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Research Article

Automated Platelet Counter with Detection Using K-Means Clustering

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Abstract: Platelet is a blood cell type that is stored and circulated in the human body. It acts as a blood thickening agent and prevents blood from overflowing whenever bleeding occurs. An excessive or inadequate number of platelets could lead to platelet-related diseases. The current practice of platelet counting involves the manual counting process using a haemocytometer, Wright's Stain which uses the dyes to facilitate the differentiation of blood cell types, and a tally counter. Yet, this process can be time-consuming, demanding, and exhausting for haematologists, and likely to be prone to errors. Thus, this paper presents a study on automated platelet counter and detection using image processing techniques. The K-Means Clustering was employed to count and detect the presence of platelets in microscopic blood smear images. Several processes were performed prior to the K-means clustering, including image enhancement and YCbCr image formatting. Subsequently, image masking, as well as area thresholding were applied to eliminate every unwanted entity and highlight the visibility of the platelets before the number of platelets could be detected and counted. A comparative experiment was designed in which the K-Means Clustering platelet count and detection were compared with the actual number of platelets reported by haematologists. The platelet counts and detection were categorized into three detection categories which are Less Detection (LD), Accurate Detection (AD), and Over Detection (OD). The proposed study was evaluated to 90 testing platelet images. Out of the 90 testing images, 75 platelet images were perfectly counted and detected which returned 91.67% of accuracy. This signifies that the K-Means Clustering algorithm was discovered to be efficient and dependable for automated platelet counter and detection.

Keywords: ***Detection; Image Processing; K-Means Clustering; Platelet Counts***

1. Introduction

Clinically, water makes up 70% of our body weight despite the fact that it decreases over time. Water could be present in both inside and outside cells, regardless of where in the body it is found. The cells hold two-thirds of the water in the body, while the remainder is found in extracellular fluid. White blood cells (WBCs), plasma, platelets, and red blood cells (RBCs) are the four basic components of blood that account for approximately 10% of total body fluid [1]. Plasma is the fluid portion of the blood that has numerous compounds distributed into it, accounting for more than half of the total blood volume. Unlike RBCs, which carry oxygen throughout the body, WBCs act as defensive mechanisms against pathogens by eliminating them. Platelets, on the other hand, cluster together and block the opening of wounded blood vessels, preventing them from bleeding.

Immune thrombocytopenia (ITP) refers to a well-known disorder in which a patient's platelet count controls their bleeding pattern variability. The ITP patients have fewer platelets, and severe ITP occurs when the count drops below 20,000 per microliter [2]. Diagnostic procedures like the Complete Blood

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Count (CBC), Flow Cytometer, and Serologic Assays are commonly used to evaluate the number and condition of platelets in suspected patients as early detection. The CBC is among the most typical blood examinations performed on individuals. The purpose of the CBC is to discover the amount of blood cells in the human body. If a person has been diagnosed with any blood disorders, such as platelet abnormalities, the findings of the CBC will be revealed. The procedure begins with a phlebotomist collecting blood from the arm; the blood is then processed and kept by haematologists for further processing. The haematologist must then transfer the processed blood sample onto a glass slide and capture its image under a compound microscope.

The current practice of platelet counting involves the manual counting process using a haemocytometer, Wright's Stain which uses the dyes to facilitate the differentiation of blood cell types, and a tally counter [3]. Manual platelet counts can be performed using a commercial dilution method, haemocytometer, and scientific microscope. However, automated numbers are more dependable than such statistics since platelets can be difficult to distinguish. The manual counting process could also be time-consuming, burdensome, and exhausting for haematologists [4], particularly when there are numerous patients on one occasion. Additionally, the manual platelet count may lead to miscounting the number of platelets due to human error [5]. The platelet may have overlapping blood cells that make counting with the naked eye difficult. The reports made from sample platelets that have been counted should be treated meticulously as platelet-related disorders may be misdiagnosed or over diagnosed.

The simplest method for humans to assess information is through vision. On the other hand, image processing aims to develop an imitation of human vision whenever an image is produced electronically. It entails improving visual information for human perception as well as processing scene data for machine interpretation. It has been successfully applied in various applications [6] for instance biometrics, pattern recognition, medical image processing, image denoising, image compression, and many more.

