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Performance Comparison of Firefly and Cuckoo Search Algorithms in Optimal Thresholding of Cancer Cell Images

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Abstract **-** This research presented a performance comparison of the two methods in cancer cells image processing. Each method consisted of two stages. The first stage was image enhancement using fuzzy sets. The second stage was optimal fuzzy entropy based image thresholding. In the thresholding stage, the first method used Firefly Algorithm (FA) and the second used Cuckoo Search (CS). In both methods, four performance metrics (Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structured Similarity Indexing Method (SSIM), and Feature Similarity Indexing Method (FSIM)) and variance and entropy of the images were computed to validate the comparison. The image histograms of both methods show that the distribution of red, green, and blue channel is better than the histograms of original images. In terms of the four metrics, the method that uses FA shows higher performance than CS. In terms of image variance and entropy, the method using CS shows better results than FA. These results suggest that when the performance metrics used are MSE, PSNR, MSSIM, and FSIM, the method using FA is more suitable for cancer cells image enhancement and thresholding. However, when the variance and entropy of the images are used as the performance metrics, the method using CS is more suitable for cancer cells image enhancement and thresholding. Both methods will be useful to assist in the analysis of cancer cell images by the experts in the field.

Keywords: performance comparison, Firefly algorithm, Cuckoo Search algorithm, cancer cells

I. INTRODUCTION

The limitation of capturing equipment quality and illumination causes the need for using digital image processing in the analysis of cancer cell images in the medical field. With the increasing advances in image processing techniques, the identification and analysis of human cells will be more accurate by utilizing digital image processing methods such as computerized segmentation or thresholding method automatically. The characteristic in each object on the processed image is utilized to analyze the image.

One of the significant areas of research on digital cell images is the enhancement of contrast. The goal is to improve the image clarity or quality (Kaur & Kaur, 2016). In the image detection stage, the clarity of the resulted image should be adequate to be analyzed. Therefore, the most crucial stage to assist experts in cell diagnosis during cell images detection and analysis is the image enhancement process. The type of techniques includes neighborhood operation, which is used for edge smoothing and enhancing the contrast of an image. Neighborhood operations combine a small area or neighborhood of pixels to generate an output pixel (Kaur & Kaur, 2016).

One of the techniques used in image enhancement is using the fuzzy set. In image processing areas like contrast enhancement, fuzzy set theory is suitable because of its ability to handle and manage the imprecision encountered in images effectively (Patel, Trivedi, & Mishra, 2014). A method which can deal with the imprecision is required. A technique based on fuzzy sets can provide a framework for incorporating human knowledge in the solution of problems with a formulation based on imprecise concepts (Gonzalez, Woods, & Eddins, 2009). The studies of Kaur and Sidhu (2015), Gupta, Chauhan, and Shrivastava (2016), and Sharma and Bhatia (2015) presented the application of fuzzy set theory in image enhancement.

There are many previous studies on cancer cells image processing which have been conducted. Maolood, Al-Salhi, and Lu (2018) studied the use of fuzzy sets to segment cancer images. The proposed method was implemented based on fuzzy entropy with a level set thresholding. It was performed on the ultrasound image, brain Magnetic resonance imaging (MRI), and dermoscopy image. The results showed good performance compared to previous algorithms in detecting cancer image segmentation in terms of accuracy, precision, specificity, and sensitivity. Next, Sunny, Srikanth, and Eswar (2017) used Otsu thresholding and Watershed transformation as the two methods of segmentation to detect the cancer cell. It was performed on gray level Computed Tomography (CT) cancer images of different patients obtained from various hospitals. These images included less noise compared to X-ray and MRI images. The captured CT images were processed in the region of interest. The result showed that in the pre-processing stage, the Gabor filter and Watershed segmentation gave the best results. Then, the method could identify the tumor from the original image.

