OPTIMIZED HAEMATOLOGICAL TYPE IDENTIFICATION WITH NON-INVASIVE IMAGE PROCESSING

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Abstract - Haematological type is a critical step in many medical procedures, but traditional methods of detection are susceptible to human error. A more efficient and error-free approach is to use technology to accurately determine the Rh factor and blood group of a sample. This process involves taking a photo of the sample blood slide and applying algorithms such as grayscale, binary, and canny edge detection to determine agglutination. The procedure is faster and eliminates the possibility of human error, and results from the experiment have been found to be accurate compared to real-time data analysis. The process is simplified and made more precise using numeric values determined from real-time data analysis using a mobile camera.

Key Words: Agglutination, Rh factor, Canny edge detection

I INTRODUCTION

A study by the World Health Organization (WHO) found that road accidents result in an average of 0.35 million (8%) deaths and 4.4 million injuries annually, often requiring urgent blood transfusions (Jayawardena, 2021). Blood typing is also necessary in various scenarios such as public health centers, battlefields, schools, veterinary care centers, and forensic sites, particularly in rural areas of developing countries where access to labs and trained technicians is limited (Dong et al., 2017). The conventional method of blood typing may be life-threatening due to the lack of technicians, and in emergency situations, the universal donor blood is often administered, which may cause adverse reactions and reduce stock levels (Yasmin et al., 2017).

Blood is an essential part of the human body that circulates essential elements like oxygen and nutrients (Khaleduzzaman et al, 2021). For medical procedures, it is crucial to know the blood type and other features like RBC count and CBC(Sklavounos et al.,2021). The traditional methods of detecting blood group, such as the plate test and the tube test, are not efficient and require complete analog procedures with human observation (Petäjä et al., 2004). Other techniques, like micro plate testing and gel centrifugation, are costly and require skilled personnel and specialized equipment. In an emergency situation, this might not be feasible. The process of blood group

analysis depends on the agglutination of a sample blood. The blood is mixed with three antigens, A, B, and D, and the agglutination determines the blood group. Image processing techniques, such as threshold morphological operations, have been used for the detection of composite organisms from a sample blood slide. However, human observation can lead to errors (Myhre & McRuer, 2000). To determine the correct blood group, an impeccable operation with logical and mathematical calculations and flawless image processing is needed to detect residual errors. The literature has suggested different methods for detecting blood groups, such as cross matching (Dada et al., 2007; Odeh et al., 2021), IMAQ Vision software (Ferraz et al., 2011; Ferraz, 2013), watershed algorithm (Sharif et al., 2012), algorithm based on Standard Deviation (HasanTalukder et al., 2015), NiBlack segmentation (Panpette et al., 2017), thresholding and morphological operation (Ravindran et al.,2017), adaptive thresholding (Saddami et al., 2018), and blob detection (Dhande et al., 2018. However, these existing methods are expensive and require a significant amount of time. Therefore, this study aims to overcome the limitations of the existing algorithms and enhance the accuracy of the results by utilizing straightforward techniques. The paper introduces an automatic system that employs image processing techniques to extract results from a glass slide's image. This system enables quick and reliable blood typing, even in remote locations.

II PROPOSED METHOD

This paper introduces a novel approach to detect blood groups using a four-step process. The first step is to convert the input image into a grayscale image that represents the range of light in each pixel. The second step is to convert the grayscale image into a binary image, where each pixel is assigned one of two values. The third step involves segmenting the binary image into three individual images. Finally, the Canny approach is used to identify edges in the image by evaluating the brightness discontinuities and complexity of the image's shape. The proposed approach achieves a perfect accuracy of 100% in detecting blood groups. It is shown in Figure 1.

The four-step process introduced in this paper aims to improve the accuracy and efficiency of blood group detection. The grayscale conversion and binary conversion steps are common image processing techniques used to simplify the image for further analysis. The segmentation of the image into three individual images is an innovative step that allows for the detection of specific features of blood groups, such as the presence or absence of antigens. The Canny approach is a well-established edge detection technique that enhances the accuracy of the image analysis by identifying the edges of the blood cells and other features in the image.

