International Journal of Synthetic Emotions
Volume 10 • Issue 2 • July-December 2019

Segmentation of Leukemia Cells Using Clustering:
A Comparative Study

Eman Mostafa, Shoubra University, Cairo, Egypt
Heba A. Tag El-Dien, Shoubra University, Cairo, Egypt

ABSTRACT

Leukemia is a blood cancer which is defined as an irregular augment of undeveloped white blood cells called "blasts." It develops in the bone marrow, which is responsible for blood cell generation including leukocytes and white blood cells. The early diagnosis of leukemia greatly helps in the treatment. Accordingly, researchers are interested in developing advanced and accurate automated techniques for localizing such abnormal blood cells. Subsequently, image segmentation becomes an important image processing stage for successful feature extraction and classification of leukemia in further stages. It aims to separate cancer cells by segmenting the microscopic image into background and cancer cells that are known as the region of interested (ROI). In this article, the cancer blood cells were segmented using two separated clustering techniques, namely the K-means and Fuzzy-c-means techniques. Then, the results of these techniques were compared to in terms of different segmentation metrics, such as the Dice, Jac, specificity, sensitivity, and accuracy. The results proved that the k-means provided better performance in leukemia blood cells segmentation as it achieved an accuracy of 99.8% compared to 99.6% with the fuzzy c-means.

KEYWORDS

Fuzzy-C-Means, Image Segmentation, K-Means, Leukemia

INTRODUCTION

Human blood is classified into white blood cells (WBCs), red blood cells (RBCs), and platelets (Liu et al., 2019). Leukemia is a wide category of cancers that influence white blood cells. Generally, white blood cells can be classified into five categories, namely neutrophils, eosinophils, basophils, lymphocytes, and monocyte. Leukemia can prevent white blood cells from battling diseases and causes them to duplicate wildly, which leads to critical health problems that threatens the patient's life (Chatap, & Shibu, 2014). It has two main categories, including acute leukemia and chronic leukemia. Acute leukemia is diagnosed when the larger part of the influenced white blood cells cannot work normally, causing fast degeneration, while chronic leukemia is diagnosed when a few of the influenced blood cells cannot work regularly, causing a slower degeneration. Furthermore, acute leukemia is sub-categorized into acute lymphocytic leukemia (ALL) and acute myeloid leukemia (AML), whereas chronic leukemia is sub-categorized into chronic lymphocytic leukemia (CLL) and chronic myeloid leukemia (CML).

Manual detection methods of leukemia depend on the physician experience and naked eye inspection which are inaccurate and time consuming. Thus, recently automated detection methods

DOI: 10.4018/IJSE.2019070103

Copyright © 2019, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

are used. The segmentation of cancer cell images has a direct effect on the classification process, which in turn helps in the process of diagnosis and treatment. Mainly, there are four basic processes for image in computer-aided diagnoses which are image acquisition, image preprocessing, and image segmentation in addition to image classification. Generally, image segmentation is a significant process in image processing, which divides the whole image into several regions for extracting the region of interest. In the microscopic blood samples, the blast cell is extracted for leukemia detection.

The blood cell segmentation is considered a challenging task due to the cells' complex morphology, including shape, texture, color and size. In addition to the ambiguity, uncertainty, and inconsistencies in the captured microscopic images with varying illumination, as well as the existence of overlapping between the cells (Reyes et al., 2015). Thus, a highly efficient method is required for segmentation of leukemia blood cell. There are several types of image segmentation, such as watershed, edge-based, threshold, region-based, and clustering methods. The cluster method includes different methods for example K-means, fuzzy c-means (FCM), hierarchical clustering, and model-based clustering (Dhanachandra, & Chanu, 2017). In the present work, the performance of k-means and FCM clustering methods is investigated.

