ISSN 2278-3091
Volume 8, No.1.3, 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse6981.32019.pdf
https://doi.org/10.30534/ijatcse/2019/6981.32019

Comparative Analysis of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) for White Blood Cells' Classification

Shafaf Ibrahim[1], Muhammad Hazrin Che Rozan[2], Nurbaity Sabri[3]
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Melaka Kampus Jasin, 77300 Merlimau, Melaka, Malaysia
[1]shafaf2429@uitm.edu.my
[2]hazrinvault@gmail.com
[3]nurbaity_sabri@uitm.edu.my

ABSTRACT

White blood cells (WBCs) are significant element in the immune system to shield against infections. The health condition of a person can be determined from the WBCs as it functions to produce and react to illnesses. However, there are challenges in processing a massive amount of blood samples due to time constraint and skills, which limit the speed and accuracy of classifying the WBCs. Thus, this paper conducts a comparative analysis of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) techniques for WBCs classification. A process of feature extraction is performed to analyze the characteristics of WBCs by extracting the colour, texture, and shape. The classification performance of each technique is tested to 200 of WBCs images. The classification of the WBCs is divided into five different types of neutrophil, basophil, eosinophil, lymphocyte, and monocyte. Upon the testing conducted, the SVM reflected 88.5% of classification accuracy, whereas the CNN on the other hand returned a higher percentage of 94%. Thus, it is proven that CNN is observed to return a better WBCs classification outcome as compared to the SVM.

Key words: Classification, Convolutional Neural Network **(**CNN), Support Vector Machine **(**SVM), white blood cells (WBCs).

1. INTRODUCTION

White blood cells (WBCs) are significant element of the immune system. It is produced by a multipotent cell in the bone marrow [1]. Generally, WBCs act as the third line of defence against harmful pathogens and some of them have specific functions. The health condition of a person can be determined from the WBCs as it produced and reacted to illnesses. Additionally, any changes in WBCs production could determine whether the person might be suffering from the infection, allergies, inflammation or maybe stress [2]. Due to the nature of WBCs, it became an important component in extracting valuable diagnostic information, especially for haematologists.

The WBCs are categories by their texture, colour, size, and morphology of the nucleus and cytoplasm [3]. It can be categorized into five types which are basophils, eosinophil, neutrophils, lymphocytes, and monocytes [4]-[5]. The neutrophil is the most populous and short-lived cell, eosinophil has large granules that appear in red or pink, basophil has granules that are deep blue-purple, lymphocyte is a granular cell with very clear cytoplasm and monocyte is the largest of the leukocyte [1].

Up till now, even with the advancement of medical technology, the standard method of classifying the WBCs or leukocytes is still done manually using a microscope [6]. Although the usage of the blood smear is still acceptable, yet it is only based on visible colour and shape of the WBCs [7]. Testing the same sample repeatedly might lead to some variations in the result of identification and counting of blood cells [8].

The knowledge and experience of medical operators could also affect the correctness of the WBCs analysis [9]. There are also challenges in processing a massive amount of blood samples such as the time constraint and skills which limit the speed and accuracy of processed blood samples [10]. The manual analysis of blood smear images is tiresome and time-consuming for lab researchers [3].

Feature extraction is a part of image processing which is used to extract informational features from an image. The most common features in feature extraction are visual features which include colour, texture, and shape. On the other hand, image classification relates to the identification of images in one of several predefined categories. Many classification techniques for image classification have been developed such as Artificial Neural Network (ANN), Decision Tree (DT), Support Vector Machine (SVM) and Fuzzy Classification [9], to name a few.

Thus, based on the problems discussed, a comparative analysis of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) techniques for WBCs classification is presented. The WBCs is divided into five distinct types of neutrophil, basophil, eosinophil, lymphocyte, and monocyte. The techniques of Colour Moment, Grey-level

Co-occurrence Matrices (GLCM) and Regionprops techniques are proposed to extract the colour, texture, and shape features correspondingly. The feature extraction process is implemented to determine the patterns and characteristics of the various types of WBCs. This can be used to assist the SVM and CNN classification process. The classification accuracy of the WBCs classification results for the corresponding SVM and CNN are then measured.