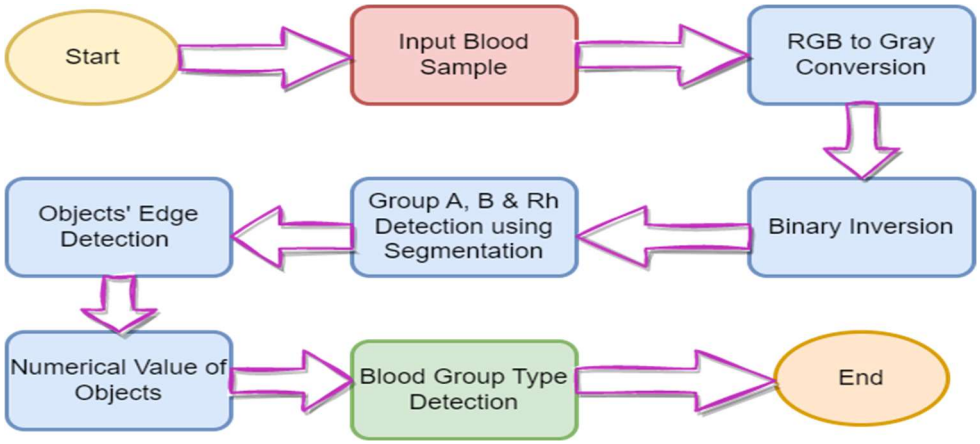


Figure 1 Block diagram of the proposed method for Blood group type detection

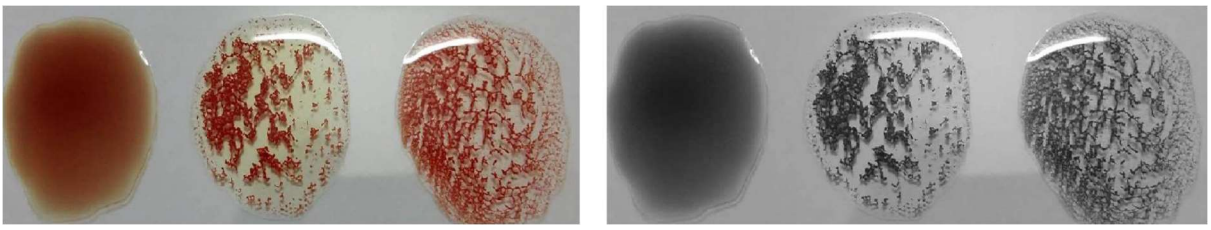
(a) Colour Image to Gray Scale Image Conversion

Converting a colour image to a grayscale image is a common image processing task. Grayscale images have only one channel, representing the brightness or intensity of the pixels, while colour images typically have three channels representing red, green, and blue colour values. The process of converting a coloured image into a grayscale image requires the computation of a solitary gray value for every individual pixel present in the initial colour image. There are several methods for converting colour images to grayscale, each with its own advantages and disadvantages. One of the most common methods is the luminance method, which calculates the grayscale value of a pixel as a weighted average of its red, green, and blue colour values. The weights used in the calculation can vary depending on the application, but a common set of weights is:

$$Y = 0.2999R + 0.587G + 0.114B \quad (1)$$

where **Y** is the grayscale value, **R**, **G**, and **B** are the red, green, and blue colour values, respectively.

This method is based on the fact that the human eye is more sensitive to green light than to red or blue light, so the green colour value is given more weight in the calculation. The coefficients used in the above equation are based on the sRGB colour space, which is commonly used for computer displays and digital images. The blood sample is depicted in both RGB and Gray scale formats in Figure 2.



(a) (b)

Figure 2 (a) RGB image (b) Gray scale image of blood sample

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(B) Binary Inversion

Figure 3 depicts a popular technique used in detecting blood group type, which involves converting an image of a blood sample from grayscale to binary to extract the blood type information. This is because binary images only contain two-pixel values (black and white), which can simplify the image processing and analysis required to identify the blood type.

The conversion from grayscale to binary involves thresholding the image, which means selecting a pixel intensity value (or range of values) that separates the foreground (blood cells) from the background (the surrounding liquid or tissue). This threshold value can be determined manually or automatically, depending on the complexity of the image and the desired level of accuracy.

Once the threshold value is chosen, all pixels with intensity values above the threshold are set to white (representing blood cells) and all pixels with intensity values below the threshold are set to black (representing the background). The resulting binary image can then be processed using techniques such as image segmentation, edge detection, and pattern recognition based on object connection to extract the blood type information.

