

Enhancement of White Blood Cells Images using Shock Filtering Equation for Classification Problem

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Article Info

Article history:

Received May 27, 2021
Revised August 16, 2021
Accepted August 31, 2021
Published December 26, 2021

Keywords:

Image Enhancement
Image Processing
K-Nearest Neighbor
Shock Filtering Equation
White Blood Cell (WBC)

ABSTRACT

Medical image processing has developed rapidly in the last decade. The autodetection and classification of white blood cells (WBC) is one of the medical image processing applications. The analysis of WBC images has engaged researchers from medical also technology fields. Since WBC detection plays an essential role in the medical field, this paper presents a system for distinguishing and classifying WBC types: eosinophils, neutrophils, lymphocytes, and monocytes, using K-Nearest Neighbor (K-NN) and Logistic Regression (LR). This study aims to find the best accuracy of pre-processing images using original grayscale, shock filtering, and thresholding grayscale. The highest average accuracy in classifying WBC images in the conducting research is 43.54% using the LR algorithm from 2103 images. It is obtained from the combination of thresholding grayscale image and shock filtering equation to enhance the quality of an image. Overall, using two algorithms, KNN and LR, the classification accuracy can increase up to 12%.

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1. INTRODUCTION

White blood cells (WBCs) or leukocytes are an essential component of blood cells formed in the bone marrow through the hematopoiesis process. WBCs act as immune cells that fight against infection and phagocytosis[1,2]. Generally, WBCs can be divided into four groups: neutrophil, lymphocyte, monocyte, and eosinophils. Recognition and identification of WBC play a critical role in assisting pathologists in diagnosing hematological diseases such as blood disorders like leukemia, immune deficiency such as acquired immune deficiency syndrome (AIDS), and other blood-related diseases [3].

Distinguishing the types of WBCs is still challenging in the medical field and often leads to misidentification because they are not inherently stable. Nowadays, expert operatives perform a peripheral blood smear using traditional methods under a microscope to carefully observe the morphological characteristics, which are time-consuming, very tedious, can lead to statistical bias and inconsistent results[4-6]. Therefore, the development and use of computer-based systems instead of traditional methods will enormously accelerate the image analysis process and more definite results[6].

Medical image processing has significantly developed and taken an extensive role in diagnosing disease with the advancement of medical imaging and computer technology, primarily image recognition[7,8]. WBC detection is a crucial evaluation method in ruling out someone's general condition. The automatic detection of WBC is one of the examples of development in medical image processing and analysis. A computer-aided system based on digital image processing techniques can improve accuracy, efficiency, and reliability in examining and diagnosing many variabilities on shape, diameter, edge, and localization of WBC[9].

In This digital era, there are so many techniques to improve and enhance the quality of an image[10]. Image Enhancement is the initial process in image processing. The definition of image enhancement is the improvement process in perceiving information in and preparing a higher quality input for the next steps of automated image processing procedures[11]. The shock filtering method is known as the image enhancement

technique. Shock filter enhanced the image by dilation and erosion to create ruptures at the edge pixels resulting in edge enhancement and segmentation. Enhancing the image's edge is essential for a medical image such as a white blood cell image, but segmentation also has an important role[13,14].

Edge enhancement, contrast optimization, noise reduction, and producing exquisite tissue uniformity in medical image enhancement will help physicians interpret medical images precisely, which is a vital foundation for better diagnosis and treatment[14]. Therefore, image enhancement will be done in this research by pre-processing the image before identifying WBC image types.

2. METHOD

In this research, the dataset is obtained from Kaggle. The dataset consists of a collection of white blood cells images. The data has been divided into four groups of white blood cells: eosinophil, lymphocyte, monocyte, and neutrophil. The complete information is 2,103 datasets with specification 503 eosinophil, 557 lymphocyte, 544 monocyte, and 499 neutrophils images. The data initially underwent pre-processing with grayscale as the original image. The data will be pre-processed using shock filtering, and lastly, the output from shock filtering will go through threshold processing. To evaluate the model's performance, the data in the model are divided into 80% of data train and 20% of data test. The pre-processing image will be trained and tested by processing 30 iterations using K- Nearest Neighbor (KNN) and Logistic Regression.

2.1 Shock Filtering Equation

The shock filter equation is one of the morphological methods to enhance image quality using the partial differential equations (PDEs) approach. It works to improve the quality of the edge of the image or “shocks” the image by dilation also erosion to create ruptures between the maxima and minima[15]fea. The shock filtering equation that was used for each pixel image in this paper is given as follows [16], [17]:

$$I(x, y, t)_t + |\nabla I(x, y, z)|F(\Delta I(x, y, t)) = 0, \quad (1)$$

where variables x and y are the cartesian coordinate position of pixel value, function $I(x, y, t)$ denotes image pixel intensity over time t and a particular position. Equation (1) also consists of a Lipschitz function which is denoted by F . Moreover, the gradient and Laplace operator are denoted by Δ and ∇ respectively.