The organization of the remainder of this paper is as follows: Section 2 provides our methods, including an overview of the methodology, and the description of SVM and CNN algorithm structure. Our results and discussions are discussed in Section 3. Finally, in Section 4, we present our conclusion.

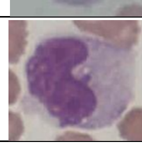
2. METHODS

The SVM and CNN techniques are applied for the WBCs classification. The key concept in this classification algorithm is the feature extraction of color, texture, and shape of the WBCs. It is used as the objective function in both techniques of SVM and CNN. The experiments start by extracting the region of interest (ROI) from the WBCs images in order to identify the patterns and characteristics of each type of WBCs. Subsequently, the SVM and CNN techniques will be applied respectively to classify the WBCs to the type it belongs to.

2.1 Data Collection

A total of two hundred images of WBCs were collected from UiTM Medical Specialist Centre, Sungai Buloh, Selangor. The size of images obtained from the imaging device is 2560x1920 pixels. Table 1 tabulates the samples of each type of WBCs images which are neutrophil, basophil, eosinophil, lymphocyte, and monocyte.

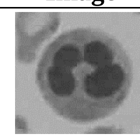
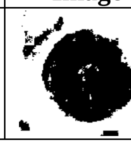
Table 1: Samples of WBCs Images

WBCs Type	Image
Basophil	
Eosinophil	
Neutrophil	
Lymphocyte	
Monocyte	

2.2 Pre-processing

The pre-processing phase comprises three processes which are image enhancement, grayscale conversion, and binary conversion. These processes were performed on the image before it goes through the feature extraction and classification process. Image enhancement is used to expand the appearance of an image so that it is easy to be examined or interpret [12]. A method of unsharp masking is proposed for image enhancement. This sharpening method unsharpens an image and uses the distinction between the original images as a mask to surge the contrast of the image [13]. Next, the grayscale conversion converts the true-colour Red Green Blue (RGB) image to the grayscale intensity image. It works by removing the hue and saturation information without affecting the luminance. On the other hand, the binary conversion converts the grayscale image to binary image, by replacing the value of 1 (white) to all pixels in which the luminance is greater than level. Whereas, all other pixels are replaced with the value of 0 (black). Table 2 depicts a sample image and each stage of pre-processing as mentioned.

Table 2: Sample Image and Stages of Pre-Processing

Original Image	Enhanced Image	Grayscale Image	Binary Image
			

2.3 Image Segmentation and Feature Extraction

This study is focussing on three types of features which are colour, texture, and shape [14] using Colour Moment, Grey-level Co-occurrence Matrices (GLCM) and Regionprops techniques correspondingly. A technique of Color moment is proposed to extract the color features which returned the values of mean, standard deviation and skewness of each RGB color. The texture of the WBCs is distinguished by a powerful texture extraction technique which is GLCM which covers the values of contrast, correlation, energy, homogeneity, and entropy. On the other hand, the shape of the WBCs is distinguished using a technique of Regionprops which reflected the parameter values of area, solidity, eccentricity, and perimeter.

The color moment is one of the simplest yet very effective features. It is very helpful to distinguish color based image analysis techniques. It distinguishes images according to their color features, and to calculate the color similarity between the images. The source of color moments assumes that the color distribution in an image can be interpreted as a probability distribution [15]. The low order moments can be used to extract the information of color distribution in an image.

The values of mean, standard deviation and skewness [16] are the common moments, and the corresponding equations used can be defined as in Table 3.