RELATED WORK

Fatma, & Sharma (Fatma, & Sharma, 2014) applied two leukemia image segmentation methods, K-means and threshold. In addition, contrast level and the RGB (red-green, blue) image were converted to HSI image before K-means and thresholding. Also, a median filter was applied for noise removal. The results depicted that the better performance was obtained using K-means clustering. In other work, ElDahshan et al. (ElDahshan et al., 2015) compared the performance of ALL segmentation using RGB and HSV (hue-saturation-value) color space. Initially, local contrast stretching (LCS) was applied to improve image contrast then segmented by using the histogram to select the threshold value. Finally, a median filter was used to remove noise, while the RGB image was converted to HSV then extract H channel and segmentation done by the color histogram. The segmentation based on the hue channel of HSV color achieved 99.17% accuracy, while the RGB-based segmentation achieved 94.42% accuracy. Also, Toh et al. (Toh et al., 2018) presented the combination technique of color thresholding based on the RGB color information from acute leukemia images and median filter to remove noise. The average accuracy for both Acute Myeloid Leukemia (AML) and ALL were 97.63% and 97.64%, respectively. In addition, to k-means clustering was applied to the AML and ALL images for the comparison purpose. The obtained average accuracy for both AML and ALL images by k-means clustering were 88.40% and 96.25%, respectively. Furthermore, Bouzid-Daho et al. (Bouzid-Daho et al., 2016) studied the segmentation of irregular blood cells to help leukemia location. Firstly, the image was resized and RGB image was converted to gray scale, then the median filter was used for noise removal. In the last step, morphological operators were applied for better visualization of abnormal cells. This method was produced remarkable and satisfactory results. While, Biji, & Hariharan (Biji, & Hariharan, 2016) segmented the blood cell images of patients with acute leukemia by exploiting adaptive k Means (AKM), FCM, and Standard K-Means (SKM) clustering algorithms without applying any filtering method, then the image enhancement using the mean shift algorithm. The result illustrated an improved segmentation performance using the suggested AKM compared to FCM, and SKM. As well as, Li et al. (Li et al., 2016) introduced a segmentation method of acute lymphoblastic leukemia images using dual-threshold technique to improve the traditional single-threshold methods. Afterward, mathematical morphology and median filtering were utilized to remove the noise. The results proved that the segmentation accuracy reached to 97.85%. However, Karthikeyan, & Poornima (Karthikeyan, & Poornima, 2017) compared FCM with k-means for image segmentation with the use of adaptive median filter for noise removal. In addition, adaptive histogram equalization was used to enhance contrast, and then the segmentation was performed using both methods. Also, Kumar et al. (Kumar et al., 2018) applied a K-mean clustering algorithm for automated

detection of acute leukemia. The noise and abnormal components were removed from the image using Wiener filter and morphological operations. At that point, the histogram equalization procedure was used for improving the image contrast, then image segmentation using k-means clustering algorithms. The segmentation accuracy of 92.8% was achieved.

METHODOLOGY

Image Segmentation Using Clustering Methods

Clustering is the process of analysis segmenting an image dataset into some discrete groups or clusters. It can be considered the foremost imperative unsupervised learning problem that deals with finding a structure in an unlabeled data collection, including the k-means clustering algorithm, hierarchical clustering procedure, and FCM clustering algorithm. Each method follows a set of rules different from the other to determine the similarity between the data points. Hard clustering and soft clustering are two types of clustering. In hard clustering, each one of the data point exists in only one cluster, such as k-means clustering algorithm, but in soft clustering point each one of the data point exists in more than one cluster, such as FCM clustering algorithm.

Image Preprocessing

In image preprocessing, image enhancement techniques are applied to the digital image for improving the image quality by removing the noise and adjusting the image contrast, brightness to achieve the best results of segmentation. The HSV color model appears as a cone or cylinder. The HSV model describes colors as seen by the human eye, but the RGB does not closely relate to the human visual perception of color. The hue channel (H) represents the color types while the saturation channel (S) is the amount at which that color is blended with white and the value (V) is the amount at which that color is blended with black (gray level). In RGB, the image color information cannot be separated from luminance; however, HSV is used to separate image luminance from color information. Thus, in this study the images are transformed from the RGB to the HSV color plane, then, the S channel image is applied to the segmentation process.

K-Means Clustering Algorithm

K-means is a simple unsupervised clustering procedure that deals with a large number of variables (Yang et al., 2012; Dhanachandra et al., 2015; Zheng et al., 2018). The basic idea of K-means is dividing the image into groups, in which each group called cluster, the number of groups refer to K value. It depends on two main steps, which determine the center of each cluster and find the closest points for each center by measuring the Euclidean distance between each point of data and center of cluster. After that, the new center is recalculated for each cluster and therefore the Euclidean distance is measured between the new center and each data point in cluster to find out whether these points are closest to the center or not. The K-means algorithm is an iterative process, where the preceding steps are repeated until the cluster center does not change and the best results are obtained. These steps of K-means algorithm can be summarized as follows:

1. Choose the value of k (number of clusters) and the center of each cluster;

Estimate the Euclidean distance using the following equation:

$$d = p\left(x, y\right) - c_k \tag{1}$$

where for an image $p\left(x, y\right)$ the center for cluster is denoted by c_k.