Thus, due to the great capabilities of image processing, a study on automated platelet counter and detection using image processing techniques is proposed. Several image processing steps were implemented such as image enhancement, YCbCr image formatting, K-Means clustering, image masking, and area thresholding before the number of platelets could be detected and counted. The performance of the proposed study was then evaluated in which the K-Means Clustering platelet count and detection were compared with the actual number of platelets reported by the haematologist. The employment of image processing techniques is expected to reduce the dependency on expert haematologists and avoid manual errors in platelet count and detection. It is also hoped that the findings of this research would aid in the medical field particularly to assist haematologists in achieving a more efficient way of platelet counts and detection.

The following section is laid out in such manner: Section 2 explores the related works on platelet counting and detection, Section 3 explains the methodology, including the discussions of the techniques and a flowchart. Section 4 discusses the results and discussions. Eventually, our conclusion is outlined in Section 5.

2. Related Works

To date, the adoption of image processing for blood cells detection from blood sample microscopic images is becoming a current research focus. Image processing can be divided into two approaches in the automated blood cells count which are traditional and Deep Learning-based methods. Pre-processing, feature extraction, segmentation, and classification are some of the steps involved in traditional methods. It can be done in a variety of techniques such as thresholding, colour-based segmentation, transformation, texture-based, and many more. Alomari *et al.* [7] presented a technique for both WBCs and RBCs segmentation and count in microscopic blood images. The counting is performed based on the blood cells' circularity features which are retrieved by a structured circle detection technique. The segmentation was then performed based on thresholding and morphological processes. The suggested model has a higher chance of the right circle selection from candidates, the capacity to recognise irregular cells, the dynamic number of iterations usage, and better identification of occluded cells.

Several researchers have concentrated their efforts on transformed colour space segmentation, for example Hue Saturation Value (HSV), to make cytoplasm segmentation easier via threshold-based approaches. Cruz *et al.* [8] suggested segregating WBC from its background using a single-threshold based on the hue channel of the HSV colour space. The HSV colour space was adopted because of the inherent interdependence between brightness and chrominance in Red Green Blue (RGB).

Numerous computer vision applications, for instance, object detection, classification, and segmentation have incorporated deep learning networks as a significant component. A vast number of independent experiments in a variety of modalities and applications, such as those for autonomous cell counting, have demonstrated the efficiency and utility of Deep Learning in the medical imaging area. Nirav *et al.* [9] implemented the Deep Learning approach which effectively and rapidly processes the images for the count of WBCs, RBCs, and platelet.

The WBCs and RBCs detection have been studied extensively, whereas platelets have received relatively little attention [10]. Platelet count is an important pathological diagnostic that aids in the diagnosis of a variety of diseases, including dengue fever, malaria, yellow fever, and many more. Kaur *et al*. [11] employed the Circular Hough Transform (CHT) for platelet counter. Dey *et al*. [12] used Red Green Blue (RGB) to L*A*B conversion, Average Filter, Binary thresholding, and Morphology. Cruz *et al.* [8] adopted Hue Saturation Value (HSV) conversion and HSV thresholding. Table 1 lists several related studies on blood cells (RBC, WBC, and platelet) count and detection.

Table 1. Related Studies on Blood Cells Count and Detection

Year	Author	Technique	Description
2016	Kaur, Sharma, & Garg [11]	Circular Hough Transform	Focus: **platelets**. The results of the human and machine methods were compared.
2016	Dey, Roy, Bhattacharjee, Nasipuri, & Ghosh [12]	RGB to LAB conversion, Average filter, Image Binarization Block, Morphological Operation Block	Focus: **platelets**. The results were compared to manual platelet count.
2018	Cruz, Jennifer, Valiente, Leonardo, Castor *et al.* [8]	HSV thresholding, morphological equation	Focus: **platelets**, RBCs, and WBCs. The results of manual and machine methods were compared.
2019	Shafique, Tehsin, Anas, & Masud [13]	Zack's Algorithm, roundness ratio, Histogram equalization, watershed segmentation, Support Vector Machine	Focus: WBCs. The results were compared with CBC results.
2020	Nirav, Shail, Ramchandra, & Pankaj [9]	Faster Region-based Convolutional neural network (CNN)	Focus: WBCs, RBCs, and **platelets**.
2021	Kumaran, Saranya, Ananthi, Rachamalla, Sally *et al.* [14]	Hear wavelet, Blob algorithm	Focus: blood cells.