Table 3: Color Moment Equations

Features	Equations
Mean	$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij}$ (1)
Standard Deviation	$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^2\right)^{\frac{1}{2}}$ (2)
Skewness	$\gamma_i = \left(\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^3\right)^{\frac{1}{3}}$ (3)

Alternatively, the GLCM has proven to be a well-known statistical method to extract the textural feature from images. Referring to a study in [17], a probability matrix is used to define 14 textural features to extract the characteristics of texture statistics in remote sensing images. A GLCM is represented using a few parameters of *i, j, d, θ* and *N* [18],

where:
i = probability of a gray-level
j = neighbourhood of gray-level
d = distance
θ= angle
N= total number of gray levels N

However, there are only four important features of GLCM selected which are Angular Second Moment (energy), Inverse Difference Moment, Entropy and Correlation. Table 4 illustrates the details and equations of the four features.

In another note, segmentation is used to highlight the area of interest from the image background such as features, object, and structures [19]. It is important to apply the segmentation before applying any measurement to the image. The Canny edge detection is one of the most frequently used image processing tools which detect the edges in a very powerful way. It is commonly regarded as the industry's standard edge detection technique [20]. Canny edge detection is a standout amongst the most regularly utilized picture handling instruments, recognizing edges in an exceptionally mighty way. Figure 1 shows a sample image of Canny edge detection of the WBCs image.

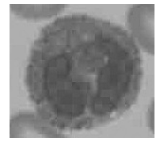
Before Edge Detection	After Edge Detection
	

Figure 1: Sample of Canny Edge Detection Process

After the Canny edge operator has traced the image boundaries, the shape features of the binary image will then be extracted. The proposed technique of Regionprops is implemented to extract the shape features. It returns the measurements given by the features for each connected component (object) in the binary image for the set of properties. The extracted features are tabulated in Table 5.

Table 5: Parameters of Regionprops

Parameter	Details
Area	Amount of white pixels in a binary image.
Solidity	A scalar specifying the percentage of pixels in the convex hull in the region
Perimeter	A distance around the boundary of the white blood cells region
Eccentricity	A distance ratio between the ellipse's focal length and its major axis length

Table 4: GLCM Equations

Features	Details	Equations
Angular Second Moment	Refers to Energy. Return the total of entries squares. It measures the homogeneity of an image.	$\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p^2{}_{ij}$ (4)
Inverse Difference Moment	The local homogeneity. Returns a high value if the local gray level is uniform, and inverse GLCM is high.	$\frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p_{ij}}{1+(i-j)^2}$ (5)
Entropy	Indicates the amount of image information that is required for image compression. It calculates the information loss.	$\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} - p_{ij} * \log p_{ij}$ (6)
Correlation	Measures the linear dependency of grey levels of neighbouring pixels.	$\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)\,p(i,j) - \mu_x\mu_y$ (7)

2.4 WBCs Classification

The classification is the process of classifying by which variables are classified into their classes. It includes variables with known values to predict the unknown or future values of other variables [21]. In this study, a comparative analysis of SVM and CNN for WBCs classification is evaluated.

2.4.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is an effective machine learning which is suitable for binary classification, regression and outlier's detection. It classifies given data samples by mapping them to high dimensional spaces and constructs hyper-planes. A set of hyper-planes are built in infinite dimensional space which divides the data into partitions such that data belonging to the same class is put into the same partition [22].

The SVM implementation involved the two phases of training and testing which are as follow:

1) Pre-processing: Process the images into a decent form for the subsequent steps.
2) Feature extraction: consumes the previously extracted features of the WBCs images, and filtering the most relevant information, which represents in terms of vector or scalar values.
3) WBCs classification: Compare the feature vectors and find the closest match. Only one can match the feature vectors obtained.

2.4.2 Convolutional Neural Network (CNN)

In this study, the pre-trained GoogLeNet model is used. GoogLeNet model is intended to utilize a number of smaller convolutional kernels for limiting the quantity of parameters and neurons [23]. One of the important characteristics of GoogLeNet is that it is built very deep with 22 layers with parameter [24]. The Inception Modules of the Google Net is used to perform distinctive sizes of convolutions and concatenate filters for the subsequent layer [25].