Among the techniques commonly utilized in images segmentation, the thresholding technique is the preferred one. This technique separates objects in an image from the background that eases the process of analysis and interpretation (Naidu, Kumar, & Chiranjeevi, 2018; Wonohadidjojo, 2018). One of the categories of image thresholding is fuzzy entropy-based thresholding technique (Sesadri, Sankar, & Nagaraju, 2015). However, the automated analysis of microscopic images becomes a complicated problem because of many complexities. They are the various conditions of staining and illumination, cells and nuclei shape, noise in the background, and overlapping cells (Thomas & John, 2017). The inconsistencies of image capture conditions and illumination determine the contrast of cell boundary and its background. This condition causes inadequacy of conventional thresholding methods to give acceptable results. Therefore, to perform thresholding in digital images of cancer cells, the ordinary thresholding technique is not sufficient. In the case of multiple thresholds segmentation, the optimum values of the threshold need to be found. It can be achieved by exploring all the possible combination of trails for the number of thresholds.

The computational complexity and the requirement of accurate measure in the case of multiple thresholds motivate the use of an efficient search algorithm. At the thresholding stage of the process, the optimum threshold values should be determined. Therefore an optimization algorithm is required to find these values and processing the thresholding stage. The Firefly algorithm (FA) is based on the flashing pattern of tropical fireflies. In the last two decades, more than a dozen new algorithms such as Particle Swarm Optimization algorithm, Differential Evolution algorithm, Bat algorithm, Firefly Algorithm (FA), and Cuckoo search algorithm (CS) have appeared. They have shown great potential in solving tough engineering optimization problems. Among these new algorithms, it has been shown that the FA is very efficient in dealing with multimodal, global optimization problems (Yang & He, 2013). CS is based on the brooding parasitism of some cuckoo species and Lévy flights. It enables the algorithm to be free from the problem of being trapped in local minima. Thus, it is more capable of finding global optimal solutions. The CS algorithm is equipped with the technique to balance the local and global random walks through the control of a probability parameter (Nandy, Yang, Sarkar, & Das, 2015). Therefore, in this study, a method using FA and CS is implemented and analyzed.

As metaheuristic algorithms, FA and CS use two foremost characteristics, namely intensification and diversification, or exploitation and exploration. Diversification generates diverse solutions to explore the search space on a global scale. Meanwhile, intensification refers to focus on the search in a local region by exploiting the information that a current good solution is found in this region (Yang, Deb, & Fong, 2014). By combining this with the selection of the best solutions ensures that the solutions will converge to the optimal solution. The character of diversification via randomization is able to avoid the solutions from being trapped at local optima. This also increases the diversity of the solutions. The good combination of these components ensures the achievable global optima.

The contribution of this study is to provide a method for assisting analysis of cancer cells. It consists of an image enhancement stage and thresholding stage in digital images of cancer cells. There are studies on entropy based image thresholding using FA (Vennila & Thamizhmaran, 2017; Naidu & Kumar, 2017b; Raja, Rajinikanth, & Latha, 2014; Pare, Bhandari, Kumar, & Singh, 2018) and image segmentation using CS (Naidu & Kumar, 2017a; Nandy *et al*., 2015). However, there are no researchers that conduct performance comparison of FA and CS in image thresholding method in cancer cell images. This study will assist in the process of cancer research and ease further analysis. This will significantly improve the ability of analysts to identify the various types of cell line without the need to observe each image of microscopic manually.

II. METHODS

There are two methods of image processing in this study. Each image consists of two stages. These are depicted in Figure 1. The first stage is image enhancement using fuzzy sets. The second stage is fuzzy entropy-based image thresholding optimized by a metaheuristic algorithm in each method. FA is in the first method, and CS is in the second. The performances of FA and CS are to find the optimum threshold values in the thresholding stage of cancer cell images. Then, the results are compared. The metrics used for performance comparison are Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structured Similarity Indexing Method (SSIM), and Feature Similarity Indexing Method (FSIM), variance, and entropy of the images.