3. Methods

This study attempted to automize the process of platelet counter and detection using image processing techniques. Figure 1 portrays the flowchart of this research.

The automated platelet count and detection process begins with the input of the blood sample image. Following that, image enhancement is deployed to enhance the visibility of the platelet's presence. The YCbCr conversion is then employed to tackle the irregularities presentation in the image. Next, K-means clustering is executed to group image into the preferred number of grayscale colours. The process continues with the image binarization masking that is utilized to transform the grayscale image into a binary image and is necessary to eliminate every unwanted entity and highlight the visibility of the platelets. Subsequently, the area thresholding is applied to get rid of any tiny or big white blobs to ensure sure that only platelet blobs are selected. The final process is the platelet counting which results in the detected number of platelets. The detailed elaborations of each process involved are explained further in the next sections.

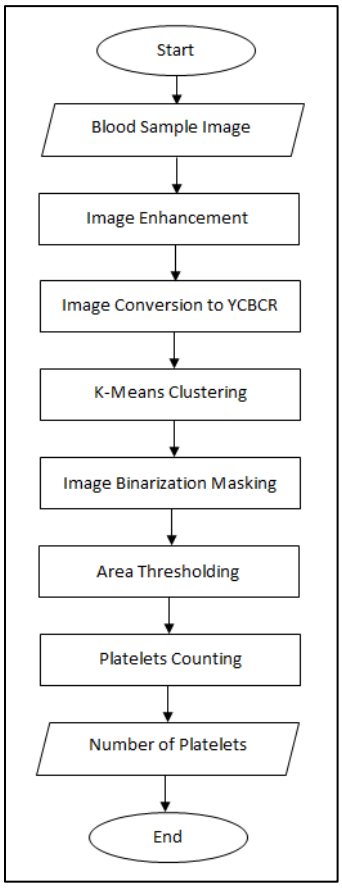


Figure 1. Flowchart

3.1. Image Enhancement

Image enhancement is concerned with processing any input image and producing a result that is more accurate than the original image. Image enhancement techniques can be utilised to enhance the accuracy of an image in several different ways. At this stage, the platelet image underwent the process of enhancement, which in this case enhances the visibility of the platelet's presence. The contrast limits were specified to produce an output image that only displays the selected amount of grey levels that have been set and limit, as well as filtering any unwanted and unimportant intensities.

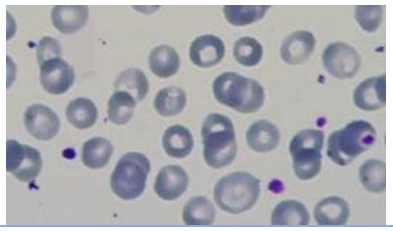
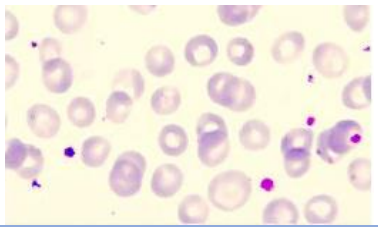
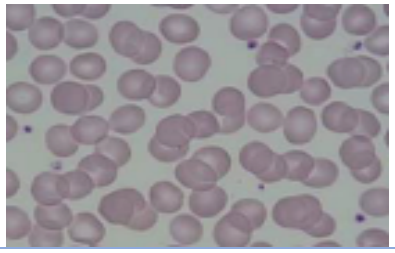
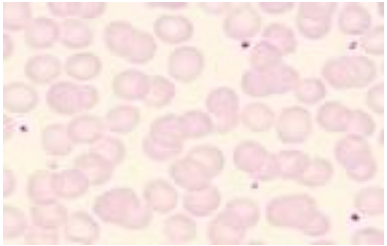
Image	Before Enhancement	After Enhancement
1		
2		

Figure 2. Samples of Point Operation Image Enhancement

A technique called Point Operation was implemented to perform the image enhancement. Point Operation is a spatial domain that represents the simplest and effective solutions for image enhancement. When enhancing an image, a global transformation was used to remap each input grey level into a specific output grey level. Non-homogeneous Point processing was employed in this investigation to account for

uneven lighting during image capture. The image's grey levels are given by *I[x, y].* Every grey layers was mapped to a different value, *Q[x, y]*, using the random function *f(xy).* The indices of the mapping function showed the element's dependency on the pixel's location. The indices can be omitted if the function was not dependent on the position of pixel and was concerned about the pixel value. The samples of Point Operation platelet image enhancements could be seen in Figure 2.