Shock filtering equation (1) is used to enhance or to keep the contour of edges of an image. This is contrary to the heat equation form which is used to eliminate the noise or smooth the edge of an image. Function F in Equation (1) should be met some conditions as follows,

$$\begin{cases} F(0) = 0 \\ sgn(z)F(z) > 0, z \neq 0 \end{cases} \quad (2)$$

where function $sgn(z)$ is called signum function and defined as bellow,

$$sgn(z) = \begin{cases} 1, & z > 0, \\ 0, & z = 0, \\ -1, & z < 0. \end{cases} \quad (3)$$

Finally, the shock filtering equation (1) can be converted becomes,

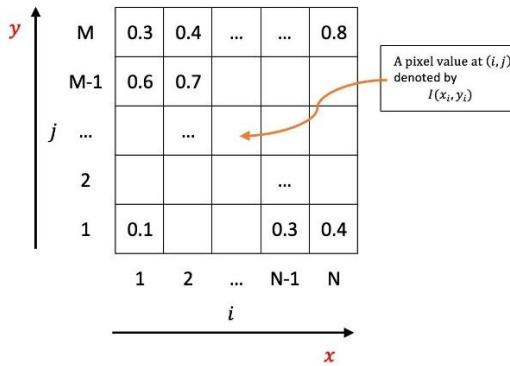
$$I(x, y, t)_t + |\nabla I(x, y, z)| sgn(\Delta I(x, y, t)) = 0, \quad (4)$$

$$I(x, y, z) = I^0(x, y), \quad (5)$$

where $I^0(x, y)$ describes the initial condition of an image pixel.

To find the solution of (4), then the finite difference method (FDM) will be used to find the approximation solution. Here, some steps of discretization are given as follows [17]:

- In the image, the domain is in two-dimensional form. Let $i \in \{1, 2, \dots, N\}$ and $j \in \{1, 2, \dots, M\}$ where $N, M > 0, \in \mathbb{Z}^+$. Therefore, the pixel value at coordinate (i, j) is denoted by $I(x_i, y_i)$. For image cases, the discrete space of domain must be equal, where, $x_i = \Delta x \times i = i$ and $y_i = \Delta y \times j = j$. See Figure 1 for the illustration of $I(x_i, y_i)$ and the discretization points.
- For discrete-time, given $n \in T = \{1, 2, \dots, T_n\}$ where $T_n > 0, \in \mathbb{Z}^+$, thus discrete-time $t^n = \Delta t \times n$ with $\Delta t > 0$ is obtained.

Figure 1. The grid illustration in the discretization of image domain (size $N \times M$)

Finally, FDM for approximating (4) is given as follows,

$$\frac{I_{i,j}^{n+1} + I_{i,j}^n}{\Delta t} + \sqrt{\left(\frac{I_{i+1,j}^n - I_{i,j}^n}{\Delta x}\right)^2 + \left(\frac{I_{i,j+1}^n - I_{i,j}^n}{\Delta y}\right)^2} \times \text{sgn}(\Delta I_{i,j}) = 0 \quad (6)$$

where $I(x_i, y_j, t^n)$ is stand for by $I_{i,j}^n$, and,

$$\Delta I_{i,j} = \frac{I_{i+1,j}^n - 2I_{i,j}^n + I_{i-1,j}^n}{\Delta x^2} + \frac{I_{i,j+1}^n - 2I_{i,j}^n + I_{i,j-1}^n}{\Delta y^2}$$

FDM (6) is a simple discretization using forward time and space for discretized first partial derivative in (4). Therefore, this FDM is a straightforward method for estimating the solution of a partial differential equation, where the scheme is derived from Taylor series expansion. For the next step, some images of white blood will be enhanced to increase the quality of the classification problems using (6).

2.2 K – Nearest Neighbors

The K-Nearest Neighbors (K-NN) is a simple machine learning algorithm. K-NN is a classification algorithm that does data grouping or classification based on the distance of new data to their nearest neighbor. The main idea of the K-NN algorithm is the thought that objects that are close to each other will have characteristics that are very much alike. So, if one of the characteristics of the objects is known, then the nearest neighbor can be predicted. K-NN is the concept that any new instance can be categorized by the most votes of its K's neighbors[18].