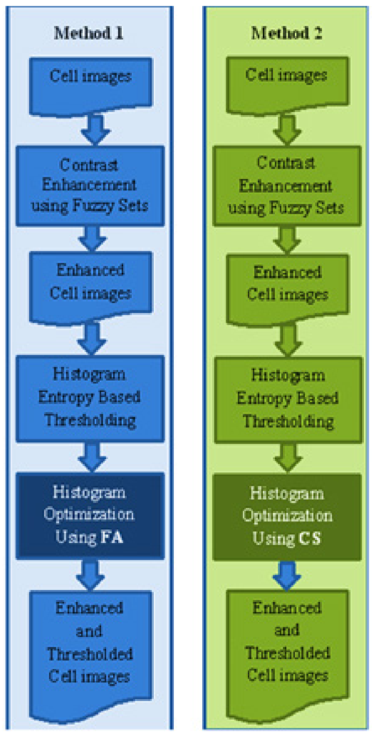

Figure 1 Cancer Cells Image Processing

The fuzzy algorithm consists of four phases. The first phase is the initialization of parameters of the image by finding the minimum and maximum grey levels and calculation of the mid-gray levels based on the minimum and maximum grey levels. The second phase is fuzzification of the gray levels where the sets of gray levels are determined using the membership values to the dark, gray, and bright. The third phase is the inference procedure, where the modification of the grey level is performed. Finally, the fourth phase is defuzzification to find the new enhanced gray level. The output is using minimum, maximum, and medium of the gray level.

The fuzzy algorithm is applied to enhance the image contrast. Contrast enhancement using fuzzy algorithm is one of the principal applications of intensity transformations. It can be expressed in terms of the following rules by Gonzalez *et al.* (2009) as follows:

IF a pixel is dark, THEN make it darker
IF a pixel is gray, THEN make it gray
IF a pixel is bright, THEN make it brighter

The terms of dark, gray, and bright are considered to be fuzzy. The researchers can express the concepts of dark, gray, and bright by the membership functions in Figure 2(a). In the vertical axis, the degree of membership is [0, 1]. Then, in the horizontal axis, the pixel values are normalized to [0, 1]. In terms of the output, the researchers can consider darker as degrees of a dark intensity value; brighter as degrees of a bright shade; and gray as degrees of the intensity in the middle of the grayscale. In the output, increasing contrast can be achieved by darkening and brightening the intensity. It can increase the separation of dark and light on the grayscale. To increase the richness of the image, the mid-grays is narrowed. These objectives can be achieved using a set of output membership functions shown in Figure 2(b).

The entropy of a histogram is a measure of states spread which corresponds to the gray levels which the individual pixels can adopt. A low-entropy distribution is concentrated on a few values. Meanwhile, a high entropy distribution is distributed evenly across values. Given a histogram with N bins, the entropy of the histogram is given by Equation (1), where pi is the probability of bin i.

$$E = \sum_{i=1}^{N} p_i log_2(p_i) \tag{1}$$

Large magnitude entropy indicates a large spread. It means that the variation of the data is large. The method for histogram entropy-based image thresholding using the FA is proposed. In FA, there are two important issues, namely the variation of light intensity and formulation of the attractiveness. For simplicity, it is assumed that the attractiveness of a firefly is determined by its brightness, which in turn it is associated with the encoded objective function. The algorithm of optimizing the histogram entropy using FA is presented by Yang (2010) as follows:

```
begin
Objective function f(x), x = (x1, ..., xd)T
Generate initial population of fireflies xi (i = 1, 2, ..., n)
Light intensity Ii at xi is determined by f(xi)
Define light absorption coefficient
while (t <MaxGeneration)
        for i = 1 : n all n fireflies
            for j = 1 : i all n fireflies
                if (Ij > Ii)
                Move firefly i towards j in d- dimension
                via L´evy flights
                end if
                 Attractiveness varies with distance r
                 via exp[−r]
                Evaluate new solutions and update light
                intensity
            end for j
        end for i
        Rank the fireflies and find the current best
end while
Postprocess results and visualization
end
```

