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Gray Level Co-occurance Matrix for Blood Type Identification

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Abstract. *Blood type identification is an important step to ensure the safety of blood transfusion. Direct observation of blood samples that have been tested with anti-A and anti-B serum can lead to errors in identification due to lack of accuracy or haste in observing. Recognition of blood type can be determined from different textures of blood samples that have agglutination or non-agglutination. This research proposes the application of the GLCM method to obtain texture characteristics found in blood samples based on statistical values, namely contrast, correlation, energy and homogeneity. The calculation results of the feature values obtained show that the distribution of values tends to be separate for agglutinating and non-agglutinating blood samples. So it can help the classification or identification process to determine blood type.*

Keywords *: Blood Group, Contrast, Correlation, Energy, Homogeneity*

BACKGROUND

Blood is a red body fluid and is found in a closed circulatory system and is very important for human survival. Blood functions to enter oxygen and food throughout the body and take carbon dioxide and metabolism from the tissues. Knowing a person's blood type is very important for medical purposes, one of which is for transfusions (Cruz et al., 2020) . Blood type is not only an individual identity but has a very important function for humans. Blood group type plays an important role in several medical procedures, especially in blood transfusions, although cross-testing or *crossmatching* must still be carried out for compatibility between donor and recipient. Apart from that, with the increasing development of research on the function of blood groups, blood group types can also be used in the process of making decisions about genetics , health, diet and determining human traits and characteristics that can be developed in various blood group types (Tsuchimine et al., 2015) . Conventionally, detecting blood type manually by dripping anti-A serum and anti-B serum onto the blood to be recognized and then directly observing the reaction of the serum droplets. Computerizedly, blood types can be identified through patterns from blood images that have been dripped with

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anti-A and anti-B serum. After going through several stages of image processing, the system will carry out a classification process to determine the type of blood type from the blood image (Gupta, 2024) .

Blood type identification is an important step to ensure the safety of blood transfusion. In an emergency case of blood transfusion, this step is very necessary to be able to identify the blood type quickly and accurately because it is related to the patient's survival (YF Dong et al., 2017) . Blood transfusions can only be carried out if the blood type between the recipient and donor is the same. In the medical world, human blood groups are divided into 4, namely: A, B, AB and O. Thus, in blood transfusions, tests are also carried out to determine human blood groups (Y. Dong et al., 2017) .

THEORETICAL STUDY

was first identified by the Austrian scientist K arl Lands teiner at the beginning of the twentieth century . It categorizes blood into four types based on the presence or absence of specific antigens on red blood cells: A, B, AB, and O. The most important blood group antigens are antigens A and B. Characteristics of these antigens is at the end of the sticky sugar directly on the wall cell or attached to a series of proteins and lipids located in the red blood cell membrane (Dean, 2005) .

Conventionally, blood type recognition is done by taking a blood sample to be identified. The blood will be placed in a preparation and divided into 2 parts. Each part of the blood will be tested for anti-A and anti-B serum. After mixing, direct observation will be carried out of the reactions that occur in the blood that has been dripped with serum. From the results of this observation, it will be determined whether the blood belongs to group A, B, AB or O. Computerizedly, blood type can be identified through the pattern of the image of blood that has been dripped with anti-A and anti-B serum. After going through several stages of image processing, the system will carry out an identification process to determine the type of blood type from the image. Identification of blood types using *image techniques processing* has attracted attention with the aim of obtaining a fast, accurate and automatic blood group identification system (Yamin et al., 2017) . Several identification and feature extraction methods that have been used, such as the GMI (*Geometric Moment Invariant*) and SOM (*Self-Organizing Maps*) methods, have shown accuracy of up to 92.5% (David M et al., 2018) . The blood group identification system can also be carried out based on the histogram value of the sample image to obtain the minimum and maximum RGB values and classification is

carried out using an *Artificial Neural Network* (ANN). From the test results using 12 samples, it was found that the average blood group identification error was 16.67% (Syafaah et al., 2021)

Image

Image is a two-dimensional image produced from a continuous two-dimensional analog image into a discrete image through a sampling process. Theoretically, images can be grouped into two types, namely continuous images and discrete images (digital images). Digital images are images that are expressed discretely, both in terms of coordinate position and color. Thus, a digital image can be described as a matrix, where the row index and column index of the matrix state the position of a point in the image and the values of the matrix elements state the color of the image at that point (Hlavac, 2011) .

Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-Occurrence Matrix (GLCM) is the most frequently used method for texture analysis introduced by Haralick in 1973 (Mulkan, 2012). GLCM is a matrix that describes the frequency of appearance of pairs of two pixels with a certain intensity within a distance d and directional orientation with a certain angle θ in the image (Hartadi, 2011). Usually, there are four directions used, namely 0 º , 45 º , 90 º and 135 º which are shown in Figure 1.

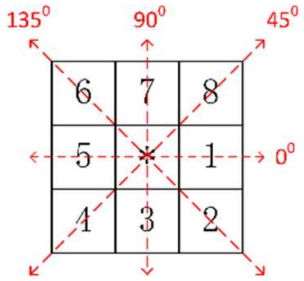


Figure 1 Neighborhood relationships between pixels as a function of orientation and spatial distance (Gao et al., 2021)

Co-occurrence means co-occurrence, namely the number of occurrences of one pixel value level adjacent to another pixel value level within a certain distance (d) and angular orientation (θ). Distance is expressed in pixels and orientation is expressed in degrees (Budiarso, 2010). Orientation is formed in four angular directions with 45° angle intervals, namely 0°, 45°, 90°, and 135°. Meanwhile, the distance between pixels is usually set at 1 pixel, 2 pixels, 3 pixels and so on. The co-occurrence matrix is a square matrix with the number of elements equal to the square of the number of pixel intensity levels in the image. Each point (i,j) in the oriented co-occurrence matrix contains the probability of the occurrence of pixel

value i neighboring pixel value j at distance d and orientation (180 − θ) (Vadakkenveettil et al., 2012) .

RESEARCH METHODS

In general, the method used in this research is based on the digital image processing process shown in Figure 2 below:

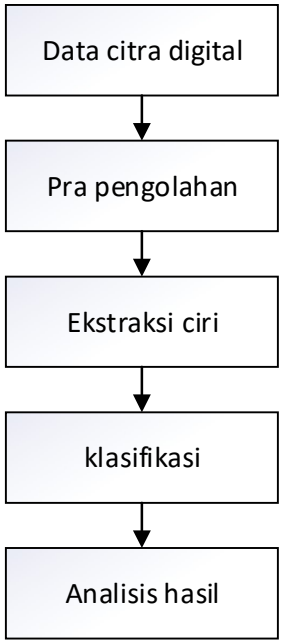


Figure 2 Research Stages

Digital image data is taken from a blood sample that has been dripped with antigen A and antigen B. After mixing thoroughly, a physical reaction will occur between the two samples. Where the physical reaction is in the form of clumping (agglutination). This agglutination will form a different texture so that it can be analyzed to determine blood type. After that, the data is taken using a camera with 1080p resolution which is conditioned by sufficient lighting so that a digital image is obtained on the blood card as in Figure 3 below:

Figure 3 blood image

The pre-processing stage is carried out to get better data than the previous data. At this stage, apart from cropping to get a new image size, segmentation is also carried out to get the desired image and discarding unused areas.

Feature extraction is carried out with the aim of obtaining the characteristics of each type of blood group, namely blood groups A, B, AB and O. At this stage, the features are taken based on statistical values to examine the texture which takes into account the spatial relationship between pixels, namely using the *gray level coocurance method. matrix* (GLCM). So that several statistical characteristics are obtained in the form of contrast, correlation, energy, and homogeneity (Nixon & Aguado, 2012) .

a) Contrast

Shows the size of the spread (moment of inertia) of the image matrix elements. If it is far from the main diagonal, then the contrast value is large. Visually, the contrast value is a measure of the variation between the degrees of gray in an image area

$$\sum_{i,j=0}^{N-1} P(i,j)(i-j)2$$

Where, P(i,j) = element value of the co-occurrence matrix

b) Correlation

Shows a measure of the linear dependence of the degree of gray in the image so that it can provide an indication of the existence of a linear structure in the image

$$\sum_{i,j=0}^{N-1} P\ i,j \left[\frac{i-\mu x(j-\mu y)}{\sqrt{(\sigma x2)(\sigma y2}}\right]$$