For training and testing purposes, 200 WBCS images were used to test the accuracy of the whole system. The WBCs images will pass through the first architectural layer, which is a convolutional layer in which all features are extracted and the result is transported to the next layer. The next layer would be a pooling layer that reduces image volumes without data loss and the max pooling layer is used to get the most maximum values of each divided region.

The next layer is a fully connected layer that connects this layer directly to each node in the previous layer. Fully connected layer transforms the data dimension to allow data to be linearly classified. It modifies the input image into vector resulting output in array size and the number then applies to softmax to change to probability. For the softmax layer, the result that obtained from fully-connected layer will be processed to an array of probabilities for each of the category. The maximum probability is the class that it predicts.

2.5 Performance Evaluation

The performance of the WBCs classification is evaluated using a confusion matrix. It is performed by comparing the SVM classification result with the actual pathology report. A total of 200 WBCs images, in which 40 images for each type of WBCs were tested. The number of TRUE and FALSE result of the classification in the form of a confusion matrix for respective SVM and CNN is tabulated in Table 6 and Table 7.

Table 6: Proposed Confusion Matrix of Tested Data for SVM

		SVM Classification Result				
		Basophil	Eosinophil	Lymphocyte	Monocyte	Neutrophil
Pathology Report	Basophil	**36 (TRUE)**	0	0	2 (FALSE)	2 (FALSE)
	Eosinophil	0	**36 (TRUE)**	2 (FALSE)	0	2 (FALSE)
	Lymphocyte	3 (FALSE)	2 (FALSE)	**34 (TRUE)**	1 (FALSE)	0
	Monocyte	1 (FALSE)	3 (FALSE)	0	**36 (TRUE)**	0
	Neutrophil	0	1 (FALSE)	4 (FALSE)	0	**35 (TRUE)**

Table 7: Proposed Confusion Matrix of Tested Data for CNN

		CNN Classification Result				
		Basophil	Eosinophil	Lymphocyte	Monocyte	Neutrophil
Pathology Report	Basophil	**38 (TRUE)**	0	0	2 (FALSE)	0
	Eosinophil	0	**39 (TRUE)**	0	0	1 (FALSE)
	Lymphocyte	3 (FALSE)	0	**36 (TRUE)**	1 (FALSE)	0
	Monocyte	0	3 (FALSE)	0	**37 (TRUE)**	0
	Neutrophil	0	0	0	2 (FALSE)	**38 (TRUE)**

Next, based on the confusion matrix obtained in Table 6 and Table 7, the WBCs classification accuracy for each type of WBCs is calculated using (8):

$$Accuracy, A = \frac{\sum TRUE}{\sum WBCs\, images} x100 \quad (8)$$

3. RESULTS AND DISCUSSION

Two hundred testing images are tested for each type of WBCs. The performance of the WBCs classification is demonstrated in Table 8.

Table 8: Performance of WBCs classification

WBCs Type	Total Number of Images	Number of TRUE classification		% of Accuracy	
		SVM	CNN	SVM	CNN
Basophil	40	36	38	90	95
Eosinophil	40	36	39	90	97.5
Lymphocyte	40	34	36	85	90
Monocyte	40	36	37	90	92.5
Neutrophil	40	35	38	87.5	95
		Overall Mean % of Accuracy		**88.5**	**94**

From the calculation of accuracy, it is observed that the WBCs classification produced a good performance for both SVM and CNN. As compared to the SVM, CNN is monitored to produce higher percentage of accuracy for all types of WBCs. The classification of eosinophil produced the highest percentage of accuracy which is 97.5%. It is followed by the basophil and neutrophil which returned 95% of classification accuracy.

The SVM is also cannot be underestimated as it returned 90% of classification of accuracy for basophil, eosinophil, and monocyte. However, a slightly low percentage of accuracy is noticeable for both lymphocyte and neutrophil which demonstrated 87.5% of accuracy, and lymphocyte which is 85% of accuracy respectively. The lymphocyte is observed to demonstrate the lowest percentage of accuracy for both SVM and CNN. This might be caused by the confusion in distinguishing the almost similar representation between the lymphocyte with the other type of WBCs which is basophil.

