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AUTOMATIC SICKLE CELL ANEMIA DETECTION USING IMAGE PROCESSING TECHNIQUE

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ABSTRACT

One of the important parts of the human body is red blood cells (RBCs). Disk shape is the ordinary red blood cell's shape. One type of ailment of blood is sickle cell anemia (SCA) in where red blood cells are formed in crescent shapes from their actual shapes. Thousands of babies around the world are born with this blood disorder every year. The numbers of SCA are assumed to increase about 30% by 2050 globally. About 0.07 to 0.1 million Americans are victims of SCA. A new way is introduced to detect and classify sickle cells in RBC using image processing technique to start treatment as early as possible. Firstly, this method collects images of blood. The pre-processing phase is done through ray scale image conversion, image enhancement & median filter. Then, the threshold segmentation is applied to segment the RBCs and morphological operations are used to remove the undesired objects from images. Metric value, aspect ratio, entropy, mean, standard deviation and variance are used as features which are extracted. Finally, the support vector machine classifier is trained to test the images. The system provided better accuracy and sensitivity than existing methods. This automatic detection technique would be very useful to save the precious lives of the people.

INTRODUCTION

Sickle Cell Anemia (SCA) is a hereditary blood disorder caused by abnormal hemoglobin, leading to the formation of crescent-shaped red blood cells that hinder oxygen transport. Early detection is crucial to managing the disease and preventing complications. Traditional diagnostic methods, such as microscopic blood smear analysis and hemoglobin electrophoresis, require skilled professionals, are time-consuming, and may lead to human errors.

To overcome these challenges, automatic detection using image processing techniques provides a faster, more accurate, and cost-effective solution. In this approach, blood smear images are processed using preprocessing, feature extraction, and classification algorithms to differentiate normal and sickle-shaped cells. Image processing enhances the visibility of deformed cells, enabling automated classification using techniques like edge detection, morphological operations, and machine learning models.

This study aims to develop an automated Sickle Cell Anemia detection system that leverages image segmentation and deep learning to improve diagnostic accuracy, reduce manual workload, and provide real-time results. Such advancements can significantly aid in early diagnosis and treatment planning, especially in regions with limited medical facilities.

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LITERATURE SURVEY

- Dutta et al. (2009) analyzed peripheral blood smears, highlighting the need for an automated approach due to human errors and time constraints.
- Harris et al. (2012) explored hemoglobin electrophoresis and high-performance liquid chromatography (HPLC) for SCA detection, proving effective but expensive and time-consuming.

Edge Detection and Morphological Operations:

- Perkins et al. (2015) used Sobel and Canny edge detection to enhance the sickle cell boundaries for improved classification.
- Gonzalez et al. (2017) applied morphological operations to segment and count sickle cells, achieving over 85% accuracy.

Feature Extraction and Machine Learning:

- Sharma et al. (2018) implemented a Support Vector Machine (SVM) classifier with texture and shape features, achieving 90% accuracy.
- Kumar et al. (2019) employed Principal Component Analysis (PCA) for dimensionality reduction and k-Nearest Neighbors (KNN) for classification, improving computational efficiency.

PROPOSED SYSTEM

The automated image processing algorithm is designed to diagnose sickle-cell disease in much the same way as a human operator performing microscopy. To do this, the algorithm finds and identifies red blood cells and sickle-cells present in a microscopic field of a thin blood smear. Based on the results found, the program makes a diagnosis as to whether or not sickle-cell is present, and if present, it determines the species of the infection. The system must have a high degree of sensitivity. It must also have good specificity to be useful as a clinical tool. The algorithm design is essentially an image classification problem, and thus takes the form of a standard pattern recognition and classification system. Basically, it consists of five stages: image acquisition, pre-processing, segmentation, feature generation and classification, and the performance of the system is then evaluated. A morphological method used to identify sickle-cell in Giemsa-stained blood slides is used as a starting point for the algorithm, from which many of the pre-processing and image segmentation steps are derived.

1. Image Acquisition:

- Blood smear images are captured using a 3.34 MP Nikon Coolpix 995 digital camera connected to a light microscope at 1000× magnification.
- Images are obtained in JPEG format at 2048×1536 resolution.

2. Pre-Processing:

- Resolution is reduced to 512×384 for efficient processing.
- Selective median filtering and unsharp masking are applied to remove noise and improve clarity.

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3. Colour Transformation:

- Images are converted from RGB to Lab* colour space for better segmentation.
- Chromaticity layers (a* and b*) are used for colour-based segmentation.