3.2. YCbCr Image Conversion

Fundamentally, an image is made up of three layers of different colours which are called RGB format. A combination of each of the colours would produce a full colour spectrum, ranging from the brightest white to the darkest black. YCbCr is a colour image processing format that is utilized in a variety of applications. It is a non-linear RGB signal that is extensively utilized for image compression due to its simplicity in getting rid of some redundant colour information. Similar to RGB, the YCbCr image format is also made up of three different layers, in which the Y refers to luma, which is brightness, Cb means blue minus the brightness, and Cr, means red minus the brightness. The YCbCr colour space is distinguished by its ease of modification and unambiguous separation of luminance and chrominance components.

Different degrees of recolouring articulation are prompted by irregularities in recolouring process. Due to the characteristics of the platelet images which occasionally are uneven, dull in a high centre of attention location, and dark in the area of a focal point, the YBrCr conversion is sufficiently robust to deal with these varieties. Figure 3 illustrates some samples of YCbCr platelet image conversion.

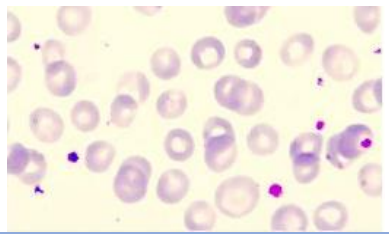
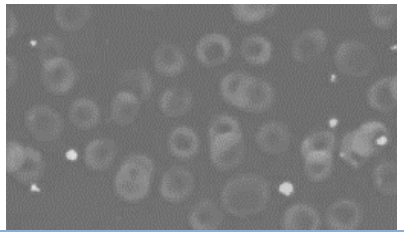
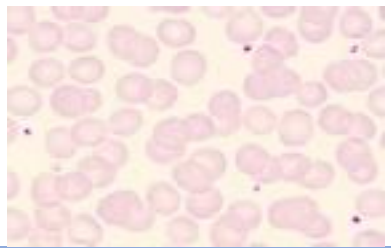
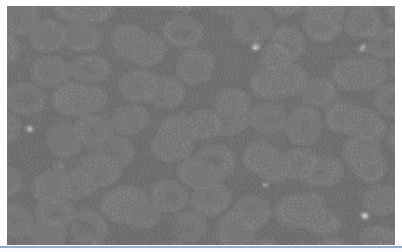
Image	Before Conversion	After YCbCr Conversion
1		
2		

Figure 3. Samples of YCbCr Image Conversion

3.3. K-Means Clustering

The third and the most crucial step in this whole process is the K-Means clustering algorithm. This step continued the process by using the image produced from previous steps and clustered it up into the preferred number of grayscale colours. It is an unsupervised Machine Learning approach that separates data into K groups. Every data point owns by the group with the shortest distance between them. It is a proof-of-concept for clustering method, and new centres will be repeatedly computed using items from the similar group. As soon as the centres stopped moving, the procedure halts. In comparison to other methods, the K-means clustering is a computation that is used to reduce grouping errors. This study required the number of grayscale colour levels to be set to generate an output which in this case, three partitions of different grayscale intensities. Given a set of data P and s samples, the data can be customized as (1):

$$P = (x_1, x_2, x_3, \ldots . x_s) \quad (1)$$

Clustering is accomplished by reducing the total distance between items and the group's centroid. The following equation (2) was used to calculate the distance between items:

$$D_{m,n} = \sum_{m=1}^{s} \sum_{m=1}^{n} (||x_m - c_m||) \quad (2)$$

Where $D_{m,n}$ is the distance between of m^{th} and n^{th} centre. There is a total of s samples that required to be grouped into groups, K. The centre for each group might be determined as in (3):

$$c_n = \frac{\sum_{x \in c_n} X}{N(x_m \in c_n)} \quad (3)$$

Where:

$\sum_{x \in c_n} P$ = total items in n^{th} cluster

$N(x_m \in c_n$ = cluster sample size

The items were clustered in the closest shortest distance group after comparing the distance to each centre, which refers to the closest and most similar grayscale values. A similar process was iteratively repeated to update the clusters' centres and create a new cluster. The K-means iteration loop of clustering ended when the cluster centres become fixed. As a result, the centre values and their associated items can be determined, which could be described as (4):

$$\min \sum_{i=1}^{m} \sum_{j=1}^{k} (||x_i - c_j||) \quad (4)$$

Accordingly, the platelets were differentiated from other entities such as RBCs and WBCs by the appearance of a single layer of grayscale colour. The samples of platelet K-means clustering are presented in Figure 4.