The overall mean percentage of accuracy is observed to produce a very good percentage of accuracy which is 88.5% for SVM and 94% for CNN. Despite good performance of WBCs classification presented, a further work of diseases detection based on the detection of abnormal cell shapes in a blood smear is suggested in the future.

4. CONCLUSION

This paper presents a comparative analysis of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) techniques for White Blood Cells (WBCs) classification. The application to a variety of WBCs images has been successful. The classification performance of the SVM and CNN had been evaluated using confusion matrix. The performance obtained exhibit a little variation in classifying the five different types of WBCs which are neutrophil, basophil, eosinophil, lymphocyte, and monocyte. The overall mean percentage of accuracy demonstrated that SVM reflected 88.5% of classification accuracy, whereas the CNN on the other hand returned a higher percentage of 94%. It is proven that the CNN returned a better WBCs classification outcome as compared to the SVM. Therefore, it can be concluded that the proposed implementation of both SVM and CNN for WBCs classification is found to be successful. Yet, a further work of diseases detection based on the detection of abnormal cell shapes in a blood smear could be recommended in the future.

ACKNOWLEDGMENT

The research was supported by Ministry of Education Malaysia (MoE), and Universiti Teknologi MARA through the Fundamental Research Grant Scheme **(**FRGS) (600-IRMI/FRGS 5/3 (215/2019)).

REFERENCES

1. L. Zhang, L. Zhang, D. Tao, X. Huang. **Tensor discriminative locality alignment for hyperspectral image spectral–spatial feature extraction**. *IEEE Transactions on Geoscience and Remote Sensing*, *51*(1), pp. 242–256, 2013. https://doi.org/10.1109/TGRS.2012.2197860
2. M. Habibzadeh, A. Krzyżak, and T. Fevens. **White blood cell differential counts using convolutional neural networks for low resolution images**, *International Conference on Artificial Intelligence and Soft Computing*, pp. 263–274, 2013. https://doi.org/10.1007/978-3-642-38610-7_25
3. H. Lee and Y.P. P. Chen. **Cell morphology based classification for red cells in blood smear images**. *Pattern Recognition Letters*, *49*, pp.155–161, 2014. https://doi.org/10.1016/j.patrec.2014.06.010
4. H. Tulsani, S. Saxena, and N. Yadav. **Segmentation using morphological watershed transformation for counting blood cells.** *International Journal of Computer Applications & Information Technology*, *2*(3), pp. 28–36, 2013.
5. S. T. Mohamed, H. M. Ebeid, A. E. Hassanien, and M. F. Tolba, **Optimized Feed Forward Neural Network for microscopic white blood cell images classification**, The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2019), AMLTA 2019, Advances in Intelligent Systems and Computing, Vol 921. Springer, Cham, 2019. https://doi.org/10.1007/978-3-030-14118-9_74

