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Detection of White Blood Cells Using Convolutional Neural Network

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Abstract: *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.*

Background*: White Blood Cells (WBCs) are also called leukocytes or leucocytes. These are cells of the immune system that are involved in the body against both infectious disease and foreign materials. These cells help fight infections by attacking bacteria, viruses, and germs that invade the body. All leukocytes are produced and derived from a multipotentcell. This is also known as a hematopoietic stem cell. They live for about three to four days in*
the human body. The segmentation has to be done to extract the nucleus of white blood cell image

Key Word*: Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Blood Cells, etc.*

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I. Introduction

The microscopic inspection of blood provides diagnostic information concerning patients' health status. The differential blood count inspection results reveal a wide range of significant hematic pathologies. For example, the presence of infections, leukemia and certain specific types of cancers can be diagnosed based on the classification results and the white blood cell count. Experienced operators perform the traditional method for differential blood count.They use a microscope and count the percentage of each type of cell that is counted within a area of interest. This manual process of counting is obviously very tedious and slow. Furthermore, the classification and accuracy of the cell may depend on the operators ' capabilities and experiences. Consequently, the need for an automated system of differential counting becomes inevitable. Recently, a number of different approaches have been proposed to implement a white blood cell recognition system based on image processing. White blood cell classification usually involves the following three stages: a white blood cell segmentation from an image, the extraction of effective features, and a classifier design.to some extent, the performance of an automatic white blood cell classification system depends on a good segmentation algorithm to segment white blood cells from their background. We extract three types of characteristics from the segmented cell region below. These characteristics are fed into three different neural networks for the classification of five white blood cell types. We extract three types of characteristics from the segmented cell region below. These characteristics are fed into three different neural networks for the classification of five white blood cell types.

II. Related Work

1. T. Rosyadi, A. Arif, Nopriadi et al (2006) presented addresses a fast white blood cell (WBC) image segmentation scheme implemented by on-line trained neural network. A pre-selecting technique, based on mean shift algorithm and uniform sampling, is utilized as an initialization tool to largely reduce the training set while preserving the most valuable distribution information.
2. O. Ryabchykov, A. Ramoji, (2014) presented a fast segmentation scheme for automatic differential counting of white blood cells. The segmentation procedure consists of three phases. First a novel simple algorithm is proposed for localization of white blood cells. The algorithm is based on a priori information about blood smear images.

3. Experimental results show that this method works successfully in the segmentation of colour smear microscopic images by Kroegel, et al (2014). In their work, a novel White Blood Cell (WBC) segmentation scheme using scale-Space filtering and watershed clustering is proposed. In this scheme, nucleus and cytoplasm, the two components of WBC, are extracted respectively using different methods. First, a sub image containing WBC is separated from cell image.
4. Experiments demonstrate that the proposed scheme performs really well and HSV space is more appropriate than RGB space in WBC segmentation due to its low correlation given by Jiang et al (2016). Image processing technique involved five basic components which are image acquisition, image preprocessing, image segmentation, image postprocessing, and image analysis. The most critical step in image processing is the segmentation of the image. In this, they review some of the general segmentation methods that have found application in classification in biomedical-image processing especially in blood cell image processing.
5. Basically, segmentation of the image divides the whole image into some unique disjoint regions. The fact that the segmented image should retain maximum useful information and discard unwanted information makes the whole process critical is published by Robiyanti et al (2018).
6. Dorini et al (2007) found out that the cell segmentation is a challenging problem due to both the complex nature of the cells and the uncertainty present in video microscopy. Manual methods for this purpose are onerous, imprecise and highly subjective, thus requiring automated methods that perform this task in an objective and efficient way.

III. Proposed Methodology

The main task of the segmentation is to extract the objects from an image. During segmentation, the size and shape of the nucleus should be maintained. Many segmentation algorithms have been developed for various applications. To overcome from the problem of image shaping, it may use the classification of CNN. This study gives a technique for WBC detection based on Convolutional Neural Network (CNN). This proposed method effectively works for WBC detection, and effectively reduces the computational time and preserve the shapes and edges of the image. The main objective is to segment the WBC from the blood smear image to detect an immature cell.

