method for classification of AD and CN was better than using one classifier and comparable with state-of-the-art methods.

Keywords: Ensemble Machine Learning; Alzheimer's Disease; Discrete Wavelet Transform; Principal Component Analysis; Statistics Features; Magnetic Resonance Imaging

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A Proposal to Approach Cloud-Based Enterprise Imaging for Medical Universities in Iran Using Existing DICOM Infrastructure

Masood Raeesi[1, *]; Mansoor Fatehi[2]; Mahdi Shamsi[3]; Navid Towfighirad[3]

[1]*Healthcare IT (HIT) Department, Taimaz Co., Tehran, Iran*
[2]*Virtual University of Medical Sciences, Tehran, Iran*
[3]*Radiology Department, Laleh Hospital, Tehran, Iran*

**Corresponding author: Healthcare IT (HIT) Department, Taimaz Co., Tehran, Iran. Email: masoodraeesi@yahoo.com*

Abstract

Background: Exchange and share of different medical images as one of the critical parts of patients' medical records between different departments of the same hospital or even different hospitals have always been in demand in recent years. Medical universities in Iran include affiliated hospitals and medical centers. Most of those hospitals were equipped with picture archiving and communication systems (PACS) from different vendors in the past years. The main challenges concerning the functionality of current PACS-based workflow with those vendors are the lack of functionality to capture, store, and view DICOM and non-DICOM images from other departments other than radiology, as well as the lack of communication and exchange of medical imaging among hospitals since each vendor has its own protocol of communication.

Objective: Some advantages of this demand include allowing healthcare providers for on-demand access to medical imaging acquired at other affiliated hospitals using authentication, reducing unnecessary repeated imaging exams and unnecessary exposure to radiation, better managing the information technology resources in the Cloud environment, satisfying patients and healthcare providers, and providing timely access to patient medical imaging history.

Methods: In this study, we proposed a private Cloud-based enterprise imaging solution for each medical university based on the existing DICOM infrastructure, which was supported by commonly accepted standards of all vendors. In each hospital, non-DICOM medical images were converted via a "Dicomizer" to DICOM and beside native DICOM images were sent via a "Router" module to the Central Archiving solution located in private Cloud of the Medical University. By utilizing the Router module, it was possible to transfer images even in narrow bandwidth lines via lossless/lossy compression under TLS/SSL protocol, making necessary DICOM coercions and adding DICOM tags and facilitating the possibility of having some other useful features. A zero-footprint viewer was considered in the Cloud environment for the purpose of anytime/anywhere viewing of patient studies.

Results: The primary test of the Router module even through the internet network was encouraging. It seemed this module could work much more effective through the intranet of medical universities and the affiliated hospitals.

Discussion: Besides transferring images by Router, this module could add or coerce some necessary DICOM tags, facilitating the categorization of studies, automatic pseudonymization of patient data, and support of all DICOM store classes including non-image classes like structured reports.

Conclusion: The proposed method of archiving Enterprise Imaging in private cloud using the existing DICOM infrastructure seems feasible, cost-effective, and convenient since it does not affect the current workflow of archiving of medical images in affiliated hospitals of medical universities in Iran and there is no concern about different communication protocols. By full implementation of this proposal, each healthcare provider would have on-demand access to patient studies upon authentication without further need to store departmental silos of data.

Keywords: DICOM; PACS; Enterprise Imaging; Cloud Computing

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Automatic Detection and Classification of White Blood Cells in Blood Smear Images Using Convolutional Neural Network

Ramin Nateghi[1, *]; Mansoor Fatehi[2]; Ali Sadeghitabar[3]; Romana Khosravi[3]; Fattane Pourakpour[2]

[1]*Department of Electrical and Electronic Engineering, Shiraz University of Technology, Shiraz, Iran*

[2]*National Brain Mapping Laboratory, Tehran, Iran*
[3]*Avicenna Fertility Center, Tehran, Iran*

**Corresponding author: Department of Electrical and Electronic Engineering, Shiraz University of Technology, Shiraz, Iran. Email: r.nateghi.s@gmail.com*

Abstract

Background: Blood cell identification and counting are very important in the diagnosis and treatment of diseases. Of the blood cells, the identification of white blood cells (WBC) and their changes is of particular importance due to their role in the immune system. Manual cell counting is time-consuming and dependent on expert experience. Also, the accuracy of blood cell counting can be influenced by human limitations such as fatigue and mental problems. Automatic systems can be a convenient and cost-effective choice for routine clinical services and can be used for fast and accurate blood disease diagnosis. In the automated systems, blood samples are analyzed using microscopic images of stained blood cells. There are various studies on automatic blood cell segmentation based on blood smear images [1-4]. Also, some studies have focused on WBC image classification [5-6].