6. R. Tomari, W. N. W Zakaria, M. M. A. Jamil, F. M. Nor, and N. F. N. Fuad. **Computer aided system for red blood cell classification in blood smear image**. *Procedia Computer Science*, vol. 42, pp. 206–213, Elsevier Masson SAS, 2014. https://doi.org/10.1016/j.procs.2014.11.053
7. X. Wang, and Z. Wang. **A novel method for image retrieval based on structure elements' descriptor**. *Journal of Visual Communication and Image Representation*, *24*(1), pp. 63–74, 2013. https://doi.org/10.1016/j.jvcir.2012.10.003
8. M. Habibzadeh, M. Jannesari, Z. Rezaei, H. Baharvand, and M. Totonchi. **Automatic white blood cell classification using pre-trained deep learning models: ResNet and Inception**, Proc. SPIE 10696, Tenth International Conference on Machine Vision (ICMV 2017), 1069612, 2018. https://doi.org/10.1117/12.2311282
9. L. Putzu and C. D. Ruberto. **White blood cells identification and counting from microscopic blood image.** *International Journal of Medical, Health, Biomedical, Bioengineering and Pharmaceutical Engineering*, *7*(1), pp. 15–22, 2013.
10. N. H. Mahmood. **Blood cells extraction using color based segmentation technique**. *International Journal of Life Science and Pharma Research*, Vol. 2, No. 2, April 2013.
11. P. Kamavisdar, S. Saluja, and S. Agrawal. **A survey on image classification approaches and techniques**. *International Journal of Advanced*, *2*(1), pp. 1005–1009, 2013.
12. A. N. Ganar, C. S. Gode, and S.M. Jambhulkar. **Enhancement of image retrieval by using colour, texture and shape features**, *2014 International Conference on Electronic Systems, Signal Processing and Computing Technologies*, pp. 251–255, 2014. https://doi.org/10.1109/ICESC.2014.48
13. R. G. Mundada and V. V. Gohokar. **Detection and classification of pests in greenhouse using image processing**. *Iosr J. Electron. Commun. Eng.*, 5, pp. 57-63, 2013. https://doi.org/10.9790/2834-565763
14. D. Sarala, T. Kanikdaley, S. Jogi, and R. K. Chaurasiya, **Content-based image retrieval using hierarchical color and texture similarity calculation**, *International Journal of Advanced Trends in Computer Science and Engineering*, Volume 7, No.2, March - April 2018. https://doi.org/10.30534/ijatcse/2018/02722018
15. D. P. Tian. **A review on image feature extraction and representation techniques**. *International Journal of Multimedia and Ubiquitous Engineering*, *8*(4), 385–395, 2013.
16. A. Malakar and J. Mukherjee. **Image clustering using color moments, histogram, edge and k-means clustering.** *International Journal of Scientific Engineering and Research (IJSER)*, *1*(1–3), pp. 532–537, 2013.
17. R. M. Haralick, K. Shanmugam, and I. Dinstein. **Textural features for image classification**, *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 6, pp. 610–621, 1973. https://doi.org/10.1109/TSMC.1973.4309314
18. P. Mohanaiah, P. Sathyanarayana, and L. Gurukumar. **Image texture feature extraction using GLCM approach**. *International Journal of Scientific & Research Publication*, *3*(5), pp. 1–5, 2013.
19. S. Nazlibilek, D. Karacor, T. Ercan, M. H. Sazli, O. Kalender, and Y. Ege. **Automatic segmentation, counting, size determination and classification of white blood cells.** *Measurement: Journal of the International Measurement Confederation*, *55*, pp. 58–65, 2014. https://doi.org/10.1016/j.measurement.2014.04.008
20. S. Vijayarani and M. Vinupriya. **Performance analysis of canny and sobel edge detection algorithms in image mining.** *International Journal of Innovative Research in Computer and Communication Engineering*, Vol. 1, Issue 8, pp. 1760–1767, October 2013.
21. P. Thakur and R. Shrivastava. **A review on text based emotion recognition system**, *International Journal of Advanced Trends in Computer Science and Engineering*, Volume 7, No.5, September - October 2018. https://doi.org/10.30534/ijatcse/2018/01752018
22. H. T. Sencar and N. Memon. **Digital image forensics: There is more to a picture than meets the eye**, New York, NY: Springer New York, 2013. https://doi.org/10.1007/978-1-4614-0757-7
23. P. Tang, H. Wang and S. Kwong. **G-MS2F: Googlenet based multi-stage feature fusion of deep CNN for scene recognition**. *Neurocomputing. Elsevier*, Vol. 225, pp. 188-197, 2017. https://doi.org/10.1016/j.neucom.2016.11.023
24. Z. Zhong and Z. Xie. **High performance offline handwritten Chinese character recognition using Googlenet and directional feature maps**, pp. 846–850, 2015. https://doi.org/10.1109/ICDAR.2015.7333881
25. C. Szegedy et al. **Going deeper with convolutions**. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–12, 2015. https://doi.org/10.1109/CVPR.2015.7298594