To deal with the problem of continuous attributes, the difference between the attributes is determined by the Euclidean distance. For example, given the first instance is $\mathbf{p} = (p_1, \dots, p_n)$ and the second instance is $\mathbf{q} = (q_1, \dots, q_n)$, then Euclidian distance formula is given as:

$$|\mathbf{p} - \mathbf{q}| = \sqrt{\sum_{i=1}^n (p_i - q_i)^2} \quad (7)$$

Problems usually encountered when using the Euclidean distance is the frequency of the large value swamps the smaller values. To solve this issue, the value of attributes should be normalized. This can produce a similar influence on measuring the distance. K-NN can deal with both continuous and discrete attributes. In the discrete case, the distance of two instances p_2, q_2 are is equal to one if both values differ, otherwise it is equal to zero[19].

2.3 Logistic Regression

The classification algorithm based on the conditional probability concept is known as Logistic Regression (LR) algorithm. The output of logistic regression is using a sigmoid function to define a probability value for classification. In the binary case, logistic regression has two classes which are denoted by class 0 and class 1 (i.e., $y_i = 0$ or 1). Therefore, the probability of an element belonging to class 0 is given as $\pi_{i1} =$

$P(y_i = 0|x_i)$, with $i = 1, \dots, n$. However, under the assumption that the responsive variable y_i has a Bernoulli distribution with parameter π_{i1} , then the logistic model is given by,

$$\pi_{i1} = E(y_i = 0|x_i) = \frac{\exp(\beta_0 + \sum_{j=1}^p \beta_j x_{ji})}{1 + \exp(\beta_0 + \sum_{j=1}^p \beta_j x_{ji})} \quad (8)$$

where $\beta_0, \beta_1, \dots, \beta_p$ are the $(p + 1)$ coefficients that are needed to find from a dataset. Note that $\pi_{i1} = 1 - \pi_{i0}$ from binary cases, then finally, maximize likelihood function as follows

$$\max L(\beta_0, \dots, \beta_p) = \frac{1}{n} \sum_{i=1}^n \{y_i x_i^T \beta - \log(1 + \exp(x_i^T \beta))\} \quad (9)$$

Likelihood function (9) has no closed-form of a solution, therefore no exact solution can be found. In [20], the solution of (9) can be approximated by several iterative algorithms.

3. RESULTS AND DISCUSSION

The original image and the pre-processing images are shown in Figure 2. Figure 2(a) is the initial image. Figure 2(b) is an image processed using the grayscale method or the original image. Figure 2(c) is the combination of the grayscale and shock filtering method. While Figure 2(d) is the combination of grayscale, shock filtering, and threshold method. After being pre-processed, the accuracy will be measured using K-NN and LR. In this research, we use 2103 images of WBCs for the dataset. For machine learning simulation, we used 80% of the dataset as training data and the remaining 20% as testing data.

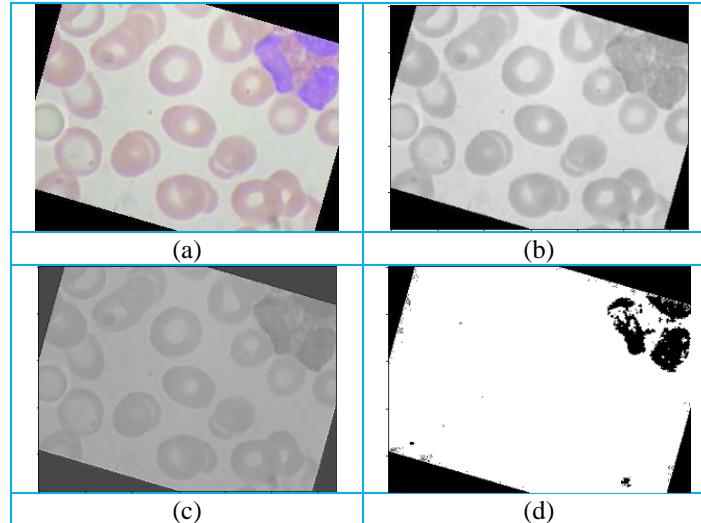


Figure 2. Image result of each method: a) Original Image, b) Grayscale Image, c) Shock Filtered Image, d) Threshold Image.

3.1. Result using K-Nearest Neighbors

In this section, the K-NN algorithm is used to distinguish white blood cells images by using several simulations. The results from 30 iterations are presented in Table 1. Based on the information shown in Table 1, the highest accuracy of the original image is $k=3$ with an average of 30.17%. Meanwhile, the image using shock filtering has the highest accuracy found in $k=9$ with an average of 30.96% and the highest accuracy of the image using Threshold found in $k=3$ with an average of 42.51% and it is also the highest accuracy obtained in using the K-NN method. While the lowest accuracy in classifying WBC using K-NN is found in the combination of the original image in $k=5$ with an accuracy of 29.37%.