3. Allocate all pixels to the closest center using the result of the computation of Euclidean distance (d);
4. Recalculate the new center of each cluster by this equation averaging all of pixels in the cluster:

$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x,y) \tag{2}$$

5. Repeat the previous process until the value of the cluster center is fixed and there are no changes in the content of each cluster of points.

In spite of the advantages of the K-means that are represented by its high efficiency and easy implementation, but it has some disadvantages. The first choice of the center is random so the final result of cluster changes with changes the first choice value of center. So the initial center must be carefully chosen to get the best result of segmentation.

Otsu Threshold Algorithm

Otsu threshold is the second step of image segmentation that applying after K-means it is a type of global threshold that based on automatic threshold selection region. Otsu threshold is depends only on gray value of the image which, separate image into two classes, namely foreground and background. Hence, it is necessary to select an acceptable gray level threshold to extract objects from their background.

Morphology Processing

The goal of use morphology processing is to enhance the output of the segmentation process. The resulting of segmented image still contains some noise, so to get a noise-free image morphological operation is applied. After that extract objects from binary image according to its size.

Proposed Model and Steps

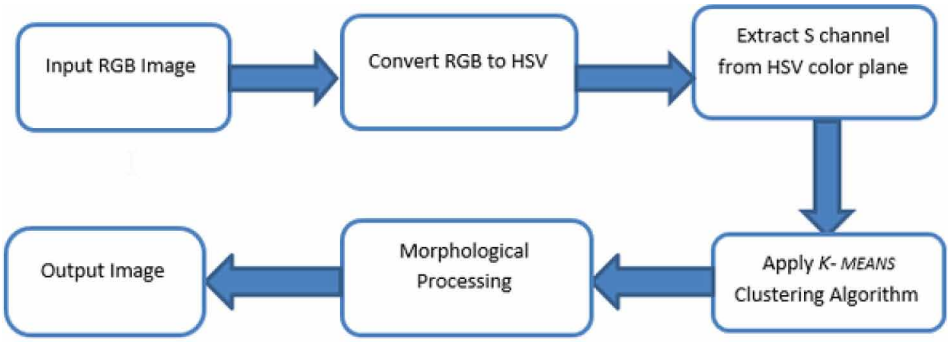
The proposed method consists of the following steps successively: color image acquisition, convert RGB image into HSV image, and then extract S channel and segmentation done by K-means clustering algorithm and Otsu threshold then image morphology is applied to removal noise and then extract largest object from binary image that represent the ROI. According to k value the number of cluster is determined and the center of each cluster, which is the initial value of center. As a result of using K-means algorithm, the image will be segmented into three clusters then the Otsu threshold is used as second level of segmentation. The image of segmentation containing some noise, so the morphology operation is applied then extracts ROI. The proposed algorithm is followed as show in Figure 1.

In Figure 1, the first step is the image of leukemia blood cell acquisition then convert RGB image to HSV color space and extract S channel. Afterward, a segmentation process is applied using K-means and Otsu threshold on S channel the output of segmentation have unwanted region. Thus, the morphology operation is applied to extract the largest object from binary image which is blast cell and also the ROI.

Fuzzy C-Means Clustering Algorithm

Fuzzy c-means (FCM) holds the same basic idea of the image segmentation through find cluster centers by iterative processing, but FCM allows finding the same data point in more than one Cluster (Zhou et al., 2009; Vania et al., 2017). Such process allows the object to belong to multiples clusters with difference in degrees of membership.it depend on minimize the object function J_{FCM}:

Figure 1. Proposed algorithm of k-means



$$J_{FCM} = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(u_{ik}\right)^{q} d^{2}\left(x_{k}, v_{i}\right) \tag{3}$$

where $X = \left\{x_1, x_2, \ldots, x_n\right\}$ is all object in image, and n is the number of objects, C is number of clusters, where ($2 \leq c < n$), u_{ik} is membership degree that tells which element x_k belongs to the ith cluster, it is a numerical value in [0, 1], q is a weighting exponent in membership, and $d^2\left(x_k, v_i\right)$ is a distance measure between object x_k and cluster center v_i. The steps of FCM algorithm can be summarized as follows:

