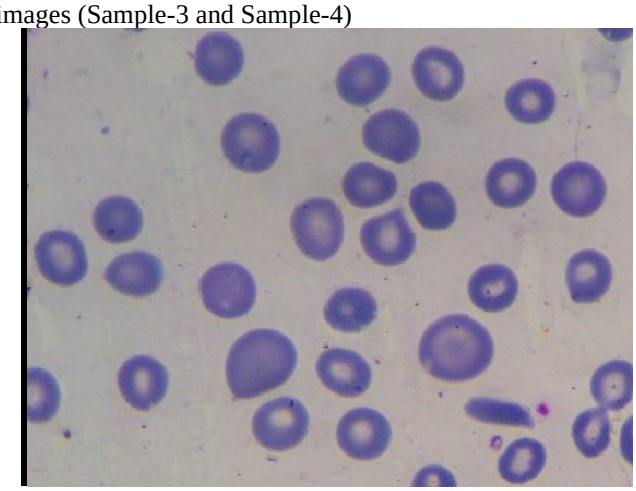

Fig.13. Original Image (Sample-3)

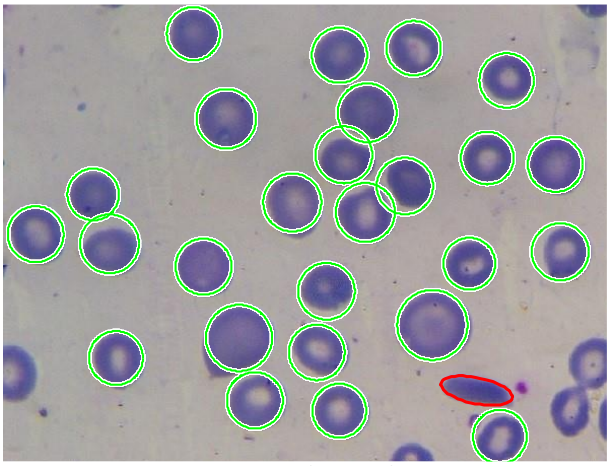

Fig.14. Detection and Classification of Sample-3 Image

Table 3. Calculated parameter values for Sample-3

Parameter		Value
Normal Cell Estimation	NCE	26
Elongated Cell Estimation	ECE	1
True Positive Rate Normal	TPRN	0.9630
True Positive Rate Elongated	TPRE	0.0370

Table 3 shows calculated parameter values for sample-3. More the number of sickle cells calculated TPRN has less value which concludes that the patient is more anemic.

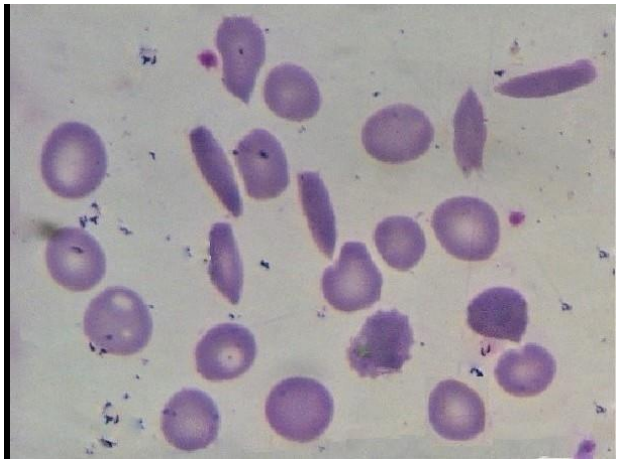

Fig.15. Original Image (Sample-4)

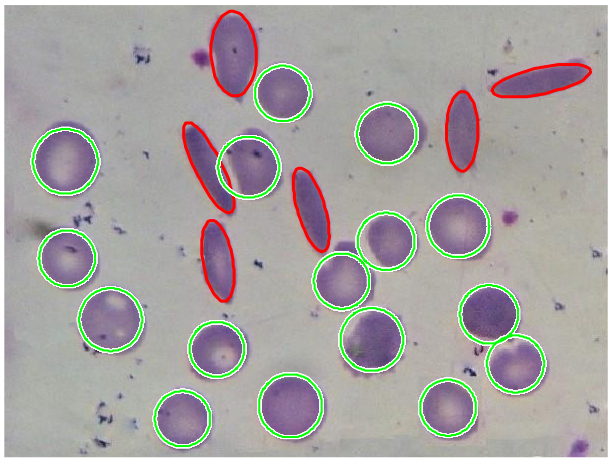

Fig.16. Classified Image of Sample-4

Table 4. Calculated parameter values for Sample-4

Parameter		Value
Normal Cell Estimation	NCE	16
Elongated Cell Estimation	ECE	6
True Positive Rate Normal	TPRN	0.7272
True Positive Rate Elongated	TPRE	0.2727

All experiments were carried out for real microscopic images which gives excellent results as compared to previous methods [9]. Our method can efficiently detect all sickle cells present in digital microscopic images of blood smear samples irrespective of its orientation

V. CONCLUSION AND FUTURE WORK

An efficient method is introduced for detecting and locating sickle cells in blood smear samples by using a morphological image processing tool. Data obtained from this method can be stored automatically in software form which is useful for a specialist for assessment in the future. This method serves a useful purpose in the diagnosis and analysis of sickle cell anemia.

Detecting the objects present in clusters having more than two sickle cells in it could be further achieved leading to improvement in an overall efficiency of the proposed work.

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