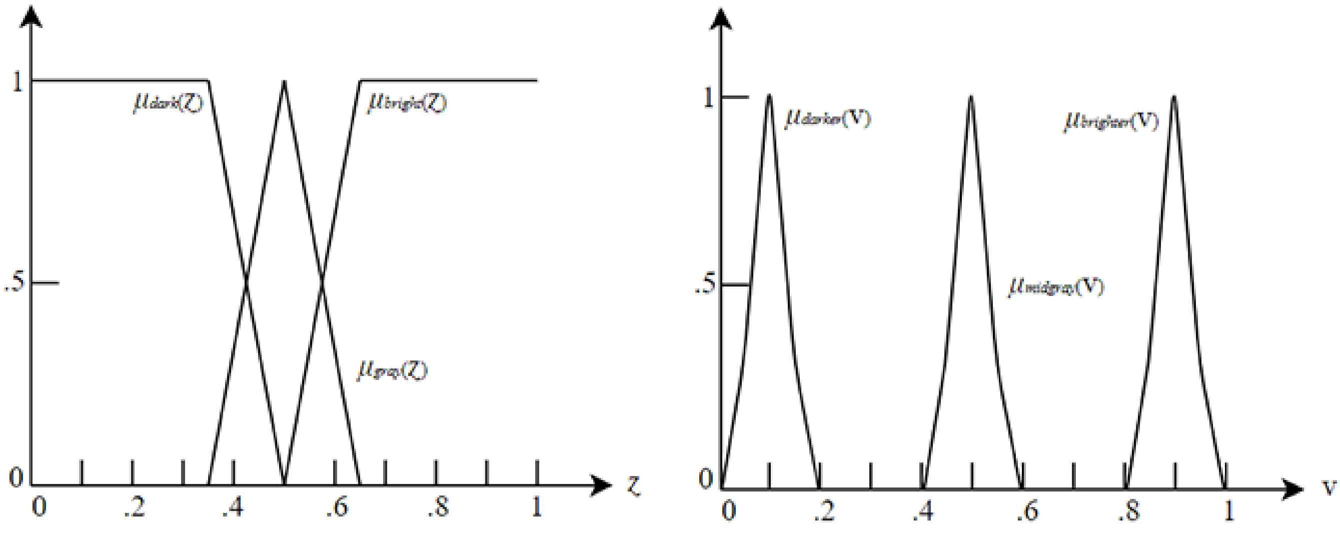

Figure 2 Membership Functions
of Fuzzy Image Processing
(Source: Gonzalez, Woods, & Eddins, 2009)

The CS algorithm can be determined by setting three rules that idealize the behavior of cuckoos to become appropriate for implementation as a computer algorithm (Yang & Debb, 2010). First, each cuckoo lays one egg at a time and dumps it in a randomly chosen nest. Second, the best nests with high-quality eggs will be carried over to the next generations. Third, the number of available host nests is fixed, and the egg laid by a cuckoo may be discovered by the host bird with a probability $p_a \in (0, 1)$. In this case, the host bird can either get rid of the egg or abandon the nest and build a completely new nest. The algorithm of optimizing the histogram entropy using CS is presented as:

Objective function $f(x)$, $x = (x_1, ..., x_d)^T$;
Initial a population of n host nests x_i *(i* = 1, 2, *..., n);*
while *(t <MaxGeneration) or (stop criterion)*;
Get a cuckoo (say i) randomly by L´evy flights;
Evaluate its quality/fitness Fi;
Choose a nest among n (say j) randomly;
if $(F_i > F_j)$,
Replace j by the new solution;
end
Abandon a fraction (pa) of worse nests
[and build new ones at new locations via L´evy flights];
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best;
end while
Postprocess results and visualization;

The images used as data are two digital microscopic images of breast cancer cells taken from Wikimedia (n.d.). All the images are JPEG formats with the same sizes (2.700 × 1.800 pixels). For each test image, independent runs using each algorithm are performed.

There are two methods implemented in the experiment. The first stage in the first and second methods is the enhancement of the image contrast by using Fuzzy sets. The second stage is the thresholding and its optimization of the image. In the first method, the optimization is performed by using the FA and in the second using CS.

The judgment of digital image quality as the result of image thresholding is subjective. It is necessary to use image performance metrics to establish an accurate measure for the image as the result of the thresholding process. It compares and evaluates the performance of the enhancement algorithms on image quality. The comparison is undertaken by comparing the algorithm systematically and using the same set of images to identify the performance of an algorithm. Each performance metric has its concept in determining the performance of the algorithm. One of the concepts is that an algorithm is capable of enhancing images that resemble the original ones.

After the thresholding process of the image, the quality of the thresholded images needs to be evaluated. In the image-based cell identification, the quality of the image is the ultimate criterion. When the priority is the authenticity of evaluation, the assessment of image quality is performed by using full reference metrics.