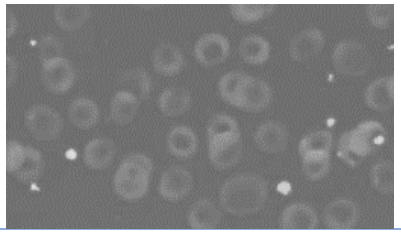
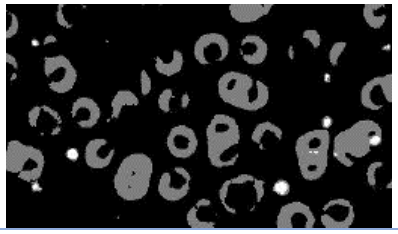
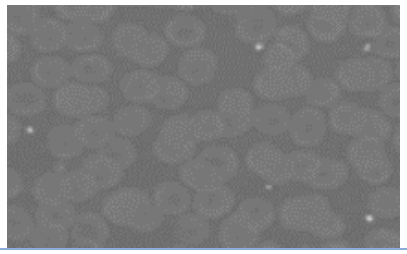
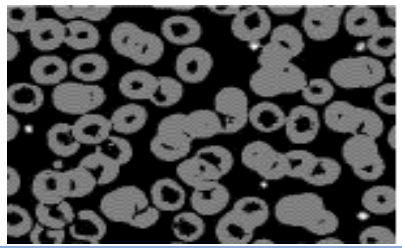
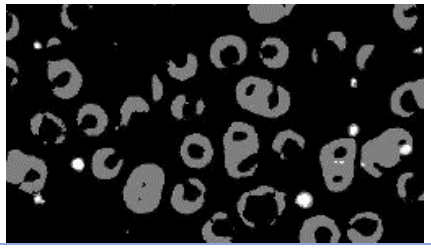
Image	Converted Image	K-Means Clustering
1		
2		

Figure 4. Samples of K-Means Clustering

3.4. Image Binarization Masking

Binarization is a technique for transforming any grayscale image into a black-and-white image. Since the presence of platelets from the previous K-Means clustering starts to group into a single grayscale category, this binarization step was necessary to eliminate every unwanted entity and highlight the visibility of the platelets. The process involved two steps, which the first is to sort out the cluster centres according to their grayscale intensities and store the value into a variable. The second step is to mask the output image from the previous stage with the variable of the selected cluster centres. At this point, the image produced is in binary form, displaying white blobs portraying the platelets, with a black background. Altogether, this stage eliminated the presence and visibility of other entities, and produced only the original location of platelets to be visible as depicted in Figure 5.

Image	K-Mean Clustering	Image Masking
1		

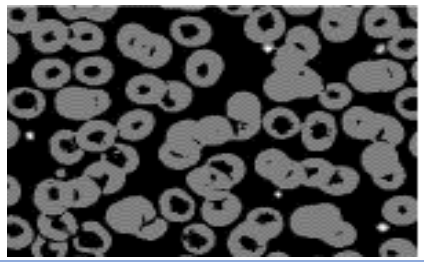
2		

Figure 5. Samples of Image Binarization Masking

3.5. Area Thresholding

The basic and most practical segmentation approach is known as thresholding-based segmentation, which splits an image into sections depending on the intensity of each pixel's value. The area thresholding was applied to get rid of any tiny or big white blobs to ensure sure that only platelet blobs were selected as illustrated in Figure 6.

