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White Blood Cells Cancer detection using Edge Detection Segmentation and Convolutional Neural Network

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Abstract: ***Establishing an accurate count and classification of leukocytes commonly known as WBC (white blood cells) is crucial in the assessment and detection of illness of an individual, which involves complications on the immune system that leads to various types of diseases including infections, anemia, leukemia, cancer, AIDS (Acquired Immune Deficiency Syndrome) etc. The two widely used methods to count WBC is with the use of hematology analyzer and manual counting. Currently, in the age of modernization there has been numerous research in the field of image processing incorporated with various segmentation and classification techniques to be able to generate alternatives for WBC classification and counting. However, the accuracy of these existing methods could still be improved. Thus, in this paper we proposed a new method that could segment various types of WBCs: monocytes, lymphocytes, eosinophils, basophils, and neutrophils from a microscopic blood image using HSV (Hue, Saturation, Value) saturation component with blob analysis for segmentation and incorporate CNN (Convolutional Neural Network) for counting which in turn generates more accurate results.***
Keywords: White blood cells, leukocytes, HSV image processing, blob analysis, convolutional neural network

I. INTRODUCTION

The immune system is a complex network which is consists of cells, tissues and organs that operates simultaneously to protect our body from millions of disease causing bacteria, parasites, and viruses [1]. Leukocytes commonly known as WBC (white blood cells) is the most critical component of our immune system and is categorized into five major subtypes:

1) Neutrophils(50-70%);
2) Lymphocytes(25-30%);
3) Monocytes(3-9%);
4) Eosinophils(0-5%);
5) Basophils(0-1%);

Percentage ranges inside the brackets are the common percentage value parallel to the WBC subtype in the blood of a healthy person [2]. Being able to recognize a variation on the type and number of WBCs of a healthy person normally serves as an indicator for various diseases [3]. Excessive monocyte and eosinophil count could be an bacterial infection. An increase in lymphocyte count could be an indication of AIDS (Acquired Immune Deficiency Syndrome).While, in flated count of neutrophil could suggest cancer [4]. Thus, generating a method which could accurately classify and count the number of WBC as per subclass is becoming a more important issue.

Traditionally, WBC classification and counting is being done manually by hematology experts with the use of a microscope. However, due to the complexity of the procedure, the process could be time consuming and is prone to error[5].

Currently, in the advancement of image processing, numerous research and alternative methodologies have been proposed for WBC classification and counting. Although some of these research was able to generate accurate results in WBC counting by utilizing various WBC segmentation techniques such as fuzzy c means and snake [6], color space conversion incorporated with Otsu's algorithm [7], machine vision system [8], and k-means clustering [9] the focus of their research was mainly for determining the number of WBCs. While other research on the other hand focused on devising a methodology that could execute both counting and classifying WBCs as per its subtype [10][11][12] these aforementioned methods can still be improved further to generate a more accurate result. Thus, this research intends to introduce an innovative approach that could simultaneously segment, classify, and count WBCs based on microscopic blood images by utilizing the authors' previous study which could accurately and efficiently segment white blood cells using saturation component of HSV color model and blob analysis. Then, incorporate CNN for classification and counting.

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II. REVIEW OF RELATEDLITERATURE

In this chapter we will demonstrate the various methods which involves different image processing techniques being currently implemented for the segmentation, classification and counting of white blood cells. Moreover, we will also be discussing some of the most recent CNN types, specifically the ones that we utilized on our proposed method.

Rosya dietal. Conducted are search that is able to classify WBC from blood cell images taken from blood smear samples using digital microscope. The researchers utilized Otsu threshold method for segmentation and K-Means clustering method for classification. Based on their research it was concluded that upon execution of k-means clustering to classify and count WBC, the most significant geometry feature is its circularity generating an accuracy of 67% [1].

Alternatively, Gautam et al. proposed a method which utilizes Naïve Bayes classifier and morphological features to classify WBC. The features which the researchers used to train their system were; area, eccentricity, perimeter and circularity. The proposed method was able to generate 80.88% accuracy [11].

In the pursuit to further improve the accuracy of previous papers, Yu et al. proposed a method which uses CNN to automatically classify WBCs. The researchers utilized the network architectures; ResNet50, Inception V3, VGG 16, VGG 19, and Xception. The proposed method was able to generate an accuracy of 88.5%[10].

Recently, the study on the field of CNN showed to be increasingly significant in the advancement of image classification. There have been various types of CNN that was used by previous researchers. However, recent models proved to be more efficient on the improvement of image classification accuracy specifically on tasks such as object detection and segmentation.