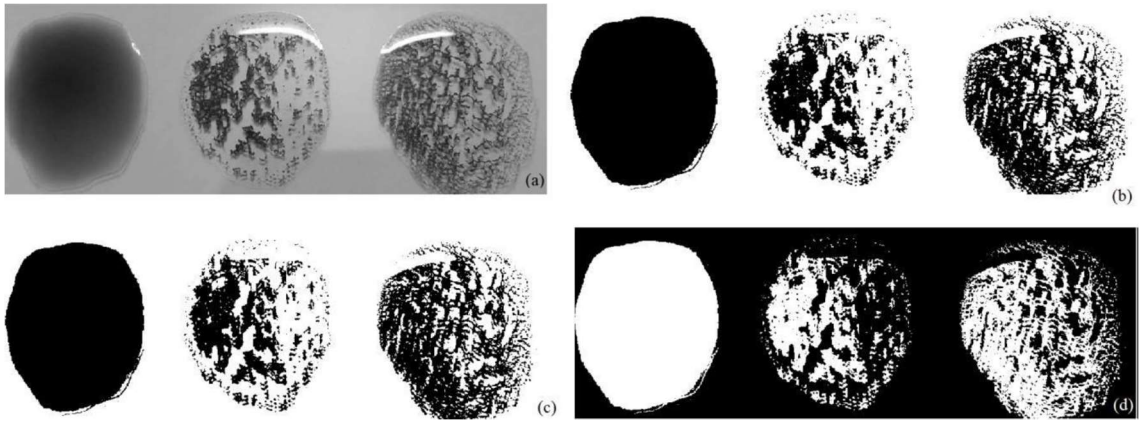

Figure 3 (a) Gray scale image, (b) & (c) Binary image (d) Binary inversion of blood sample

(C) Segmentation of Group A, B and Rh Factor

In blood group type detection, segmentation is the process of identifying and separating the relevant objects (i.e., blood cells) in an image from the background and other objects that are not of interest (Dong, 2014). The image is represented by a matrix with m rows and n columns, with each element being a pixel. Segmentation simplifies the image representation into a form of P(SI *SJ*) and separates the image into distinct groups or parts. The image is segmented into three parts, Group A, Group B, and Rh factor, using a segmentation function. It is clearly presented in Figure 4.

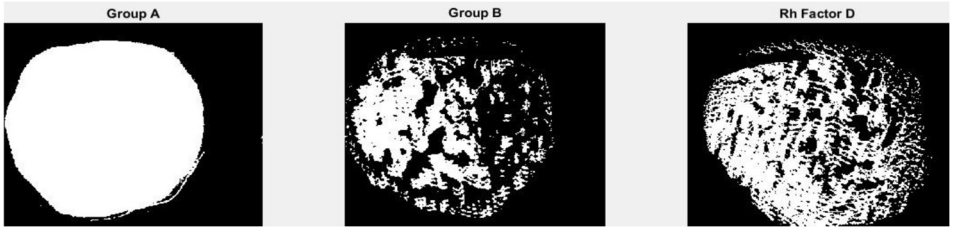

Figure 4 Segmentation of image into Group A, B and Rh factor

(D) Counting object based on Canny edge detection

Canny edge detection is a method for finding edges in an image. It involves smoothing the image with a Gaussian filter to reduce noise, finding edges with gradient magnitude and direction, non-maxima suppression to thin the edges, and linking edge segments to form continuous edges. Figure 5 depicts the canny edge detection operation of blood sample image (Yang, 2015).

Closed edges can be detected using edge detection algorithms, which are designed to identify the boundaries between objects in an image. Once the closed edges have been detected, it is possible to count the number of objects present by analysing the topology of the edges.

One common method for counting objects is to use a connected components algorithm, which groups together all pixels that are connected to each other. Each connected component is assigned a label, and the number of labels corresponds to the number of objects present in the image. In the case of blood typing, each agglutinated clump would correspond to a separate connected component.

The Canny edge detection algorithm is a process consisting of multiple steps used to detect edges from an image in pixels. One of the initial steps in this process is to apply a Gaussian filter to the image to smooth it out, which helps to reduce any unwanted noise, textures, and details. This filter works by convolving the image with a 2D Gaussian function, which is represented mathematically by a specific equation.

$$H(x,y) = \frac{1}{\sqrt{2\sigma^2}} e^{\left(\frac{x^2+y^2}{2\sigma^2}\right)} \quad (2)$$

where H(x, y) represents the value of the Gaussian function at position (x, y), σ is the standard deviation (a measure of the spread) of the Gaussian distribution, and exp is the exponential function.

Once the Gaussian function has been applied to remove noise from the image, the gradient operation is performed to determine the magnitude and direction of the image gradient at every individual pixel location of blood sample. The gradient function is represented by the following mathematical formula:

$$\Delta F(x,y) = \left[\frac{\partial F(x,y)}{\partial x}, \frac{\partial F(x,y)}{\partial y}\right] \quad (3)$$

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where F(x, y) represents the image intensity function, and ∇F(x, y) represents the gradient vector at position (x, y). The gradient vector has two components: the partial derivative of the intensity function with respect to x (i.e., the change in intensity along the x-axis) and the partial derivative of the intensity function with respect to y (i.e., the change in intensity along the y-axis).