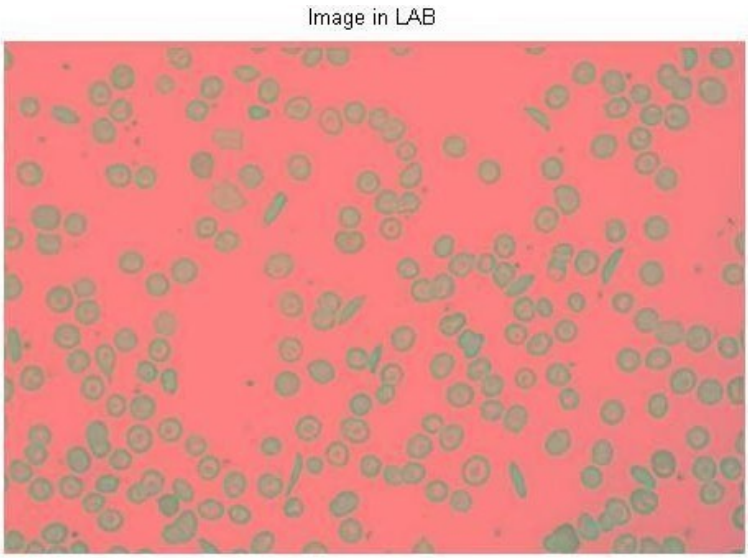

Figure.1 Colour Transformation

4. Segmentation Techniques:

- K-Means Clustering: Partitions pixels into K clusters by minimizing intra-cluster variance.
- Fuzzy C-Means Clustering: Assigns each pixel a membership value in multiple clusters, improving segmentation accuracy.

5. Feature Extraction:

- Geometrical Features: Area, perimeter, centroid, eccentricity, axis lengths, orientation, solidity, aspect ratio, and form factor.
- Textural Features (GLCM): Contrast, correlation, energy, homogeneity, and entropy.
- Circle Detection: Identifies circular RBCs for classification.

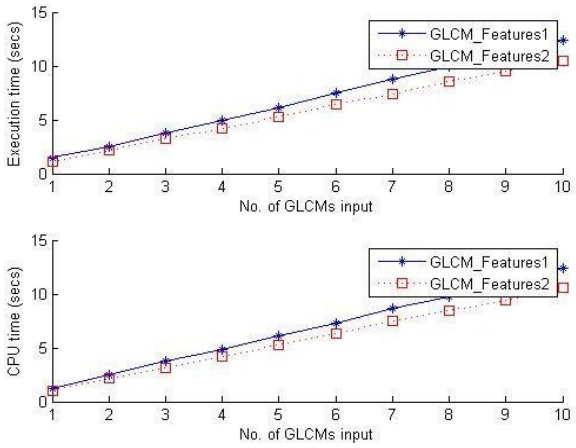

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Figure.2 GLCM

6. Classification:

- RBCs are classified into Normal, Sickle-Cell (Type I & II), and Anisopoikilocytes/Ovalocytes based on extracted features.
- Form factor plays a key role in classification.