Objectives: In this paper, the main objective is to provide the implementation of a deep learning-based automatic system to identify five main groups of WBCs in human peripheral blood smear, including Eosinophils, Basophils, Monocytes, Lymphocytes, and Neutrophils.

Method: The block diagram of the proposed method is shown in Figure 1. As can be seen, the proposed method consisted of three pre-processing, segmentation, and deep learning-based classification stages. In the pre-processing stage, color normalization was used to normalize the color appearance variability. The color appearance can significantly vary between different labs due to differences in slide digitization conditions and staining protocols. Automatic image analysis methods can be significantly affected by different smear color appearances. In the color normalization stage, images to be examined were normalized to match the color appearance of a target image with standard calibrated staining. The second task was the removal stage of the background and segmentation of the desired region of WBCs. In this stage, by subtracting the B color channel of RGB blood smear image from G color channel and then by using morphological erosion and morphological reconstruction, the WBC probability map was obtained. The value of the WBC probability map showed that the pixels how likely were related to WBCs. In WBC probability map image, the pixels belonging to the WBCs had larger values than the pixels of non-WBCs. Finally, WBCs were segmented by applying optimal Otsu's thresholding [7] on the probability map image. Detected WBCs were cropped from entire image by considering a patch with size 131 × 131 around all detected cells. The patches for segmented WBCs were then passed through a convolutional neural network (CNN) called CellDiff-Net, which returned the class of WBCs. The structure of the CNN architecture is shown in Figure 2.

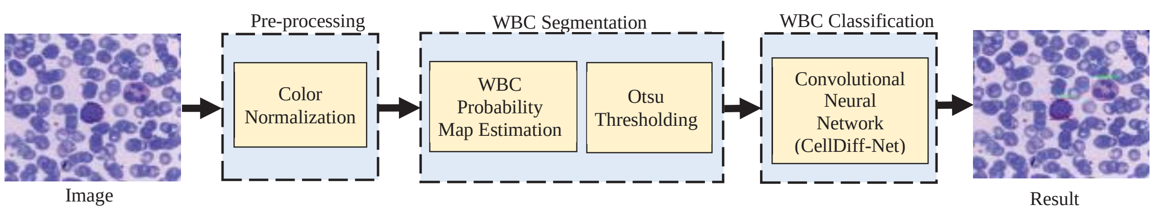


Figure 1. The proposed WBC detection and classification system

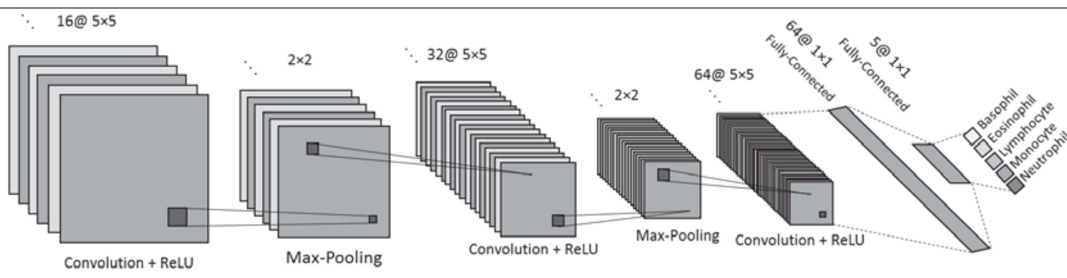


Figure 2. CellDiff-Net: convolutional neural network for WBC differential

Results: Our blood smear image database used to train the proposed method was composed of 216 images with size 1536 × 2048. They were collected and labeled by experts at Avicenna Infertility Clinic (ACECR), Tehran, Iran. Stepwise processing of a sample blood smear image for WBC segmentation is shown in Figure 3.