There are several needs in the cancer cells image analysis. Those are better structural information, better similarities between the original and resulted images, better-thresholded image, and higher image details. The metrics which are suitable to measure the structural information and similarities between two images are MSE, PSNR, MSSIM, and FSIM. The suitable metrics for measuring the quality of image thresholding and image details are variance and entropy.

Moreover, because of the simplicity of calculation, clarity in physical meanings, and convenience in mathematical implementation, the MSE and PSNR are mostly applicable as the image quality assessment metrics. MSE is calculated by the squared intensity differences of distorted and reference image pixels and averaging them with PSNR of the related quantity. They are the most commonly used and the simplest full reference metrics (Sara, Akter, & Uddin, 2019). The PSNR is expressed using Equation (2). Meanwhile, MSE is represented in Equation (3).

$$PNSR = 10log_{10}(peakval^2)/\mathrm{MSE} \tag{2}$$

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}[f(i,j) - g(i,j)]^2 \tag{3}$$

Where,

f represents the matrix data of the original image

g represents the matrix data of the degraded image

m represents the numbers of rows of pixels of the images, and *i* represents the index of that row

n represents the number of columns of pixels of the image and *j* represents the index of that column

peakval is the maximum signal value that exists in the original image

III. RESULTS AND DISCUSSIONS

The first step of image quality evaluation as the result of processing is using the subjective method. Then, it should be followed by the measurement of Image Quality Assessment (IQA) using the computational model. It needs to be consistent with subjective evaluation. As the improvement of the first two metrics, IQA measurement is performed by the structural similarity index that allows IQA to operate from pixel level to the structural level.

The MSE allows the comparison between the original image and the processed image. It gives a measure of the pixel values of the original image and processed image by averaging the errors between these images. The error is calculated as the difference of the value between the original and processed image. The ultimate idea is to maximize the PSNR. It means to make the processed image as close as possible to the original one. This also means that the MSE is minimized.

In the improvement of these metrics, two other reference metrics have been developed, namely SSIM and FSIM (Sara *et al*., 2019). The last two metrics are developed based on the perception to measure the structural and feature similarity of processed and original images. All of these metrics are used in measuring the metrics of image thresholding to give a comprehensive performance evaluation. The experiments should give consistent results.

FSIM index is based on the concept that the main perception of Human Visual System (HVS) on an image is its low-level features. The ultimate feature of FSIM is Phase Congruency (PC). It is the significance of the local structure of an image which is measured without dimension. The contrast invariant nature of PC and the perception of HVS on the image affected by contrast information causes the need for the secondary feature. This is the initialization of the parameters by the employment of Gradient Magnitude (GM). Therefore, the local quality of an image is characterized by the complementary role of PC and GM. The single quality score is derived using the PC as a weighting function. This is performed when the local quality map has been obtained (Zhang, Zhang, Mou, & Zhang, 2011).

SSIM is the recently proposed approach for image quality assessment. This method is for measuring the similarity between two images that full reference metrics value lies between [0, 1]. The SSIM is designed to improve the traditional metrics like PSNR and MSE, which can be inconsistent with human eye perception or human visual system (Wang, Bovik, Sheikh, & Simoncelli, 2004). Therefore, in order to validate the experiment in this study, the four performance metrics are utilized. Moreover, to measure the quality of image thresholding and image details, the variance and entropy of the processed image are calculated as well. In addition, the histogram of each image is also observed.

The four performance metrics (MSE, PSNR, MSSIM, and FSIM) are implemented in the experimental design to evaluate the performance of the two methods. In the experimental design, Figure 3 and Figure 6 show the original digital images of cancer cells which are used as data. Then, Figure 4 and Figure 7 depict the results of image enhancement and thresholding of breast cancer 1 and 2 using FA. Figure 5 and Figure 8 show the results of image enhancement and thresholding of breast cancer 1 and 2 using CS. Next, Table 1 and Table 2 show the performance metrics comparison of image 1 and image 2 respectively. Lower MSE and higher PSNR, MSSIM, and FSIM indicate better image quality. Both Tables indicate that FA shows higher performance than CS in terms of the four metrics.