Where, μx= average value of column elements in the matrix Pθ(i,j)

μy= average value of row elements in the matrix Pθ(i,j)

σx= standard deviation value of column elements in the matrix Pθ(i,j)

σy= standard deviation value of the row elements in the matrix Pθ(i,j)

c) Energy

shows a measure of the concentration of intensity pairs in the cooccurrence matrix . The energy value increases if the pair of pixels that meet the requirements of the co-occurrence intensity matrix are concentrated in a few coordinates and decreases if they are spread out.

$$\sum_{i,j} P(i,j)^2$$

Where, P(i,j)=cooccurrence matrix element value

d) Homogeneity

Shows the homogeneity of intensity variations in the image. A homogeneous image will have a large homogeneity value. The homogeneity value increases when the intensity variations in the image decrease and vice versa.

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|}$$

Where, P(i,j)= co-occurrence matrix value

RESULTS AND DISCUSSION

The dataset used in this research is real data taken from blood group cards. Next, digital images were taken using a Google Pixel 3XL smartphone camera with a camera resolution of 12 Megapixels. With a total of 40 images of data. The digital image results that have been obtained are as shown in Figure 4 below:

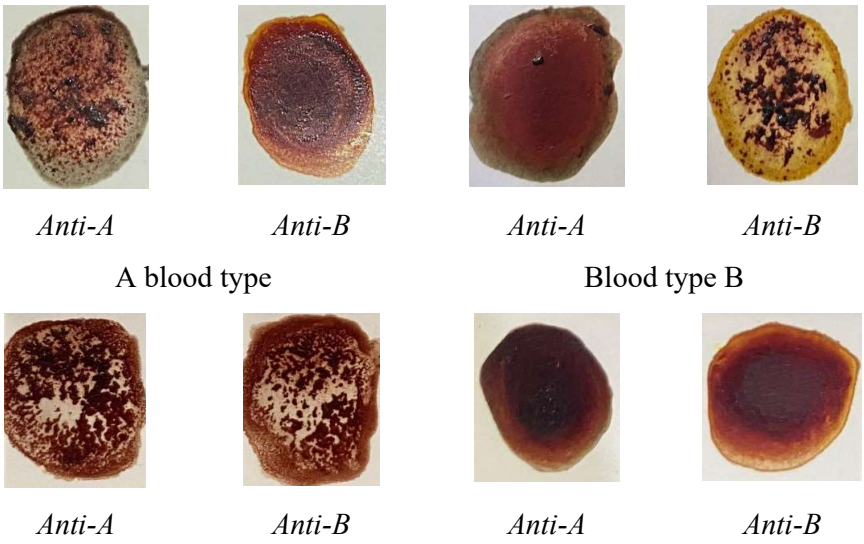


Figure 4 Image of a blood sample that has been tested with anti-A and anti-B serum