1. Select the number of cluster $\left(c\right)$, fuzziness parameter $\left(q\right)$ and stop condition $\left(\varepsilon\right)$;
2. Calculate the fuzzy cluster centers v_i with u_{ik}:

$$v_i^{(b)} = \frac{\sum_{k=1}^{n}(u_{ik}^{(b)})^{q} x_k}{\sum_{k=1}^{n}(u_{ik}^{(b)})^{q}} \tag{4}$$

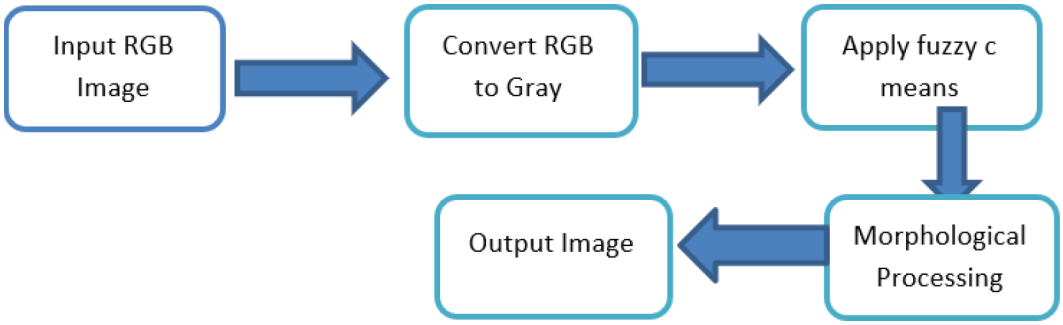
3. Calculate the membership $u^{(b+1)}$ by using v_i;
4. If $\left\|u^{(b)} - u^{(b+1)}\right\| < \varepsilon$, stop. Otherwise, set $b = b + 1$ and go to step2.

PROPOSED MODEL AND STEPS

The proposed system that used FCM to segment medical image consists of several steps, which follow as show in Figure 2.

Figure 2 illustrates the color image acquisition, conversion of RGB image into gray image and the segmentation using the FCM clustering algorithm using six clusters. The segmented image still contains some noise, so, the morphology operation is applying in it to remove noise and unwanted region. In the present work, image's contrast was adjusted, and then extracted the largest object from binary image which is blast cell and also the ROI.

Figure 2. Proposed algorithm of FCM



RESULTS AND DISCUSSION

In this paper, the MATLAB software is used in the proposed algorithm. The two different clustering-based segmentation techniques were compared and applied for leukemia detection to separate the ROI from background. The result of the segmentation is demonstrated by S and the gold standard by ground-truth (GT) in the following depiction of the measures (Taha, & Hanbury, 2015). The measured performance metrics are defined as follows.

The sensitivity which calculates the number of positive pixels in the GT is defined as:

$$\text{Sensitivity} = \frac{TP}{TN + FN} \tag{5}$$

The specificity measures the algorithm sensitivity to correct pixel detection, which is given by:

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{6}$$

The accuracy of the segmentation process is also measured using the following expression:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

The dice coefficient measures the extent to which two binary images overlap in space, which is given by:

$$\text{Dice} = \frac{2\left|S \cap GT\right|}{\left|S\right| + \left|GT\right|} \tag{8}$$

The Jaccard index is utilized to calculate the overlap of the joining divided by the union of two sets, which is given by:

$$\text{Jac}=\frac{|S \cap GT|}{|S \cup GT|} \tag{9}$$

The preceding metrics were measured to evaluate the K-means and FCM for segmenting the leukemia images. Table 1 reported a comparison study between the measured metrics.

In addition, Figure 3 illustrated the average of the measured metrics using the used 40 images dataset.