The gradient function can be used to detect edges and other features in blood sample image by identifying regions where the intensity changes rapidly. The magnitude of the gradient vector at each pixel location represents the strength of the edge or feature, while the direction of the vector represents the orientation of the edge or feature.

Then, thresholding is often used to segment the image and isolate the region of interest (i.e., the blood group). By selecting an appropriate threshold value, it is possible to distinguish the blood group region from the background and remove any unwanted information. The thresholding function is represented by the following mathematical formula:

$$G(x,y) = \begin{cases} 0 & if\ F(x,y) < T \\ 1 & Otherwise \end{cases} \quad (4)$$

where F(x, y) represents the input image, T is the threshold value, and G(x, y) represents the binary output image.

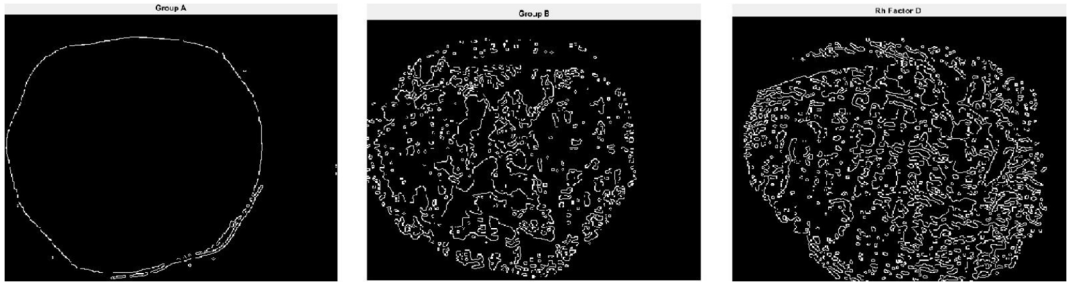

Figure 5 Application of Canny edge detection

III RESULT AND DISCUSSION

The result of the proposed method for blood group detection involves two steps: identifying the blood group (A, B, O, or AB) and determining whether the blood is positive or negative, is shown in Figure 5. The detection of the blood group is based on the observation of agglutination when the blood sample is mixed with antigens. If agglutination occurs in part A of the slide and not in part B, the blood group is detected as A. If there is no agglutination in either part A or B, the blood group is O, and if both parts A and B show agglutination, the blood group is AB. To determine if the blood is positive or negative, the focus is on the Rh-factor part. If there is any agglutination in the Rh-factor part, the blood is positive, otherwise it is negative.

The study discussed in the result focuses on using image processing techniques to detect blood groups and the Rh-factor of blood samples. The different blood groups and their pattern of

agglutination is presented in Table I. The proposed system detects the agglutination of blood by counting the number of edges in the images. The results reveal that when the number of edges is high in the image, it means that agglutination has occurred and when the number of edges is low, the absence of agglutination can be presumed. On analysing 100 blood samples, the study found that agglutination occurs when there are more than 32 edges found in any particular group. The system was tested on several images and showed promising results.

The model uses the information from Table 2 which shows the number of edges detected in different images. The information from Table 2 is further processed to determine the presence or absence of agglutination in part A, B and Rh-factor. Three variables, NA, NB, and NRH are declared for each part and their values are determined based on the number of edges. If the number of edges is greater than 32, it is considered as agglutination and the value of the respective variable is set to 1. If the number of edges is less than 32, it is considered as no agglutination and the value of the respective variable is set to 0. The final result is obtained by comparing the data from Table 2 with the pattern from Table 1.