Table 1 Performance Metrics
Comparison of Image 1

Metrics	Firefly Algorithm	Cuckoo Search
MSE	759,722114	7298,947072
PSNR	19,688722	11,001968
MSSIM	0,978510	0,892253
FSIM	0,973247	0,812743

Table 2 Performance Metrics
Comparison of Image 2

Metrics	Firefly Algorithm	Cuckoo Search
MSE	1744,923662	6547,276037
PSNR	16,536632	11,403054
MSSIM	0,973255	0,901945
FSIM	0,956001	0,845898

Figure 3 Original Image
of Breast Cancer 1

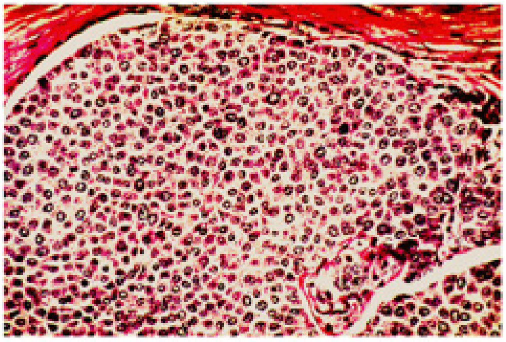

Figure 4 Image Thresholding
of Breast Cancer 1 Using FA

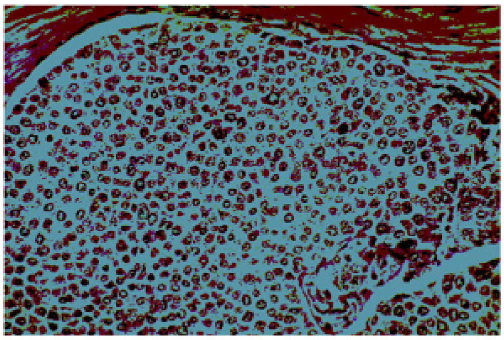

Figure 5 Image Thresholding
of Breast Cancer 2 Using CS

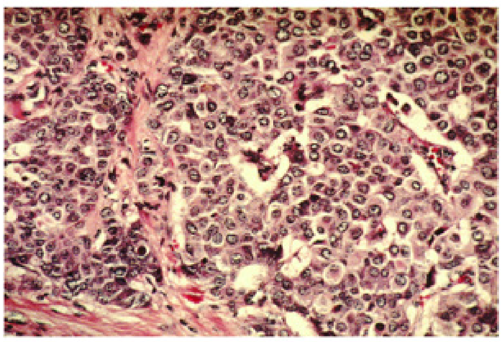

Figure 6 Original Image of Breast Cancer 2

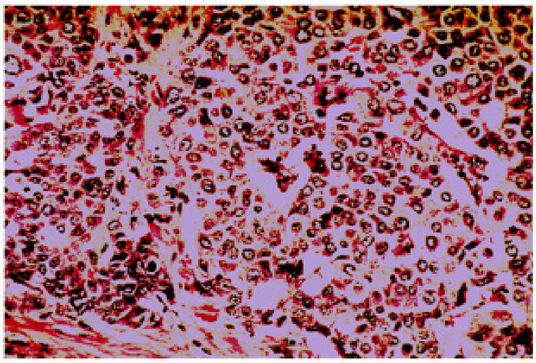

Figure 7 Image Thresholding
of Breast Cancer 2 Using FA

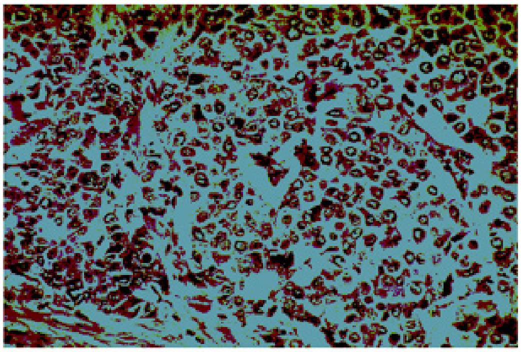

Figure 8 Image Thresholding
of Breast Cancer 2 Using CS

In the previous study by Wonohadidjojo (2018), two methods of cancer cells image enhancement and thresholding were also proposed. In the subjective evaluation, the resulting images showed better details of the cells than the original ones. The results also showed that the method using Backtracking Search Algorithm (BSA) was better than the one using Particle Swarm Optimization (PSO). In the subjective evaluation of this study, the resulting images show better details than the original ones. Furthermore, the resulting images also show that the method using FA is better than the one using CS.