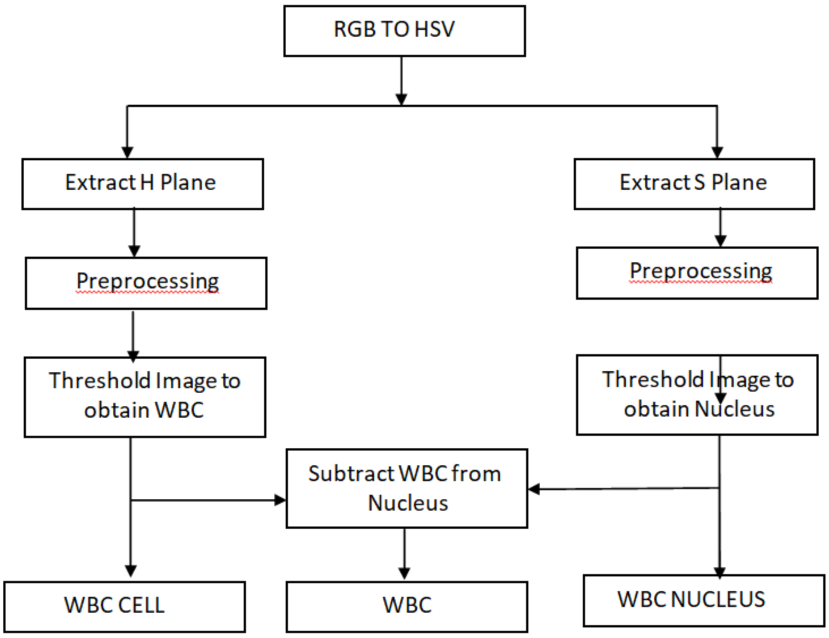


Figure 3.1 Process of cell segmentation

- Segmentation divides an image into its constituent regions or objects
- Segmentation of images is a difficult task in image processing. It is still under research
- Segmentation allows to extract objects in images.
- Segmentation is unsupervised learning.
- Model based object extraction, e.g., template matching, is supervised learning.

- WBC CLASSIFICATION

WBCs are classified according to the characteristics of their cytoplasm and nucleus by Ramesh et al (2012). Pathologists traditionally report normal WBCs as classified into five classes, i.e., monocytes, lymphocytes, neutrophils, eosinophils, and basophils. Since the chosen features affect the classifier performance, deciding which features must be used in a specific data classification problem is as important as the classifier itself. Hematology experts examine the cell shape, size, colour, and texture in combination with the nuclear features. It is important to reflect the rules and heuristics used by the hematology experts in selection of the features. Several researchers have previously proposed features to differentiate WBCs. The WBC classifications are shown in Figure 3.10.

In addition features like the ratio between the nucleus and the cell areas, the nuclear "rectangularity" (ratio between the perimeter of the tightest bounding rectangle and the nuclear perimeter), the cell "circularity" (ratio between the perimeter of the tightest bounding circle and the cell perimeter), number of lobes in nucleus, area, and mean gray-level intensity of the cytoplasm were computed. Their system was evaluated using 10-fold cross-validation.

The performance was compared using different classifiers like nearest neighbor classifiers, feed-forward neural network, radial basis function neural network, and parallel classifier built with feed-forward neural network. In this method, a preliminary classification of the WBC based on the number of lobes (single or multi-lobed) in the nucleus along with the feature set is suggested to achieve better classification rate for each of the WBC subtypes.