Thus, the proposed method in this paper utilized the models AlexNet, ResNet101, and GoogleNet for WBC classification. AlexNet was a winning model in the ILSVRC 2012 (ImageNet Large Scale Visual Recognition Challenge), GoogleNet is the winner of ILSVRC 2014 [13], and ResNet with 152 layers won ILSVRC 2015[14].

III. METHODOLOGY

This section describes the procedure undertaken in classifying the white blood cells in a blood smear image. We have collected samples with different qualities from [15]and ALL-IDB database [16][17][18][19] to test the versatility of our method in extracting the white blood cells. The images used were captured under different magnifications ranging from 100-500 and with different resolutions starting from 350x236 up to 2592x1944. The MATLAB Image Processing Toolbox was used to analyze the images. A desktop with Intel i7 processor and 16 GB RAM was used to execute the procedure. An overview for the process of classification is shown in Fig.1. To identify different types of WBC, a technique called transfer learning was used in the study. It is a method wherein a pretrained CNN is modified to classify other types of objects. Utilizing this technique is practical not only in a sense that you can save a lot of time instead of starting from scratch but also because the pretrained CNN such as AlexNet, GoogLe Net and ResNet-101 are proven to be robust and provides high accuracy results. The aforementioned CNN are trained on more than a million images and can classify images into 1000 types. The three CNN were used through transfer learning and retrained with 260 different types of WBC.A sample architecture of CNN is shown in figure2.

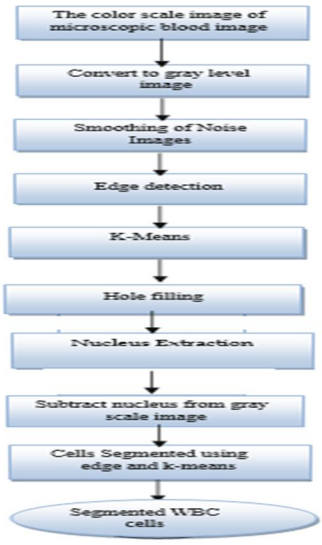

Figure 2. A sample architecture of Segmentation.

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In using CNN, the initial and the most important step before feeding a validation image is making sure that the dimension of the image is same with the requirement of the CNN. AlexNet requires an input size of 227x227 while
Sensitivity or True Positive Rate (TPR) represents the percentage of the samples which actually belong to the class and identified as such. The formula is shown in (1).
GoogleNetandResNet-101 require an in put size of 224x224.

A. Convolution

A filter image(e.g line detector) examines every location of the input image to search for a line. If it detects a line, the filter will be activated. It will move one unit to the right until it reaches the end of the input image. Every location is recorded in an array called the feature map. Locations that have a line will have a high value and those that are not will have a value of zero.

B. Max pooling

A type of pooling layer which reduces the size or resolution of the incoming input layer. By doing so, the computation cost is reduce significantly and over fitting is avoided.

C. Fully Connected Layers

This layer is located at the end of the network. It connects all the activated location in every layer preceding it. Its output is an N dimension vector where N is the number of class that the network is trained to classify—in our study we have 5 classes. Each element in the vector contains the probability that the object belongs to the class. The element with the highest probability is the classification result.

IV. RESULTS ANDDISCUSSION

To assess the performance of the methodology, 178 WBC from 21 blood smear images were used as sample images to determine the accuracy of the proposed method.
The identified and segmented WBC from the sample images were used as validation images and were classified using 3 retrained pretrained CNN namely AlexNet, GoogLeNet and ResNet-101. Fig. 3 shows the sample results from the classification. Their corresponding confusion matrices are shown in table 1, table 3 and table 5 respectively.
Furthermore, statistical measures such as sensitivity, specificity and accuracy were taken to evaluate the performance of the classification models.
The data from the confusion matrix were categorized into 4 types—True Positive (TP), False Negative, True Negative (TN) and False Positive (FP) — in order to compute for the statistical measures. TP is defined as the number of correctly identified samples as belonging to the class. FN is the number of samples belonging to the class but identified as not. TN indicates the number of correctly identified samples as not belonging to the class. And FP is the number of samples not belonging to the class but identified as belonging.
Sensitivity or True Positive Rate (TPR) represents the percentage of the samples which actually belong to the class and identified as such. The formula is shown in (1)

$$TPR = \frac{TP}{TP + FN} \quad (1)$$

Specificity or True Negative Rate (TNR) represents the percentage of the samples which actually don't belong to the class and identified as such. The formula is shown in (1).

$$TNR = \frac{TN}{TN + FP} \quad (2)$$

Accuracy (ACC) was computed as the ratio of all samples belonging to the class and .the total number of samples. The formula is shown in(3).