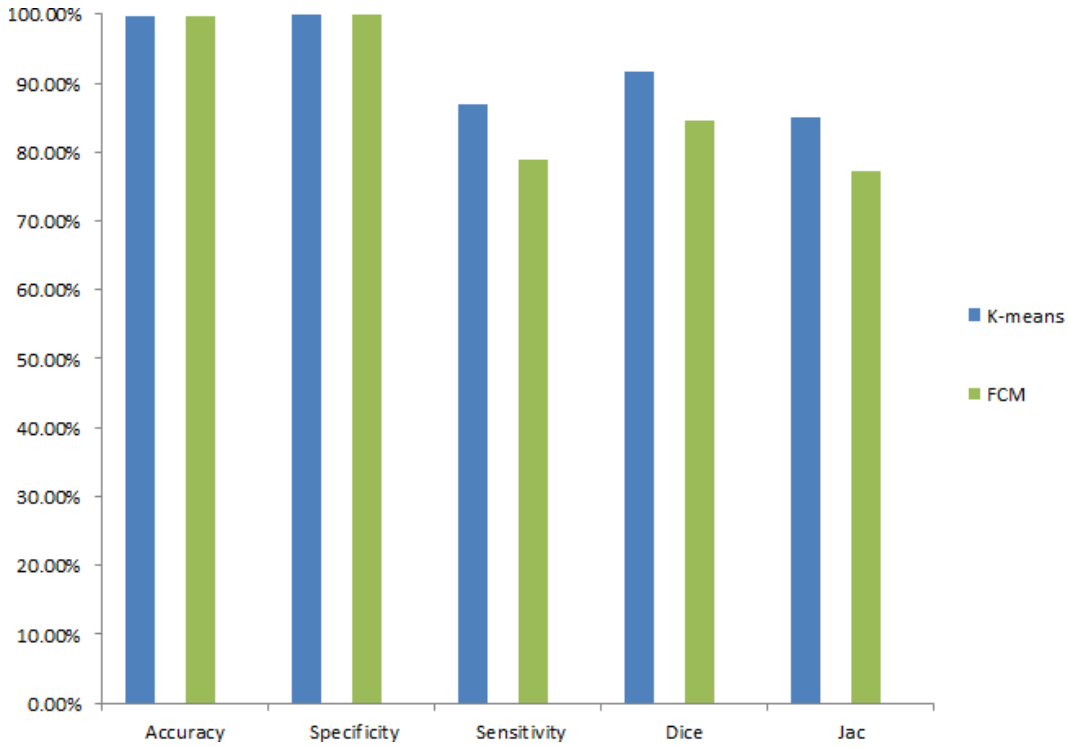
Figure 3 demonstrated the average values of accuracy, specificity, sensitivity, Dice, and Jac using three clusters with the k-means and six clusters with FCM, where these numbers of clusters were determined by trial and error to obtain the best performance with each method.

The results show that k-means has better performance in leukemia blood cells segmentation compared to the FCM in terms of the required number of clusters as well as the values of the measured metrics. The average accuracy, specificity and sensitivity of k-means were 99.8%, 99.97%, and 87%, respectively; in addition, the same metrics were 99.6%, 99.94%, and 78.9%, respectively, using the FCM. Therefore, the K-means cluster algorithm has higher segmentation accuracy compared to FCM cluster algorithm. In addition, the k-means requires less computational time as it requires less number of clusters compared to the required number of clusters by the FCM.

Table 1. Comparison of the result segmentation between K-means and FCM for ten images from the used dataset

Image ID	Method	JAC	DICE	SEN	SPEC	ACC
Image1	K-means	0.807197	0.893314	0.809768	0.999955	0.997297
	FCM	0.503181	0.669489	0.503805	0.999982	0.993049
Image2	K-means	0.896912	0.945655	0.919105	0.99974	0.998902
	FCM	0.864183	0.927144	0.888651	0.999703	0.998549
Image3	K-means	0.885123	0.939061	0.890389	0.999935	0.998751
	FCM	0.890653	0.942165	0.898398	0.999905	0.998808
Image4	K-means	0.876898	0.934412	0.881439	0.999953	0.998877
	FCM	0.883866	0.938353	0.889888	0.999938	0.998939
Image5	K-means	0.857777	0.923445	0.875657	0.999712	0.998019
	FCM	0.811721	0.896077	0.825992	0.999757	0.997386
Image6	K-means	0.945167	0.971811	0.9595	0.999787	0.999229
	FCM	0.903343	0.949217	0.930419	0.999579	0.99862
Image7	K-means	0.883471	0.938131	0.913589	0.99964	0.998741
	FCM	0.886441	0.939803	0.924006	0.999553	0.998764
Image8	K-means	0.882126	0.937372	0.910791	0.999736	0.999018
	FCM	0.879844	0.936082	0.897915	0.999833	0.999011
Image9	K-means	0.87251	0.931915	0.88941	0.999845	0.998971
	FCM	0.888546	0.940984	0.899094	0.999905	0.999107
Image10	K-means	0.850335	0.919115	0.879363	0.999668	0.998509
	FCM	0.84005	0.913073	0.861396	0.999753	0.99842

Figure 3. Comparative results of average of performance metrics using k-means and FCM



CONCLUSION

In this paper, the unsupervised approach for segmentation of medical images, i.e. cluster-based algorithms was proposed. Different images were employed to evaluate the used clustering techniques, namely k-means and fuzzy c-means. The efficiency of two algorithms was determined using different segmentation evaluation metrics, including accuracy, specificity, sensitivity, Dice, and Jac.