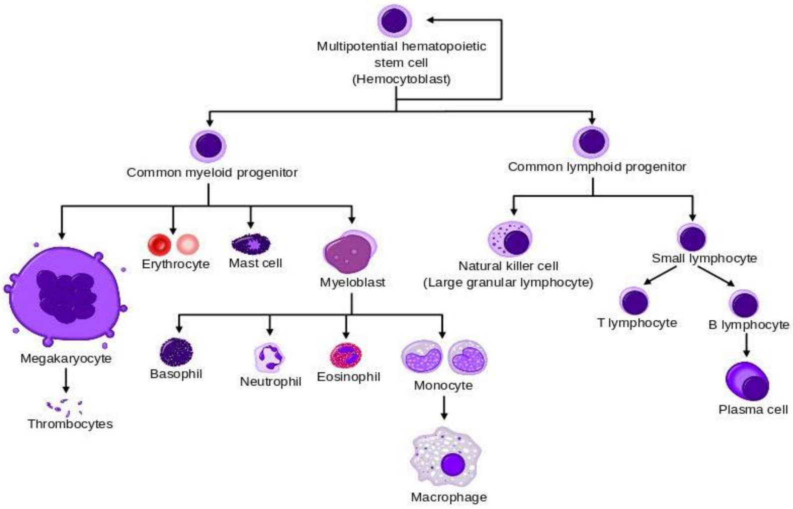


Figure 3.2WBC Classifications

The several types of features such as intensity and colour-based features, texture-based features, and shape-based features are utilized for a robust representation of WBCs. Classification methods used in this work include k-Nearest Neighbors, Learning Vector Quantization, MultiLayer Perceptron, and Support Vector Machine. Then they evaluated the binary images of the cytoplasm and nucleus to characterize the feature set. The standard set of features like area, perimeter, convex areas, solidity, major axis length, orientation, filled area, eccentricity were separately evaluated for the nucleus and the cytoplasm.

IV. CONVOLUTIONAL NEURAL NETWORK (CNN)

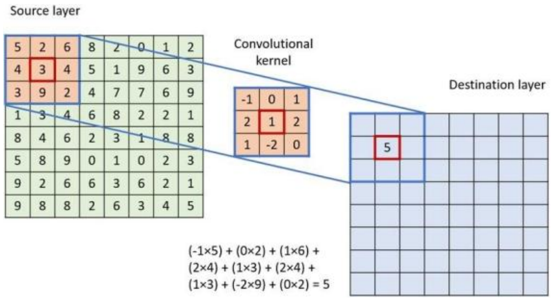
Convolutional Neural Networks (CNN) is also known as CNNs or ConvNets. They are categories of a neural network that are very effective in the computer vision tasks like image recognition and classification. CNN's are feed-forward neural networks that are used to analyze image data by processing it in the grid-like topology. An image data can be represented digitally as a matrix of pixel values. The series of pixels arranged in a grid-like manner represents pixel values about the color and intensity of the color for each pixel. After seeing the particular image, the human brain processes information related to the image. Each neuron in the brain works as an individual receptive field connected with other neurons to cover the whole visual area. Similarly, each neuron in the CNN is process data only in the receptive field. The layers of the CNN architectures arranged in a manner that processes simple information like lines and curves first. With the CNNs, it is possible to provide sight to the computer. The major four operations that exist in the CNNs are as follows:

- Convolution operation
- Non-Linearity
- Pooling

- Fully Connected layers or Classification

4.1 Convolution Operation

One of the basic building blocks of CNN is the convolution layer. The convolution layers carry the main portion of the computational load. This layer does the dot product between the matrix of learnable parameters known as the kernel and matrix with a limited receptive field. The height and width of the kernel will be spatially small. However, the depth of the kernel extends up to three RGB channels of the input image. While performing the forward pass, the kernel slides through the image's height and width, which is responsible for the image representation of a particular receptive region (Smeda, K., 2019).



4.2 Non-Linearity

To achieve the non-linearity in the CNN network, Rectified Linear Unit (ReLU) activation function is used. ReLU stands for a rectified linear unit. Once the feature set is obtained in the next step, they are forwarded to the ReLU layer (Smeda, K., 2019). It operates on each and every element of the feature set and set the value of all negative pixels to zero. It is represented in Figure 4.2.

