IJARSCT

ISSN (Online) 2581-9429

IJARSCT
Impact Factor: 6.252

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Volume 2, Issue 1, June 2022

Estimation of White Blood Cells using Convolutional Neural Network: A Review

Mr. Swami Someshwar A.[1], Prof. Dabir R. S.[2], Dr. Yerigeri V. V.[3]

Student, Digital Communication, College of Engineering Ambajogai, Beed, India[1]

Assistant Professor, Digital Communication, College of Engineering Ambajogai, Beed, India[2]

Professor, Digital Communication, College of Engineering Ambajogai, Beed, India[3]

Abstract: *Normally blood samples contain red blood cells, white blood cells and platelets. White blood cells are also called as leukocytes and they are the cells of immune system. The measure of White Blood Cells is so important for the doctors in diagnosing various diseases like leukemia or tissue damage etc. So, counting of White Blood Cells plays an important role. The manual counting of White Blood Cells in medical laboratories involves a device called Haemocytometer. But this process is extremely monotonous, time consuming, and leads to inaccurate results. In this work, image processing and deep learning mechanisms are used to locate and classify the White Blood Cells based on their categories. The White Blood Cells which are classified are counted and compared with the standard range of the types available in the human blood sample. By comparing the availability of White Blood Cells types, the normal and the abnormal blood samples are predicted accordingly. The dataset of the normal blood sample is obtained from the laboratory in biotechnology department and the datasets used for training in Convolutional Neural Network are attained from the website Leukocyte Images for Segmentation and Classification (LISC). This will increase efficiency and reduce the doctor's burden as traditional manual counting is dull, tedious, and possibly subjective.*

Keywords: RBC (Red Blood Cell), WBC (White Blood Cell), Leukocyte, leukemia etc.

I. INTRODUCTION

Image processing is defined as manipulating an image to achieve an aesthetic standard or to support a preferred reality. It can also be precisely defined as a means of conversion between human visual system and digital imaging devices. Prominent differences between the human and digital detectors will be shown for achieving translation. It can be loomed in a manner reliable with the scientific method so that others may reproduce one's results. Every human body has three types of blood cells RBCs, WBCs and Platelets.

White Blood Cells l(WBCs), also called leukocytes or leucocytes, are the cells of the immune system. They are tangled in protecting the body against infectious diseases and foreign invaders. All White Blood Cells are produced and derived from multipotent cells in the bone marrow known as hematopoietic stem cells. White

Blood Cells consists of five sub categories known as monocytes, lymphocytes, eosinophils, basophils and neutrophils. The differential WBC count in normal adult is as follows:

- Neutrophils - 40 – 70 %
- Lymphocytes - 20 – 30%
- Monocytes - 2 – 15 %
- Eosinophils - 1 – 7%
- Basophils - 1 – 3%

The number of leukocytes in the blood is often an indicator of disease and an important subset of the complete blood count is the WBC count. The normal White Blood cell count is usually 4 x 109/L and 11 x 109/L. Counting of WBCs can be done either manually or automatically. Counting large number of cells is done by automatic methods but the specialized equipment tends to be affluent. Manual methods involve a conventional light microscope setup and is more difficult, error-prone and very inexpensive.

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 indication of bacterial infection.

An increase in lymphocyte count could be an indication of AIDS (Acquired Immune Deficiency Syndrome). While, inflated 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 this 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 a fore mentioned 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, an 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.

White blood cells (WBCs) are a part of the immune system. They help fight infection and defend the body against other foreign materials. Different types of white blood cells have different jobs. Some are involved in recognizing intruders. Some kill harmful bacteria. Others make antibodies to protect your body against exposure to bacteria and viruses.

II. LITERATURE REVIEW

1. Rosyadi et al. conducted research 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%.
2. 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].
3. 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].
4. Yuehua Liu, Feilong Cao, Jianwei Zhao, and Jianjun Chu [1] introduced a new approach for locating the WBC and sub image segmentation. It is noted that almost all the WBCs have two characteristics 1) The compactness of edges in the edge map produced using the Canny detector is always concerted I regions with WBCs.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Impact Factor: 6.252
Volume 2, Issue 1, June 2022

III. PROPOSED SYSTEM

This section provides the detailed description of the proposed Estimation of White Blood cells using image processing techniques. The microscopic image of the blood sample is taken as the input where blood samples contain RBCs, WBCs and platelets. The first step involved is pre-processing where the RBCs and platelets are removed.
The proposed system works as follows.