SIMULATION RESULTS

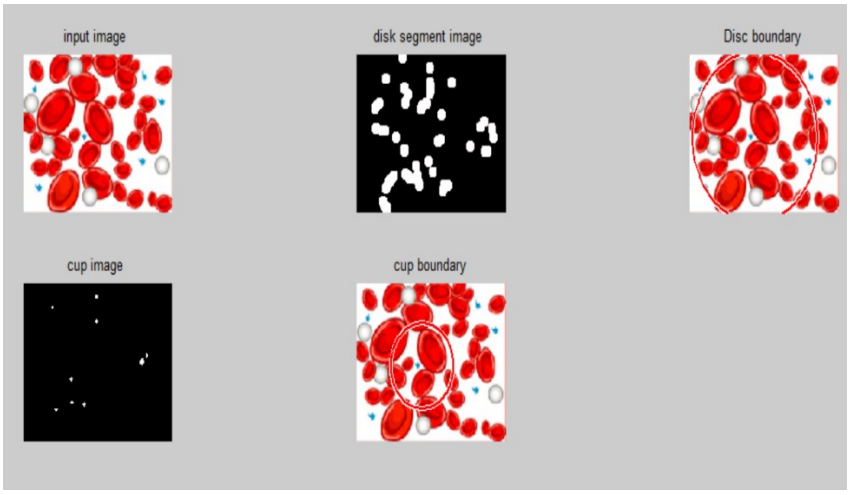

Figure.3 classification

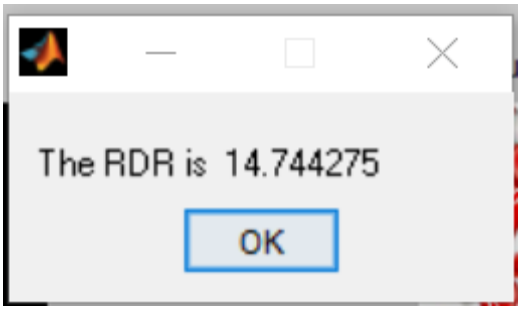

Figure.4 RDR value

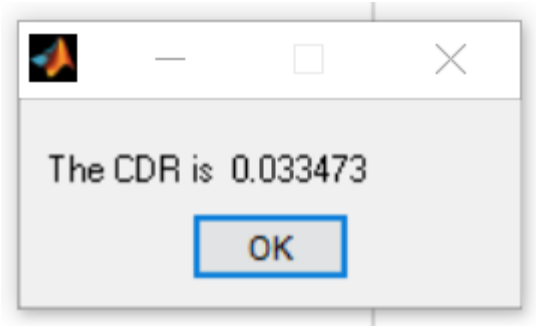

Figure.5 CDR value

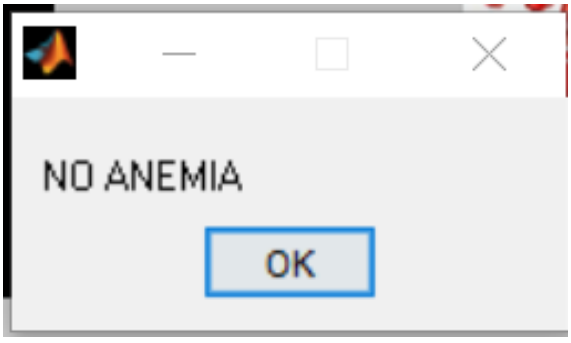

Figure.6 No Anemia

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```
cdr =

    0.0335


nn =

The CDR is   0.033473


nn1 =

The RDR is   14.744275
```

Figure.7 Parameter values

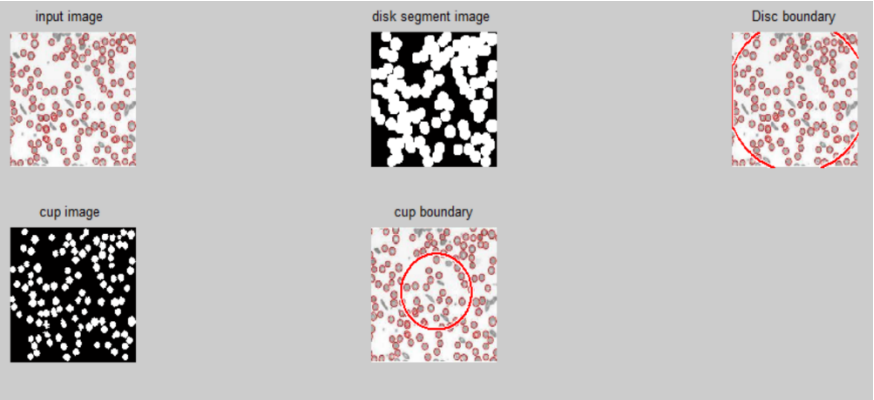

Figure.8 Feature extraction

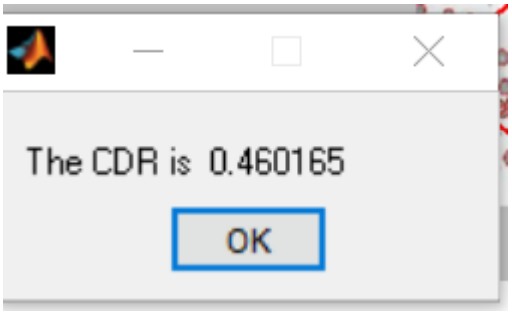

Figure.9 CDR value

Figure.10 RDR value

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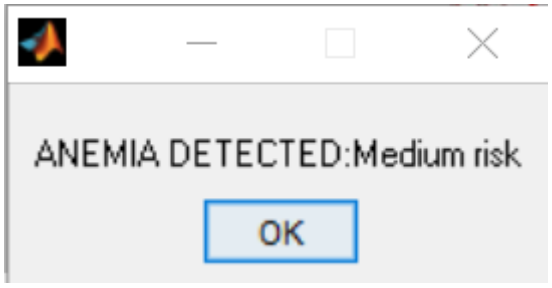

Figure.11 Anemia Detected