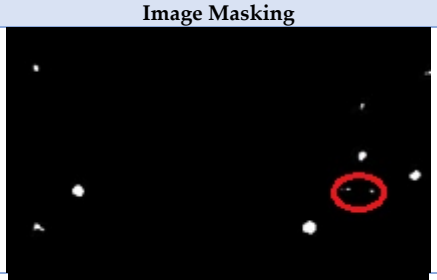
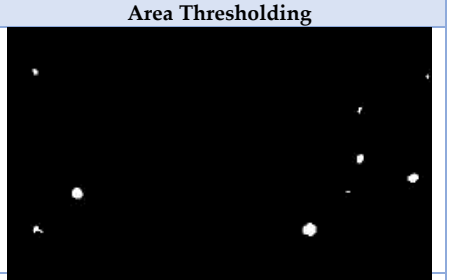
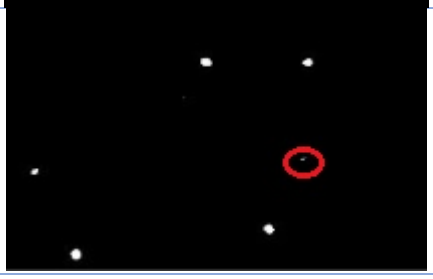
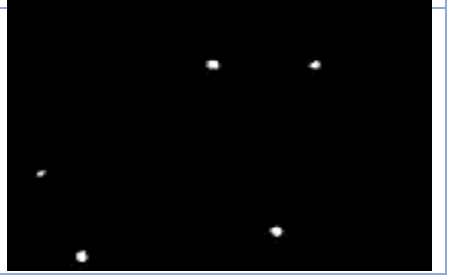
Image	Image Masking	Area Thresholding
1		
2		

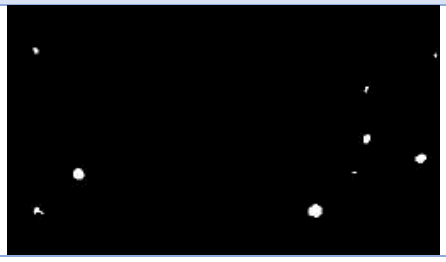
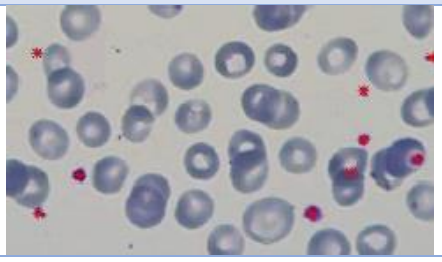
Figure 6. Area Thresholding on Platelet Images

The threshold value could be manually or automatically set depending on the image's features. The minimum and maximum values were automatically set to permit certain sizes of blobs, while the others were removed. Next, the binary image $g(x, y)$ could be interpreted as (5), where T = threshold value.

$$g(x,y) = 1 \; if \; f(x,y) > T$$
$$0 \; if \; f(x,y) < T \tag{5}$$

3.6. Platelet Counting

The final step is platelet counting which was used to count the number of white blobs produced. It was done by defining the position of each blob marked by the centroids from the previous function used. Red asterisk marks were used to mark the blobs as shown in Figure 7. The number of asterisk marks was then automatically calculated, which represents the number of platelet counts detected.

Image	Area Thresholding	Platelet Detection	K-Means Clustering Platelet Counting
1			9

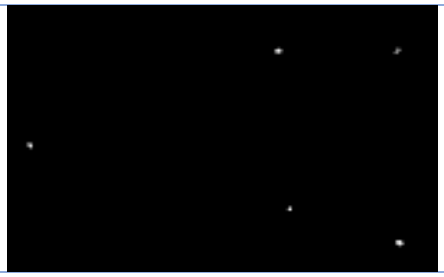
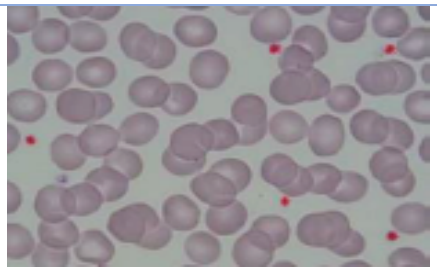
2			5