The histograms of the original image of image 1 and image 2 are shown in Figure 9 and 10 respectively. The histograms of the enhanced and thresholded images of image 1 and 2 using FA are shown in Figure 11 and Figure 13 respectively. Meanwhile, histograms of the enhanced and thresholded images of image 1 and 2 using CS are shown in Figure 12 and Figure 14. All the histograms of the enhanced and thresholded images depict better distribution in the red, green, and blue channel.

Next, Table 3 and Table 4 show the comparison of variance and entropy of the enhanced and thresholded images using FA and CS for image 1 and image 2 respectively. Lower variance indicates the better image thresholding. Meanwhile, the higher entropy indicates higher image details. Table 3 and 4 show that CS performs better than FA in variance and entropy measurements, except for the entropy of the green channel in Table 4.

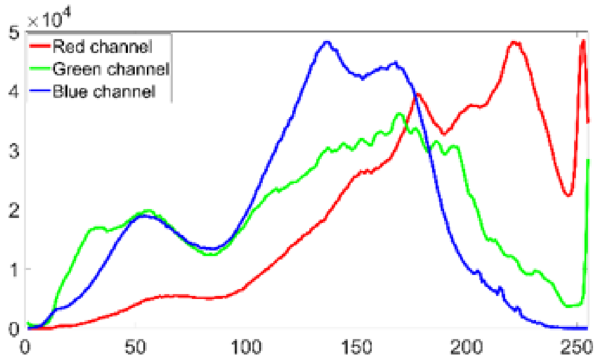

Figure 9 Histogram of Breast Cancer 1 (Original Image)

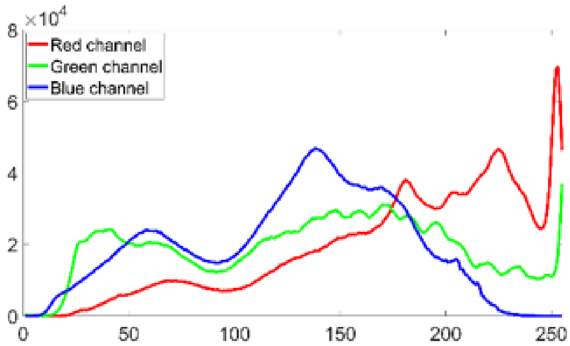

Figure 10 Histogram of Breast Cancer 2
(Original Image)