A. Pre-processing:

Pre-processing step involves

1. Removal of RBCs
2. Removal of Platelets

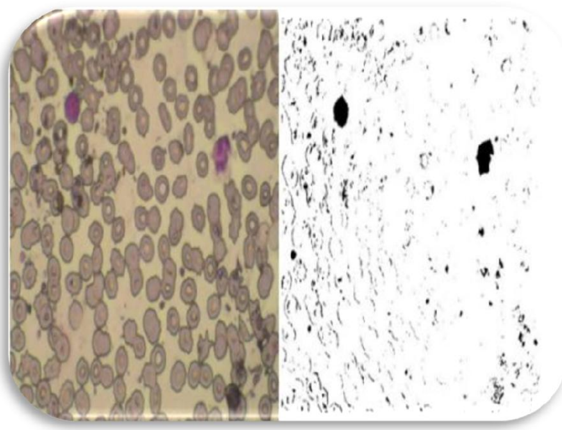

Figure 3.1: Removed RBC Image

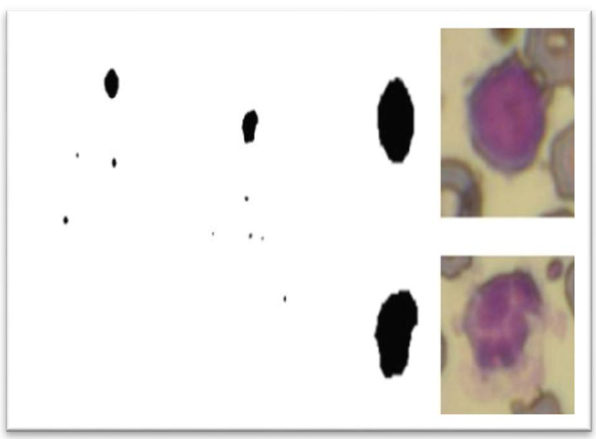

Figure 3.2: Located WBC

B. Classification of WBC

- The classification of WBC is performed by Convolutional Neural Network. The 5 types of WBC images are trained by the layers available in CNN and the features are extracted accordingly
- The located WBC in a window is given as the input to the trained CNN and the particular type located is classified. Layers used in CNN are
    1. Input Layer
    2. Convolution Layer
    3. Batch Normalization Layer

4. Rectified Linear Unit Layer
5. Max Pooling Layer
6. Fully Connected Layer
7. Softmax Layer
8. Classification Layer

C. Counting of WBC:

After the WBCs are classified according to their types the available WBCs in blood sample are counted. For each type of WBC, the percentage available in the blood sample is calculated and the result is compared with the standard range of availability in blood samples. Through this the normal and the abnormal blood samples can be identified.

IV. DESIGN OF CNN-BASED CLASSIFIERS

An CNN uses a feed-forward method for neurons feeding and back propagation for parameters training. The main advantage of the CNN approach is its ability to extract topological properties from the raw Gray-scale image automatically and generate a prediction to classify high-dimensional patterns. An CNN is composed of two distinct parts.

The first part consists of several layers that extract features from the input image pattern by a composition of convolutional and sub-sampling layers. Conceptually, visual features from local receptive fields [15] are extracted by an extended 2D convolution approach to gain the appropriate spatially local correlation present in the input images. Since the precise location of an extracted feature is inconsequent and dispensable, resolution reduction by 2 of the features is followed through the sub-sampling layers. The second distinct part categorizes the pattern into classes. In general, an CNN consists of three different layers: convolution layer, sub-sampling (max-pooling) layer and an ensemble of fully connected layers. In the current study, we use an CNN with the architecture of LeNet5 [15], see Figure 5.

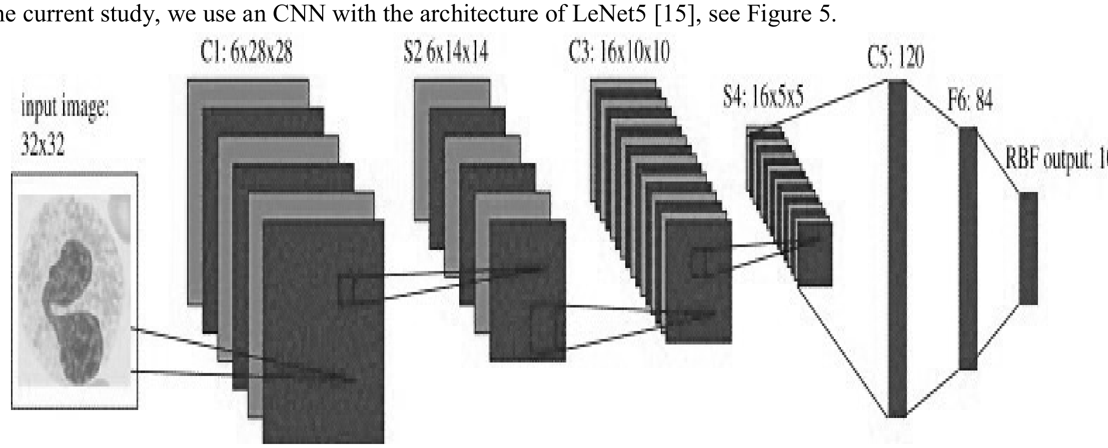

Figure 5: LeNet-5 Structure in Modelling CNN for a 28×28 Input Image

In the first layers (properties extractors) convolutional filters in a 5×5 pixels window is applied over the image. It is highly recommended to add two blank pixels at each four directions to avoid missing real data at each border in convolution computations.