```
cdr =

    0.4602


nn =

The CDR is   0.460165


nn1 =

The RDR is   0.681276
```

Figure.12 Parameter values

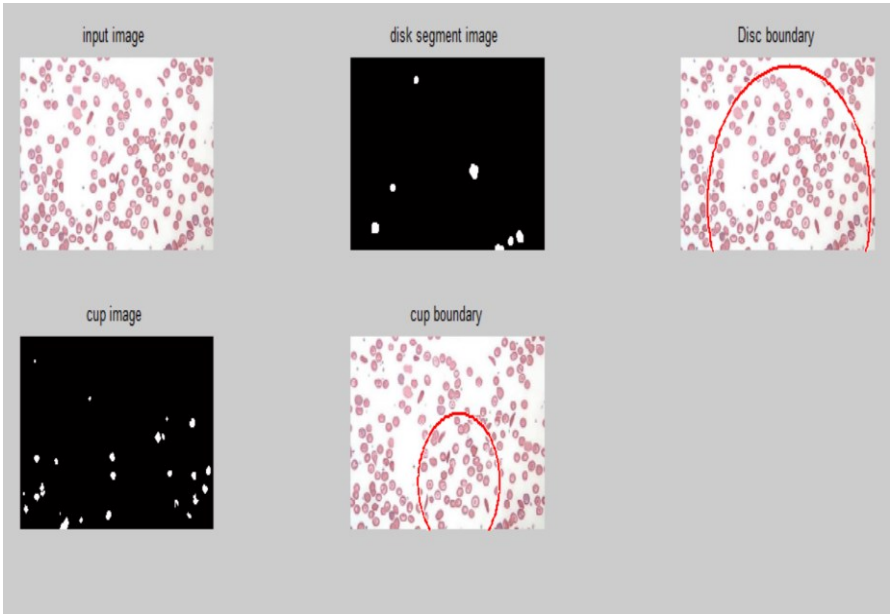

Figure.13 Blood classification

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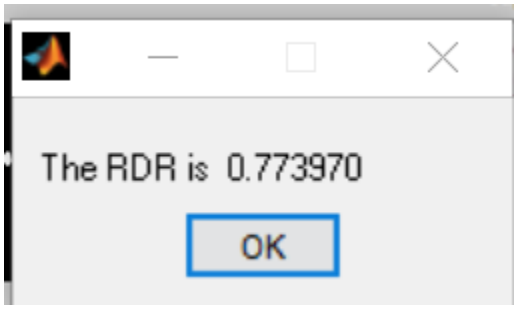

Figure.14 RDR value

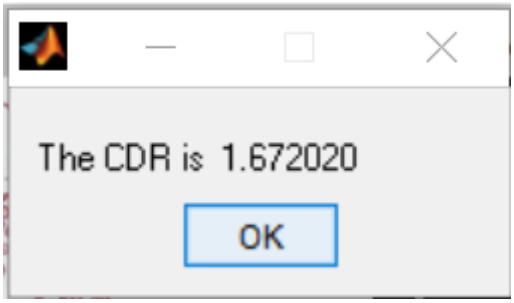

Figure.15 CDR value

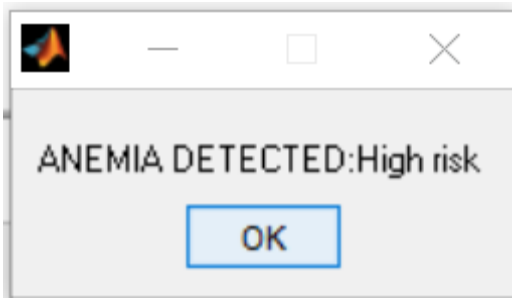

Figure.16 Anemia High risk

ADVANTAGES

- Automated method to detect sickle cells, minimize the error of dependence on the naked eye
- Indicate the sickle RBCs automatically in one shot, minimize the error of dependence on the naked eye
- Used to monitor the sickling events accurately
- Can be used as point of care(POC) to monitor the diseases severity, reduce the cost
- Robust test, can be automated to correlate the percentage of HbF and the percentage of sickled cells, biomarker of disease severity.
- Simple, low-cost, uses cellphone-like camera

CONCLUSIONS

Sickle cell anemia is a recessive hereditary malady in which abnormal erythrocytes are developed. Life expectancy is diminished by it. Detection of sickle cells from RBC within a shortest time correctly is the most challenging task. In this paper, an automated system has been developed which can be used for detection and classification of sickle cell anemia. The efficiency of algorithm is upgraded by threshold segmentation. Morphological operations are used to remove the imperfection cells from red blood cells. By analyzing the parameters, the features are extracted successfully. For classification there has used support vector machine (SVM). It has given very much satisfactory results. It is hoped that this system would prove helpful in medical sectors and save lives of people with high accuracy and high sensitivity.

The future work is to include the more amounts of data and extend the detection of ovalocytes and echinocytes for better results. The image processing techniques used in this project, which includes color altercation and clustering based image segmentation has helped us to better understand the sickle-cells present inRed Blood Cells (RBCs) in case of sickle-cell patient. Using the image segmentation technique and the following sub-imaging technique, I can obtain the images of particular affected RBCs, i.e. Sickle-cells, Anisopoikilocytes and Ovalocytes and further apply feature extraction process to determine the characteristics of affected RBCs andthus make an artificial neural network to automatically diagnose sickle-cells disease affected person

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