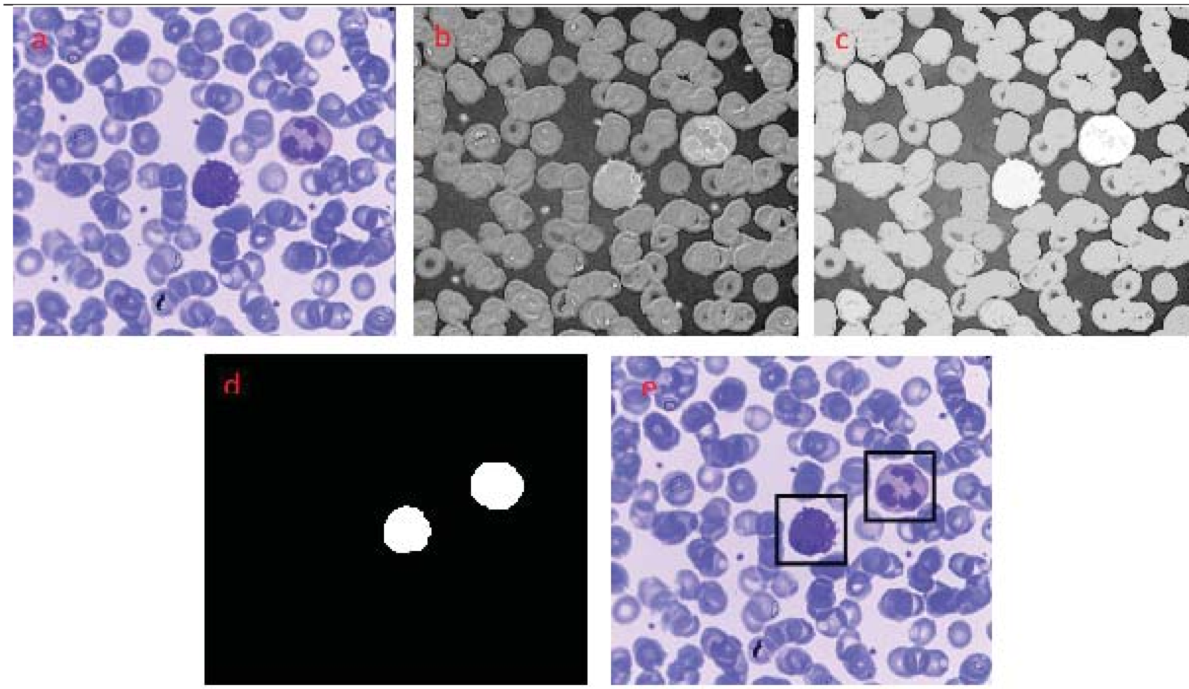


Figure 3. Results of the proposed WBC detection and classification system for a sample image: a, sample image; b, B color subtracting from G color; c, WBC probability map by morphological reconstruction; d, segmented WBCs; e, WBC patches

By the approach shown in Figure 3, all WBC patches were extracted from training images. Image augmentation (flips, rotations, and shears) was used to increase the size of the training set and balance out the classes. We tested our model for a test set of 10 blood smear samples. Then, 100 images were captured from each blood sample and all images were analyzed by the proposed method. Visualizing feature space in convolution layers for a test WBC image pass through learned CellDiff-Net is shown in Figure 4.