Figure 7. Platelet Counting and Detection

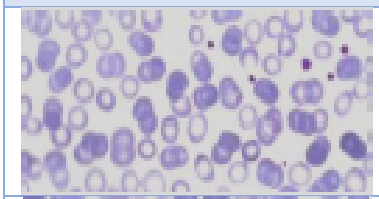
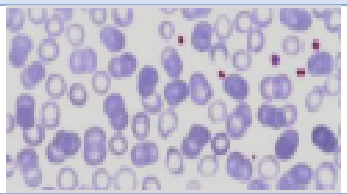
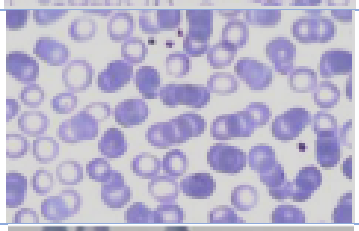
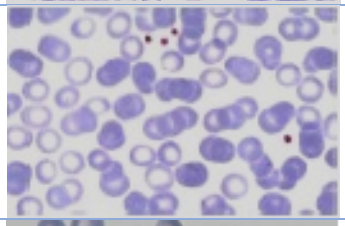
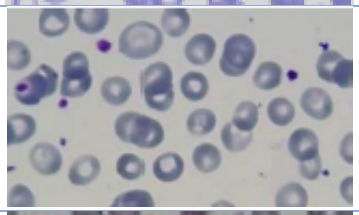
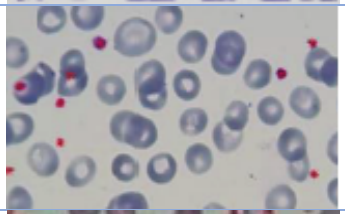
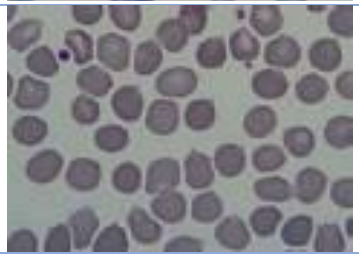
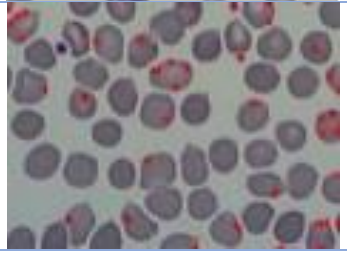
4. Results

This section describes the performance of platelet counts and detection. Ninety samples of blood images collected from the Kaggle's online database[1] were used in evaluating the accuracy in detecting the presence of platelets. A comparative experiment was designed in which the K-Means Clustering platelet count and detection were compared with the actual number of platelet reported by the haematologist**.** The results obtained from the comparative experiment were categorized into three detection categories which are Less Detection (LD), Accurate Detection (AD), and Over Detection (OD) as tabulated in Table 2. Whereas, Table 3 demonstrates the samples of K-Means clustering platelet detection outcomes.

Table 2. Detection Categories

Category	Description
Less Detection (LD)	amount of detected platelets is lesser than the actual platelet count
Accurate Detection (AD)	amount of detected platelets is equal to the actual platelet count
Over Detection (OD)	amount of detected platelets is more than the actual platelet count

Table 3. Samples of K-Means Clustering Platelet Detection – Comparative Experiment

Platelet Image	K-Means Clustering Platelet Detection	K-Means Clustering Platelet Count	Actual Platelet Count	Detection Category
		6	6	Accurate Detection (AD)
		4	4	Accurate Detection (AD)
		9	9	Accurate Detection (AD)
		3	34	Over Detection (OD)

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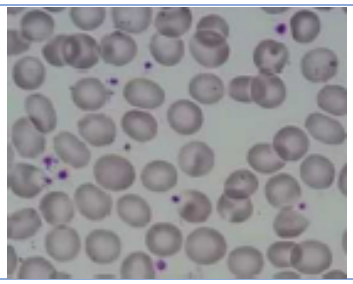	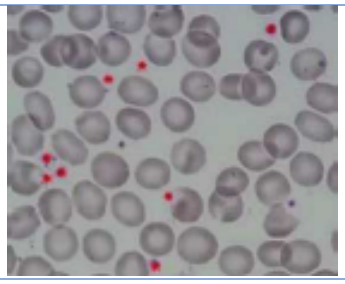	10	8	Less Detection (LD)

Next, the performance of K-Means Clustering platelet detection in the comparative experiment was measured. The percentage of correct detections was measured using accuracy (A), while the percentage of genuine platelets and non-platelets detected was evaluated using sensitivity (Sn) and specificity (Sp), respectively as presented in (6) - (8).

$$Accuracy, A = \frac{TruePositive\ (TP)+TrueNegative(TN)}{TruePositive(TP)+TrueNegative(TN)+FalsePositive(FP)+FalseNegative(FN)} \quad (6)$$

$$Specificity, Sp = \frac{TrueNegative(TN)}{TrueNegative(TN)+FalsePositive(FP)} \quad (7)$$

$$Sensitivity, Sn = \frac{TruePositive(TP)}{TruePositive(TP)+FalseNegative(FN)} \quad (8)$$

The comparative experiment summary results of K-Means Clustering platelet detection are tabulated in Table 4. As demonstrated in Table 4, it was monitored that the LD returned 12 total numbers of detection, 75 for AD, and three for OD.