Table 1. The average accuracy of K-NN after 30 Iterations

No	Grayscale (Original)				Using Shock Filtering				Using Shock Filtering + Threshold			
	k = 3	k = 5	k = 7	k = 9	k = 3	k = 5	k = 7	k = 9	k = 3	k = 5	k = 7	k = 9
1	30.87	33.01	31.16	28.74	33.49	32.77	32.07	27.79	40.14	37.52	39.66	39.19
2	31.59	26.61	27.79	28.51	29.92	32.31	32.78	30.87	46.79	41.33	38.01	35.63
3	27.79	28.26	28.74	33.25	29.21	32.54	27.08	29.69	39.66	37.29	37.29	33.02
4	28.97	27.79	29.45	31.35	27.79	29.92	28.51	33.49	45.36	36.81	38.24	34.68
...
27	33.01	29.69	29.45	27.55	31.16	30.41	32.07	28.97	40.85	39.42	43.23	36.58
28	28.02	27.79	28.51	34.44	30.41	26.84	25.89	31.57	43.23	45.13	36.58	38.01
29	29.69	30.87	33.49	27.07	32.77	32.31	31.83	33.25	38.47	40.61	40.38	37.06
30	29.92	30.16	28.26	28.74	29.92	28.51	32.78	31.35	43.94	35.39	42.04	41.57
Avg	30.17	29.37	29.64	29.91	29.71	29.63	30.49	30.96	42.51	39.88	40.17	38.24

As shown in Table 1, the accuracy improved in pre-processing images compare to the original images. The accuracy in using only grayscale is 30.17%, meanwhile using the combination of grayscale and shock filtering the accuracy becomes 30.96%. The highest accuracy is obtained by using the combination of grayscale, shock filtering, and threshold methods with an accuracy of 42.51%.

3.2. Logistic Regression

Logistic regression is used to classify the WBC. Table 2 shows the accuracy of logistic regression with 30 iterations. As shown below, the highest accuracy is using the combination of grayscale, shock filtering, and threshold method with an average accuracy of 43.54%. While the lowest accuracy was found in the original image using grayscale only with an average of 32.03%.

Table 2. Average Accuracy of Logistic Regression after 30 Iterations

No	Grayscale (Original)		Using Shock Filtering		Using Shock Filtering + Threshold	
	LR	LR	LR	LR	LR	LR
1	28.26		35.62		44.89	
2	30.87		33.01		45.13	
3	30.64		39.66		41.56	
4	33.01		33.49		44.41	
...	
27	35.15		35.62		44.65	
28	29.21		34.21		42.51	
29	33.72		33.96		44.65	
30	33.72		34.44		45.36	
Avg	32.03		33.78		43.54	

As shown in Table 2, the accuracy improved in pre-processing images compare to the original images. The accuracy in using only grayscale is 32.03%, meanwhile using grayscale and shock filtering the accuracy becomes 33.78%. Moreover, the highest accuracy is obtained by using the combination of grayscale, shock filtering, and threshold methods with an accuracy of 43.54%. From the result, the accuracy improved with the combination of pre-processing methods.

From Table 1 and 2, we can see that using shock filtering equation to enhance the quality of the image and additionally with the threshold in grayscale, it can improve the accuracy of the two algorithms. Here, two algorithms K-NN and LR can increase the accuracy up to 12 % from the average of several simulations. This result is conducted from several factors, such as the size of images, large noise, etc. For further research, the dataset needs to be cut into several small images to increase the accuracy and avoid unnecessary information in the image dataset.

4. CONCLUSION

This research is to investigate and classify the type of White Blood Cell (WBC) images using K-NN and Logistic Regression algorithm. The results show that the best feature combination is using threshold as pre-processing method to enhance the image and improve the accuracy of the classification process. The average value of accuracy is obtained 43.54% using 30 times simulation using Logistic Regression algorithm. Meanwhile using the KNN algorithm, we found that the average value of accuracy is 42.51% from 30 times of simulation. Generally, using the proposed method, the accuracy can increase up to 12 % from the original image dataset. Therefore, this result shows that the enhanced image with a threshold value in grayscale processing can produce better accuracy than using the original image. The maximum accuracy for KNN and Logistic Regression algorithm exceeds the maximum of 50% in this research. This result can be influenced by several factors such as image cutting, algorithm parameters, etc.

ACKNOWLEDGEMENTS

The authors want to say thank you very much for the Editors and Reviewers in the publication process. Moreover, we would like to express our gratitude to Telkom University for its financial support in this research.

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