The computational results in terms of the required number of clusters proved the superiority of the k-means which requires half number of clusters used by the FCM. In addition, the k-means proved its high accuracy compared to the FCM for leukemia images segmentation. Accordingly, owing to the superiority of the k-means it is suggested to apply it with further classification procedures which were reported in (Virmani et al., 2016; Hore et al., 2016; Saba et al., 2016; Sambyal, & Abrol, 2016; Dey, & Ashour, 2016; Ahmed et al., 2017; Li et al., 2017; Azzabi et al., 2017; AlShahrani et al., 2017; Khachane et al., 2017). In addition, it is recommended to combine both algorithms to overcome the drawbacks of the FCM.

REFERENCES

Ahmed, S. S., Dey, N., Ashour, A. S., Sifaki-Pistolla, D., Bălas-Timar, D., Balas, V. E., & Tavares, J. M. R. (2017). Effect of fuzzy partitioning in Crohn's disease classification: A neuro-fuzzy-based approach. *Medical & Biological Engineering & Computing*, *55*(1), 101–115. doi:10.1007/s11517-016-1508-7 PMID:27106754

AlShahrani, A. M., Al-Abadi, M. A., Al-Malki, A. S., Ashour, A. S., & Dey, N. (2017). Automated system for crops recognition and classification. In Applied Video Processing in Surveillance and Monitoring Systems (pp. 54–69). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-1022-2.ch003

Azzabi, O., Njima, C. B., & Messaoud, H. (2017). New Approach of Diagnosis by Timed Automata. *International Journal of Ambient Computing and Intelligence*, *8*(3), 76–93. doi:10.4018/IJACI.2017070105

Biji, G., & Hariharan, D. S. (2016). White Blood Cell Segmentation Techniques in Microscopic Images for Leukemia Detection. *IONS J Dent Med Sci*, *15*, 45–51.

Bouzid-Daho, A., Boughazi, M., & Tanougast, C. (2016). Segmentation of abnormal blood cells to aid leukemia detection. *Acta HealthMedica Journal*, *1*(4), 88–92. doi:10.19082/ah88

Chatap, N., & Shibu, S. (2014). Analysis of blood samples for counting leukemia cells using Support vector machine and nearest neighbour. *IOSR Journal of Computer Engineering (IOSR-JCE), 16*(5), 79-87.

Dey, N., & Ashour, A. S. (Eds.). (2016). Classification and clustering in biomedical signal processing. Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0140-4

Dhanachandra, N., & Chanu, Y. J. (2017). A survey on image segmentation methods using clustering techniques. *European Journal of Engineering Research and Science*, *2*(1), 15–20. doi:10.24018/ejers.2017.2.1.237

Dhanachandra, N., Manglem, K., & Chanu, Y. J. (2015). Image segmentation using K-means clustering algorithm and subtractive clustering algorithm. *Procedia Computer Science*, *54*, 764–771. doi:10.1016/j.procs.2015.06.090

ElDahshan, K. A., Youssef, M. I., Masameer, E. H., & Hassan, M. A. (2015). Comparison of segmentation framework on digital microscope images for acute lymphoblastic leukemia diagnosis using RGB and HSV color spaces. *Journal of Biomedical Engineering and Medical Imaging*, *2*(2), 26. doi:10.14738/jbemi.22.1065

Fatma, M., & Sharma, J. (2014). Leukemia image segmentation using K-means clustering and HSI color image segmentation. *International Journal of Computers and Applications*, *94*(12), 6–9. doi:10.5120/16393-6010

Hore, S., Chatterjee, S., Sarkar, S., Dey, N., Ashour, A. S., Balas-Timar, D., & Balas, V. E. (2016). Neural-based prediction of structural failure of multistoried RC buildings. *Structural Engineering and Mechanics*, *58*(3), 459–473. doi:10.12989/sem.2016.58.3.459

Karthikeyan, T., & Poornima, N. (2017). Microscopic image segmentation using fuzzy c means for leukemia diagnosis. *Leukemia*, *4*(1), 3136–3142.