Table 4. Comparative Experiment Summary of K-means Clustering Platelet Detection

	Less Detection (LD)	**Accurate Detection (AD)**	**Over Detection (OD)**
Platelet Detection	12	75	3

From Table 4, it can be seen that the correct platelet detection was 75 images despite three images wrongly detected non-platelets as platelets, and 12 misdetections of platelets as non-platelets. Next, Table 5 summarizes of the confusion matrix produced.

Table 5. Confusion Matrix Summary of K-means Clustering Platelet Detection

Category	**Frequency**
TP	75
FN	12
TN	0
FP	3

Subsequently, K-Means Clustering platelet detection performance was then measured utilizing the accuracy (A), specificity (Sp), and sensitivity (Sn) as tabulated in Table 6.

Table 6. K-means Clustering Platelet Detection Performance Analysis

Parameter	**Results (%)**
Accuracy (A)	91.67
Sensitivity (Sn)	86.67
Specificity (Sp)	96.67

Based on Table 6, it was monitored that the K-Means Clustering platelet detection produced a 91.67% (accuracy, A), 86.67% (sensitivity, Sn), and 96.67% (specificity, Sp). The application of area thresholding was found to contribute in LD, in which the tiny or big white blobs were removed, omitting the blobs that were supposed to be the platelets. Whereas, the OD was caused by the RBC dark edges that were wrongly detected as platelets.

Accordingly, the outcomes of the proposed approach were compared to those produced by other researchers working on platelet counting as in [8-9, 11-12], using the most often used values of accuracy, sensitivity, and specificity for counting purposes. The selected methods work on the basis of traditional image processing and Deep Learning. Table 7 tabulates comparisons of proposed platelet counting results with those obtained by other researchers.

As can be observed, the works conducted by [9, 12-13] were monitored to produce a higher percentage of accuracy than the proposed approach. It should be emphasized, however, that the results compared were obtained using different datasets, as well as a smaller number of image datasets. In particular, the number of datasets significantly could affect the percentage of accuracy. On the other hand,

the F-RCNN approach implemented by [10] was found to produce good detection of RBCs and WBCs, nevertheless, failed to return good detection of platelets which were only 57.97% of accuracy. Thus, it can be inferred that the proposed approach of the K-means Clustering platelet detection approach returned a competitive performance of platelet counting in both traditional and Deep Learning-based methods. Yet, although many platelets were counted and detected accurately, certain potential causes of inaccuracy should be tackled in future research. Additionally, the quantity of testing images could also be increased, and other advanced techniques such as deep convolutionary neural networks might be incorporated and integrated in the future.

Table 7. Comparisons of Platelet Detection Performance Analysis – State-of-Art

	Cruz [8]	**Jain [9]**	**Kaur [11]**	**Dey [12]**	**Proposed approach**
Model	HSV Thresholding	F-RCNN	CHT	Morphology	K-Means Clustering
No. of images	10	300	3	20	90
Accuracy (*A*)	Up to 90%	57.97%	96%	92.71%	91.67%
Sensitivity (*Sn*)	-	-	-	-	86.67
Specificity (*Sp*)	-	-	-	-	96.67

5. Conclusion

This paper presented a research on automated platelet counter and detection using K-Means Clustering algorithm. The current practice of manual platelet counting can be burdensome, exhausting for a haematologist, prone to human error, and time-consuming. Thus, this research attempted to automate the platelet count and detection process and to evaluate the detection accuracy of the K-Means Clustering algorithm. Several image processing steps were implemented such as image enhancement, YCbCr image formatting, K-Means clustering, image masking, and area thresholding before the number of platelets could be counted and detected. A comparative experiment was designed in which the K-Means Clustering platelet count and detection are compared with the actual number of platelets reported by the haematologist. The performance of the study was evaluated to 90 testing images with an accuracy of 91.67%. To conclude, the research has successfully been conducted to achieve its objectives. The outcomes of the study are found to be competitive to the previous related studies and expected to contribute in the medical field particularly to assist haematologists in achieving a more efficient way of platelet count and detection. Future work should consider increasing the sample size and building a much larger training database by focusing on the comparison of clustering, classifying, and neural network techniques for platelet images.

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