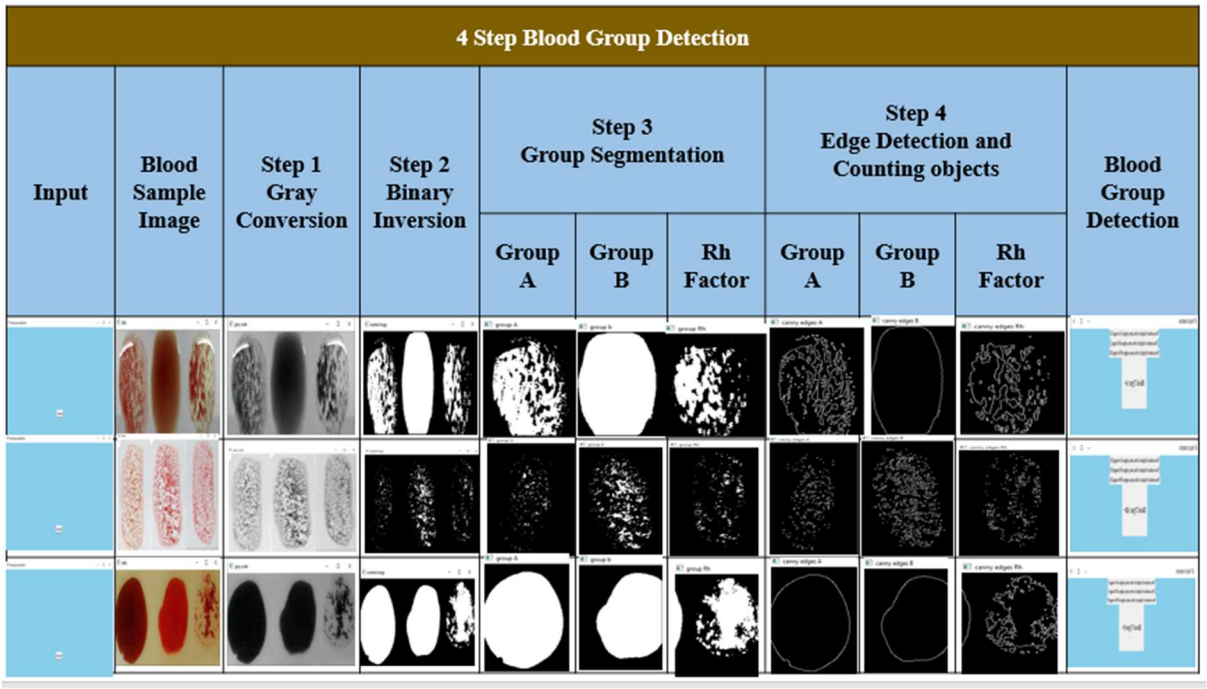

Figure 5 Result of 4 – step blood group detection method

Table 1 Blood group detection from agglutination type

Blood Samples	Group A	Group B	Rh Factor	Blood Group
S1	NA	NA	NA	O-
S2	NA	NA	A	O+

S3	NA	A	NA	B-
S4	NA	A	A	B+
S5	A	NA	NA	A-
S6	A	NA	A	A+
S7	A	A	NA	AB-
S8	A	A	A	AB+

NA – Non-Agglutination A- Agglutination

They have used a table that lists the number of edges in each of the three parts (part A, part B and Rh-factor) for 8 different samples. They have then declared three variables, NA, NB and NRH, to represent the number of edges in each of the three parts.

To determine whether a sample is agglutinated or not, they compare the number of edges in each part to 32. If the number of edges is greater than 32, they set the corresponding variable to 1, indicating that the sample has agglutinated. If the number of edges is less than 32, they set the corresponding variable to 0, indicating that the sample has not agglutinated.

Table 2 No. of edges in eight blood sample images

Blood Samples	No. of Edges in Group A	No. of Edges in Group B	No. of Edges in Rh Factor	Blood Group
S1	3	1	1	O-
S2	1	1	87	O+
S3	4	144	4	B-
S4	18	397	492	B+
S5	166	2	14	A-
S6	153	2	108	A+
S7	232	248	5	AB-
S8	253	355	203	AB+

For the first sample in Table 2, the authors found that the number of edges in part A was 166, which is greater than 32. This means that the sample has agglutinated for Type A. The number of edges in part B was 2, which is less than 32, indicating that the sample has not agglutinated for Type B. The number of edges in the Rh-factor part was 14, which is also less than 32, indicating that the sample has not agglutinated. Based on these results, the authors conclude that the blood type of this sample is A.

V CONCLUSION

This paper proposes a novel efficient model for blood group detection using image processing techniques. The model is applied to image sets captured by a mobile device and processed through various image processing methods and algorithms. The blood sample is segmented into three parts and Canny edge detection method is applied to count the detected edges to determine the blood group of the sample. The experimental result with the collected dataset of 100 blood samples shows a promising process with effective performance, compared to real-time diagnostic results. The proposed method is feasible for common people as it does not require any pathology tests for blood group detection. Diagnostic centers can capture the images for collecting data and provide accurate results. Further research is underway to detect blood group from microscopic images using shape and pattern detection methods of the specific antibody in the blood cell that reacts with the antigen. The proposed method has potential for wider application in medical diagnosis and treatment, and could provide a simple and cost-effective solution for blood group detection.

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