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

The corresponding statistical measures for AlexNet, GoogLeNet and ResNet-101 are shown in table 2, table 4 and table 6 respectively.

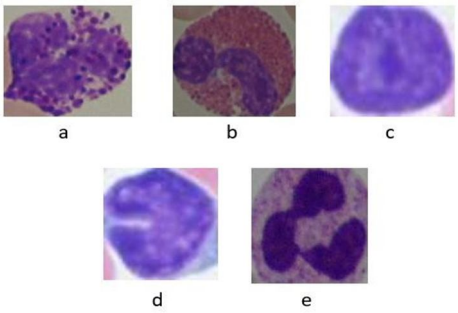


Figure 3.Sample results from the classification of the validation images (a) Basophil [16]-[19] (b) Eosinophil [16]-[19] (c) Lymphocyte [16]-[19] (d) Monocyte [20] (e) Neutrophil [20]

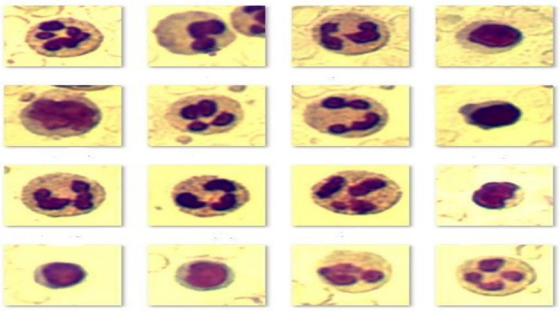
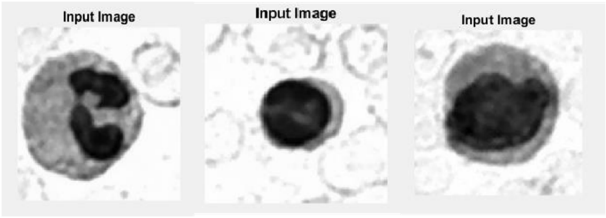
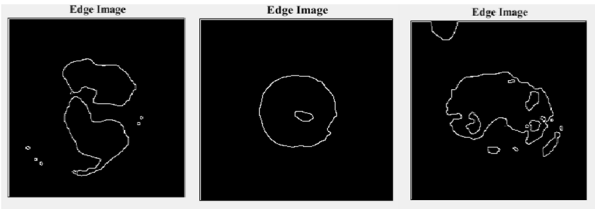


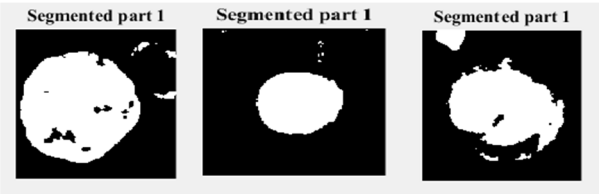
Figure 6:- Cells segmentation procedure. a Input image. b Edge detection. c. segmented part 1 d. segmented part 2. e. segmented part 3 f. Hole filling g. nucleus extraction



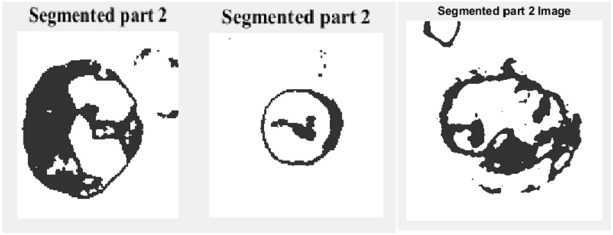
a. Input Image



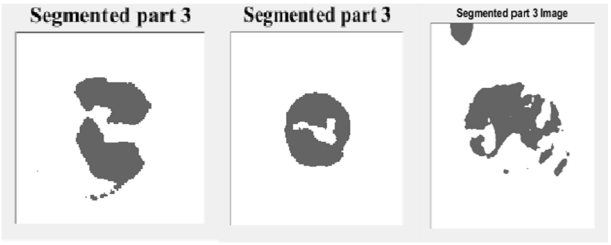
b. Image for Edge detection



c. Image for Segmented part1

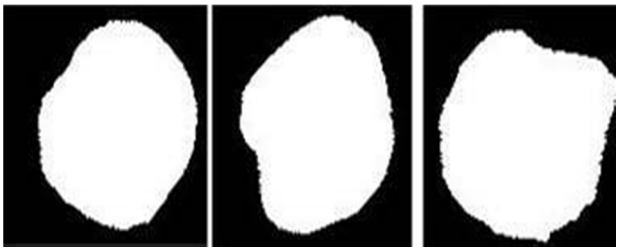


d. Image for Segmented part2



e. Image for Segmented part3

f. Holefilling



This method gives useful information about WBC maturation status by finding the dimension of WBC components, nucleus and cytoplasm.