Khachane, M. Y. (2017). Organ-Based Medical Image Classification Using Support Vector Machine. *International Journal of Synthetic Emotions*, *8*(1), 18–30. doi:10.4018/IJSE.2017010102

Kumar, S., Mishra, S., & Asthana, P. (2018). Automated Detection of Acute Leukemia Using K-mean Clustering Algorithm. In *Advances in Computer and Computational Sciences* (pp. 655–670). Singapore: Springer. doi:10.1007/978-981-10-3773-3_64

Li, Y., Zhu, R., Mi, L., Cao, Y., & Yao, D. (2016). Segmentation of white blood cell from acute lymphoblastic leukemia images using dual-threshold method. *Computational and Mathematical Methods in Medicine*. PMID:27313659

Li, Z., Shi, K., Dey, N., Ashour, A. S., Wang, D., Balas, V. E., & Shi, F. et al. (2017). Rule-based back propagation neural networks for various precision rough set presented KANSEI knowledge prediction: A case study on shoe product form features extraction. *Neural Computing & Applications*, *28*(3), 613–630. doi:10.1007/s00521-016-2707-8

Liu, S., Deng, Z., Li, J., Wang, J., Huang, N., Cui, R., & Ye, Q. et al. (2019). Measurement of the refractive index of whole blood and its components for a continuous spectral region. *Journal of Biomedical Optics*, *24*(3), 035003. doi:10.1117/1.JBO.24.3.035003 PMID:30848110

Reyes, L. E. H., Rozo, L. X. B., & Morales, F. A. R. (2015, September). Automatic leukocyte image segmentation: a review. *Proceedings of the 2015 20th Symposium on Signal Processing, Images and Computer Vision (STSIVA)* (pp. 1-9). IEEE. doi:10.1109/STSIVA.2015.7330393

Saba, L., Dey, N., Ashour, A. S., Samanta, S., Nath, S. S., Chakraborty, S., & Suri, J. S. et al. (2016). Automated stratification of liver disease in ultrasound: An online accurate feature classification paradigm. *Computer Methods and Programs in Biomedicine*, *130*, 118–134. doi:10.1016/j.cmpb.2016.03.016 PMID:27208527

Sambyal, N., & Abrol, P. (2016). Feature based Text Extraction System using Connected Component Method. *International Journal of Synthetic Emotions*, *7*(1), 41–57. doi:10.4018/IJSE.2016010104

Taha, A. A., & Hanbury, A. (2015). Metrics for evaluating 3D medical image segmentation: Analysis, selection, and tool. *BMC Medical Imaging*, *15*(1), 29. doi:10.1186/s12880-015-0068-x PMID:26263899

Toh, L. B., Mashor, M. Y., Ehkan, P., Rosline, H., Junoh, A. K., & Harun, N. H. (2018). Image Segmentation for Acute Leukemia Cells Using Color Thresholding and Median Filter. *Journal of Telecommunication Electronic and Computer Engineering*, *10*(1-5), 69–74.

Vania, M., Mureja, D., & Lee, D. (2017). Automatic Spine Segmentation using Convolutional Neural Network via Redundant Generation of Class Labels for 3D Spine Modeling.

Virmani, J., Dey, N., & Kumar, V. (2016). PCA-PNN and PCA-SVM based CAD systems for breast density classification. In *Applications of intelligent optimization in biology and medicine* (pp. 159–180). Springer International Publishing.

Yang, Y., & Huang, S. (2012). Image segmentation by fuzzy c-means clustering algorithm with a novel penalty term. *Computer Information*, *26*(1), 17–31.

Zheng, X., Lei, Q., Yao, R., Gong, Y., & Yin, Q. (2018). Image segmentation based on adaptive K-means algorithm. *EURASIP Journal on Image and Video Processing*, *2018*(1), 68. doi:10.1186/s13640-018-0309-3

Zhou, H., Schaefer, G., & Shi, C. (2009). Fuzzy c-means techniques for medical image segmentation. In *Fuzzy Systems in Bioinformatics and Computational Biology* (pp. 257–271). Berlin: Springer. doi:10.1007/978-3-540-89968-6_13