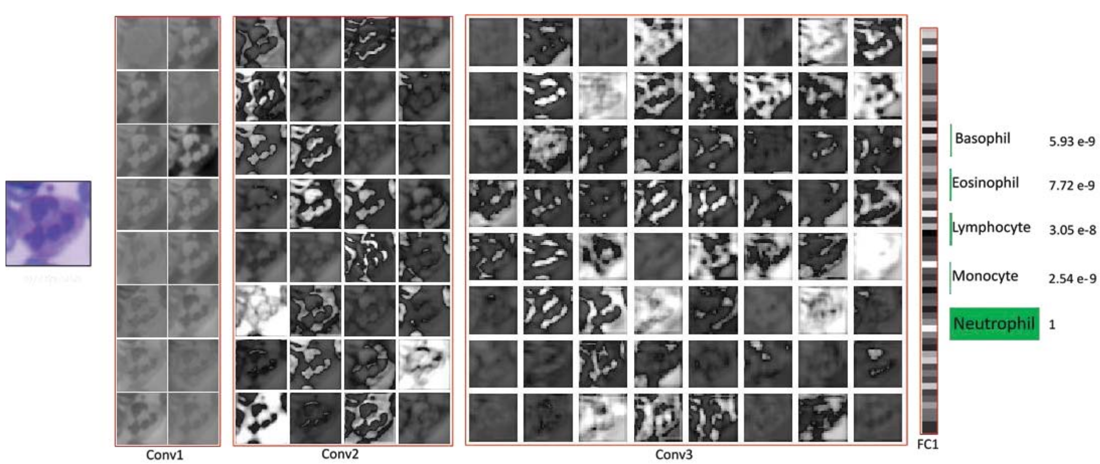
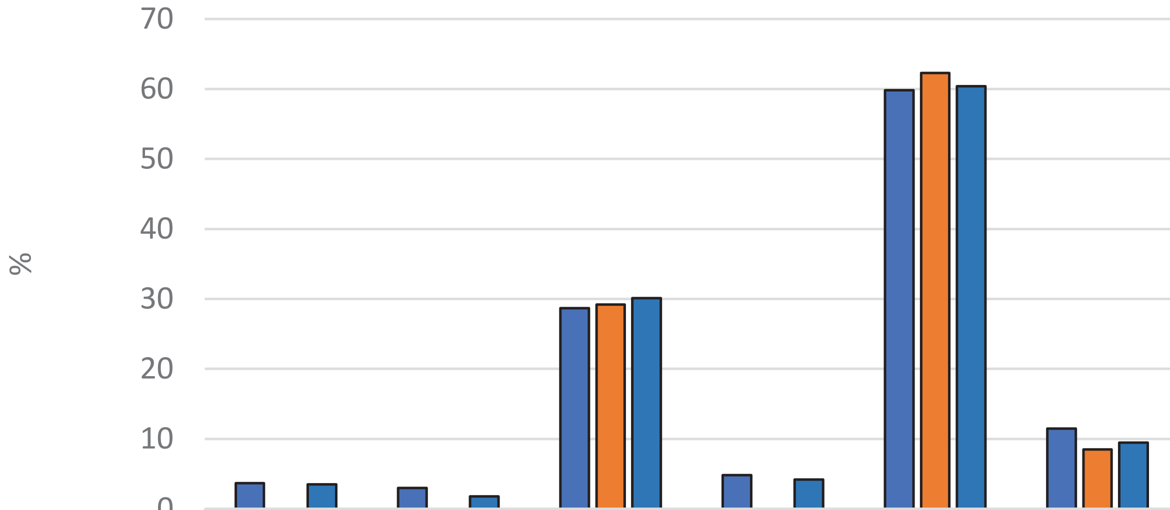


Figure 4. CellDiff-Net: convolutional neural network for WBC differential

To evaluate cell differential counts, the performance of the proposed method was compared with the results of manual counting and Sysmex kx-21 analyzer. Figure 5 compares three automated, Sysmex, and manual differential cell count results for a test sample.



	Basophil	Eosinophil	Lymphocyte	Monocyte	Neutrophil	MXD
Manual	3.7	3	28.7	4.8	59.8	11.5
Sysmex kx-21			29.2		62.3	8.5
Our System	3.5	1.8	30.1	4.2	60.4	9.5

Manual Sysmex kx-21 Our System

Figure 5. Cell differential comparison obtained by the proposed, Sysmex, and manual methods

For objective evaluation of the proposed system, three criteria of sensitivity, specificity, and accuracy were used. The manually labeled WBCs were considered as ground-truth. The ground truth for all the images was determined by an expert and used to validate the proposed method. Table 1 shows the performance of the automated proposed WBC detection and classification method.

Table 1. Performance of the proposed method

Sensitivity	Specificity	Accuracy
0.972	0.985	0.982

Conclusion: In this paper, a novel automated system was proposed for WBC detection and classification in blood smear images. The experimental results proved the performance of the proposed system in WBC detection and classification.

Keywords: White Blood Cell Classification; Image Classification; Blood Smear Images

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