The framework has been done on sub-images to have easier implementation; This calls the major limitation in our method. In blood image, there are similar color cales in WBCS with some

V. CONCLUSION

This research was able to classify and count WBCs based on microscopic blood images by utilizing CNN. Moreover, upon comparison of the three CNN models (Alexnet, GoogleNet, and ResNet-101) it was observed that AlexNet performed best on the task of classification and counting based on 21 microscopic blood sample images as compared to GoogleNet and ResNet-101, generating an overall sensitivity of 89.18%, specificity of 97.85%, and accuracy of96.63%.

VI. ACKNOWLEDGMENT

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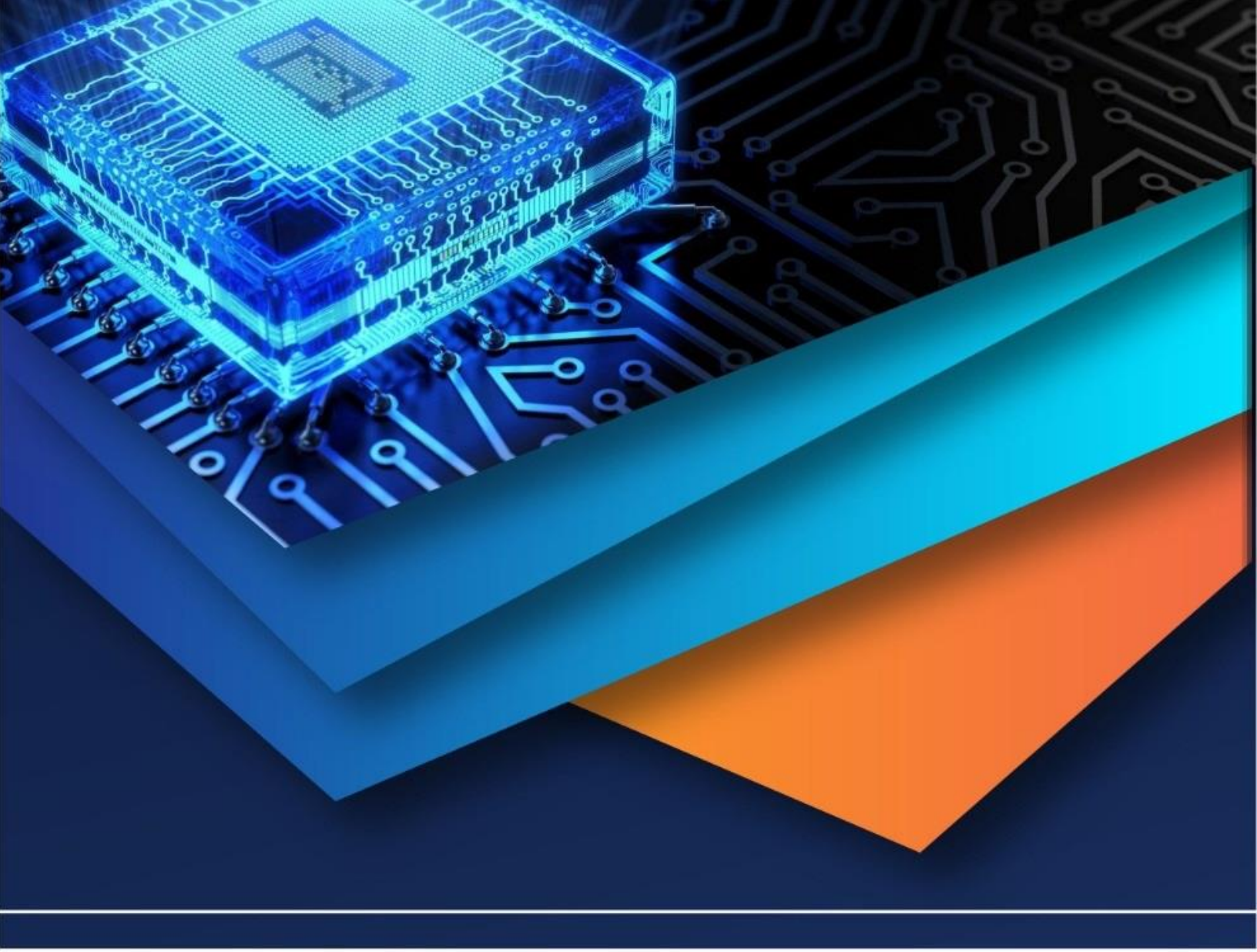

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