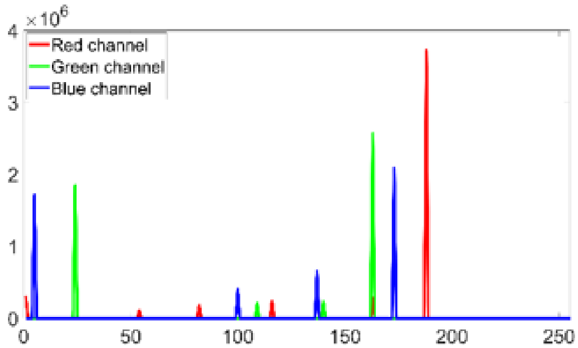

Figure 11 Histogram of Breast Cancer 1 Using FA

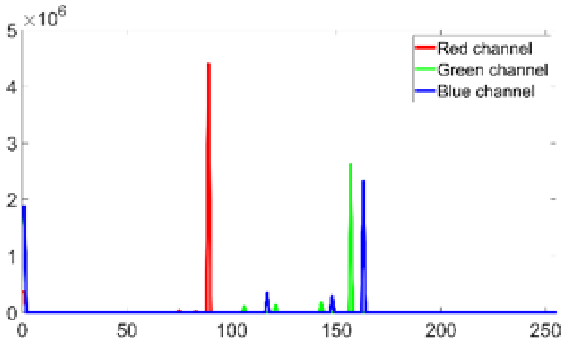

Figure 12 Histogram of Breast Cancer 1 Using CS

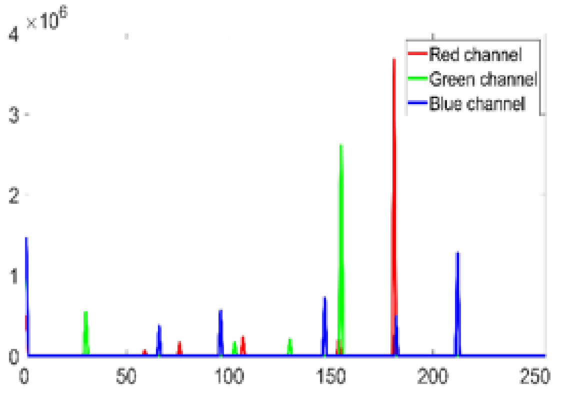

Figure 13 Histogram of Breast Cancer 2 Using FA

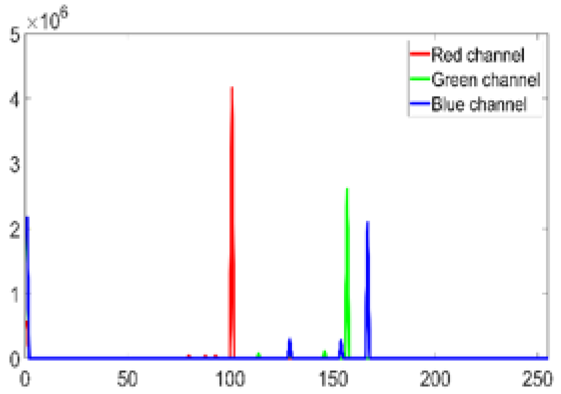

Figure 14 Histogram of Breast Cancer 2 Using CS

Table 3 Variance and Entropy Comparison of Breast Cancer 1

Metrics	Firefly Algorithm	Cuckoo Search
Variance	5,0364e+03	4,0230 e+03
Entropy	HR = 10,6793 HG = 10,2561 HB = 10,0502	HR = 10,7438 HG = 10,3046 HB = 10,1542

Table 4 Performance Metrics Comparison of Breast Cancer 2

Metrics	Firefly Algorithm	Cuckoo Search
Variance	5,7294e+03	4,4099e+03
Entropy	HR = 10,6583 HG = 10,3032 HB = 9,7472	HR = 10,7114 HG = 10,2873 HB = 10,0947

In terms of image histogram, Wonohadidjojo (2018) showed that the histograms of the resulting images had a better distribution of the red, green, and blue channel than the original images. In this study, the histogram of the resulting images also shows better distribution than the original ones. Moreover, the variance and entropy in both studies are also calculated to compare the two methods in each of them. The results in the previous study show the superiority of BSA over PSO. In this study, the results show the superiority of CS over FA. These comparison results lead to the future study on the comparative analysis of the method using BSA and FA in terms of structural information and similarities between the original and resulting images. Besides, this also leads to future study on the comparative analysis of the method between BSA and CS in terms of thresholded image and image details.

IV. CONCLUSIONS

The researcher proposes two methods of image enhancement and thresholding of cancer cells image processing. Each method consists of two stages, namely contrast enhancement using fuzzy sets and optimized thresholding methods. In the thresholding stage, two algorithms (FA and CS) are implemented. Then, the performance comparison of the two methods is presented. Performance metrics as the results of the experiment show that FA performs better than CS in terms of the four metrics (MSE, PSNR, MSSIM, and FSIM). The image histograms of both methods using FA and CS show a better distribution of red, green, and blue channel than the histograms of original images. In terms of image variance and entropy, the CS algorithm shows better results than FA. These results suggest that when the needs of cancer cells image analysis are structural information and similarities between the original and resulting images with four metrics (MSE, PSNR, MSSIM, and FSIM), the method using FA is more suitable to use. However, if the experts want the better-thresholded image and higher image details, which are the characteristics of variance and entropy, the method using CS is more suitable. These results offer two methods in cancer cells image enhancement and thresholding. Both methods will be useful to assist in the analysis of cancer cell images by the experts in the field.

In the future, the required study will be the comparative analysis of the method using BSA and FA in terms of structural information and similarities between the original and resulting images. Besides, the study will also be useful to compare BSA and CS in terms of thresholded image and image details. Furthermore, the study can also explore the possibility to assist the medical image experts in analyzing the cancer cell features such as morphology, colors, and textures. In the study, a method based on the feature extraction will be worthwhile to consider.

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