The number of alternative three main layers depends on input database and can be varied between different input size to get better performance and confidence. In this work a LeNet5 with eight layers is used (including first layer as input gray-scale image and also output layer). Each convolution layer (C-layers) has different feature maps, C1 is composed of 6 units while C3 has 16 and C5 has 120 units. Also because of convolution windows size (5×5) and input size (28×28), the size of each convolution layer is defined as shown in Fig. 3: C1 is 28×28, C3 10×10, and C5 is 1×1, a single neuron.

REFERENCES

[1] T. Rosyadi, A. Arif, Nopriadi, B. Achmad and Faridah, "Classification of Leukocyte Images Using K-Means Clustering Based on Geometry Features," in 6th International Annual Engineering Seminar (InAES), Yogyakarta, Indonesia, 2016.

[2] N. M. Salem, "Segmentation of White Blood Cells from Microscopic Images using K-means clustering," in 2014 31st National Radio Science Conference (NRSC), 2014.

[3] A. Gautam and H. Bhadauria, "White Blood Nucleus Extraction Using K-Mean Clustering and Mathematical Morphing," in 5th international Conference- Confluence the Nect Generation Information Technology Summit (Confluence), 2014.

[4] O. Ryabchykov, A. Ramoji, T. Bocklitz, M. Foerster, S. Hagel, C. Kroegel, M. Bauer, U. Neugebauer and J. Popp, "Leukocyte subtypes classification by means of image processing," Proceedings of the Federal Conference on Computer Science and Information Systems, vol. 8, no. 2300-5963, pp. 309-316, 2016.

[5] Kroegel, M. Bauer, U. Neugebauer and J. Popp, "Leukocyte subtypes classification by means of image processing," Proceedings of the Federal Confeence on Computer Science and Information Systems, vol. 8, no. 2300-5963, pp. 309-316, 2016.

[6] N. Sinha and A. G. Ramakrishnan, "Automation of differential blood count," TENCON 2003. Conference on Convergent Technologies for Asia-Pacific Region, vol. 2, pp. 547-551, 2003.

[7] D.-C. Huang and K.-D. Hung, "Leukocyte Nucleus Segmentation and Recognition in Color Blood-Smear Images," in IEEE International Instrumentation and Measurement Technology, 2012.

[8] Puttamadegowda and Prasannakumar, "White Blood cel segmentation using Fuzzy C means and snake," in 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), 2016.

[9] R. Ahasan, A. U. Ratul and A. S. M. Bakibillah, "White Blood Cells Nucleus Segmentation from Microscopic Images of strained peripheral blood film during Leukemia and Normal Condition," in 5th International Conference on Informatics, Electronics and Vision (ICIEV), 2016.

[10] W. Yu, C. Yang, L. Zhang, H. Shen, Y. Xia and J. Sha, "Automatic Classification of Leukocytes Using Deep Neural Network," in IEEE 12th International Conference on ASIC (ASICON), 2017.

[11] A. Gautam, P. Singh, B. Raman and H. Bhadauria, "Automatic Classification of Leukocytes using Morphological Features and Naïve Bayes Classifier," in IEEE Region 10 Conference (TENCON), 2016.

[12] Understanding the Immune System, NIH Publication No. 03-5423, 2003

[13] L. Xiao, Q. Yan and S. Deng, "Scene Classification with Improved AlexNet Model," in 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE), 2017.

[14] A. Filonenko, L. Kurnianggoro and K.-H. Jo, "Comparative Study of Modern Convolutional Neural Networks for Smoke Detection on Image Data," in 10th International Conference on Human Systems Interaction, 2017.

[15] Z. Pan, "enjoypath," University of Colorado, 27 July 2015. [Online]. Available: www.enjoypath.com. [Accessed 10 January 2018].

[16] R. Donida Labati, V. Piuri, F. Scotti, "ALL-IDB: the acute lymphoblastic leukemia image database for image processing", in Proc. of the 2011 IEEE Int. Conf. on Image Processing (ICIP 2011), Brussels, Belgium, pp. 2045-2048, September 11-14, 2011. ISBN: 978-1-4577-1302-6. [DOI: 10.1109/ICIP.2011.6115881]

[17] F. Scotti, "Robust Segmentation and Measurements Techniques ofWhite Cells in Blood Microscope Images", in Proc. of the 2006 IEEE Instrumentation and Measurement Technology Conf. (IMTC 2006), Sorrento, Italy, pp. 43-48, April 24-27, 2006. ISSN: 1091-5281. [DOI: 10.1109/IMTC.2006.328170

[18] F. Scotti, "Automatic morphological analysis for acute leukemia identification in peripheral blood microscope images", in Proc. of the 2005 IEEE Int. Conf. on Computational Intelligence for Measurement Systems and Applications (CIMSA 2005), Giardini Naxos - Taormina, Italy, pp. 96-101, July 20-22, 2005 [DOI: 10.1109/CIMSA.2005.1522835].