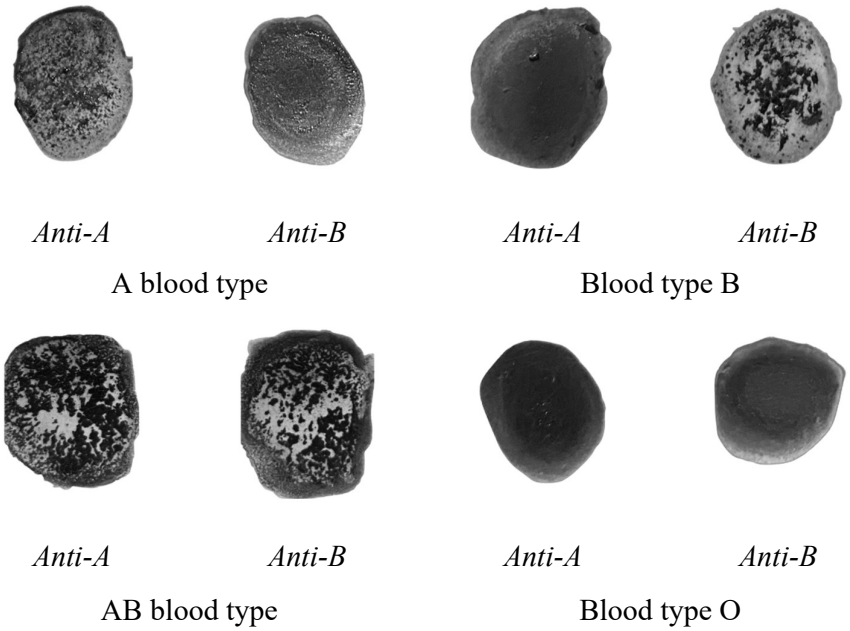


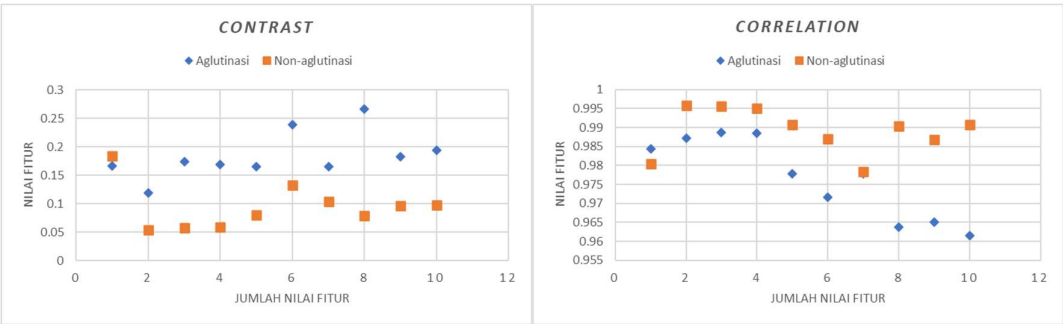
Figure 5. Segmented blood image

The feature extraction process is carried out with the aim of obtaining characteristics from each blood group image that has been processed. Each has a different texture and can be seen in anti-A and anti-B cintra after agglutination. Then the characteristic values are obtained for blood samples that have clotted and not clotted, so that from this data the type of blood type can be identified. The average value of each GLCM parameter is obtained as in table 1.

Table 1 GLCM feature extraction results

	contrast	***correlation***	***energy***	***homogeneity***
Agglutination	0.15702	0.98717	0.21655	0.93312
Non-agglutinating	0.08912	0.99180	0.27697	0.96140

The GLCM feature values obtained from blood images where agglutination occurs and where agglutination does not occur for each parameter have a distribution as in Figure 6.



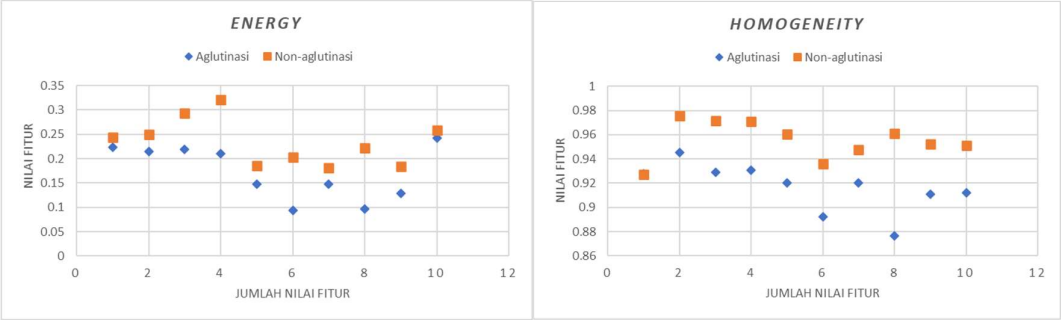


Figure 6 distribution of feature values (contrast, correlation, energy and homogeneity)

Based on this graph, it can be seen that the value of each GLCM feature shows different value areas which tend to be different for each feature. So it can be used as a characteristic or feature value to determine whether there is agglutination or not, so that based on samples anti-A and anti-B can be identified for each type. group blood .

CONCLUSIONS AND RECOMMENDATIONS

Based on the stages that have been carried out in this research, it shows that the use of the GLCM method can be used as an alternative for identifying blood groups based on the characteristic values that have been obtained in agglutinated and non-agglutinated blood samples . The distribution of characteristic or feature values for each parameter shows the difference between samples where agglutination occurs and where agglutination does not occur, so it can help in identifying blood groups.

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