4.3 Pooling Layer

Like the convolutional layer, the pooling layer is used to reduce the spatial size of the convolved features obtained after convolution operation. Applying pooling on the obtained features reduces the computational power required for data processing using dimensionality reduction. Moreover, it helps in effective

4.4 Fully Connected Layers or Classification

The fully connected layer is a typical multi-layer perceptron that uses softmax as an activation function in the output layer. The neurons in the fully connected layer are fully connected with the neurons in the preceding and succeeding layer. For the input RGB image, the output of the convolutional and pooling layer delivers the high-level features. Based on the training dataset provided to the network, the fully connected layer utilizes these features for input classification into different classes (Smeda, K., 2019). Also, fully connected layers are usually used for learning a non-linear combination of the features obtained from the previous layers. The working of fully connected layers is described in Figure 4.4.

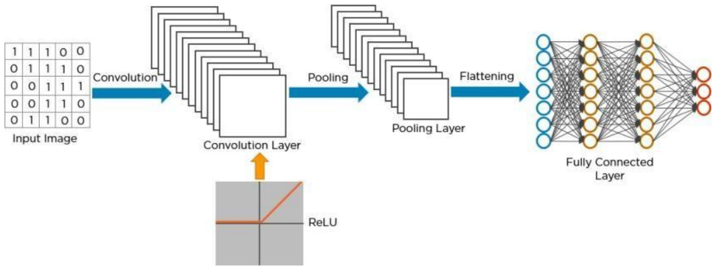


Figure 4.4 Fully Connected Layers for Classification

V. Proposed Output

White blood cells are responsible for fighting infections and an WBC elevated count may indicate that patient might be suffering from inflammation, infection or stress, however a proper diagnosis requires complete knowledge about WBC present in blood smear. A normal peripheral blood sample contains five main types of WBC (the numbers in brackets indicate typical proportion of the cell type): neutrophils (40–78%), lymphocytes (25–33%), monocytes (2–8%), eosinophils (1–4%), in addition to plasma cells (0.2–2.8%) and basophil granulocytes (0–2%).

5.1 Noisy Image :

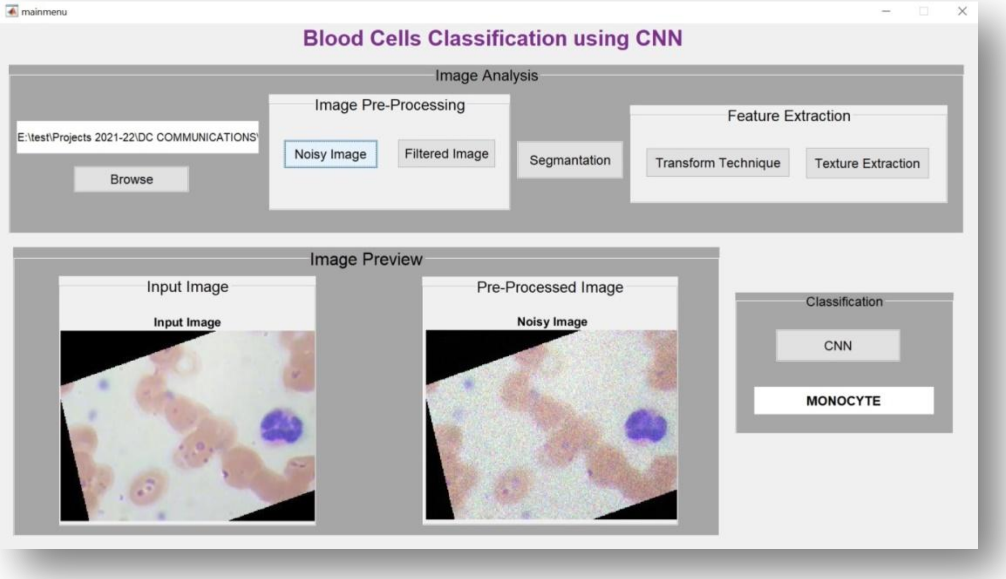


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Figure 5.1Noisy Image in Blood Cells Classification Using CNN

5.2 Segmentation:

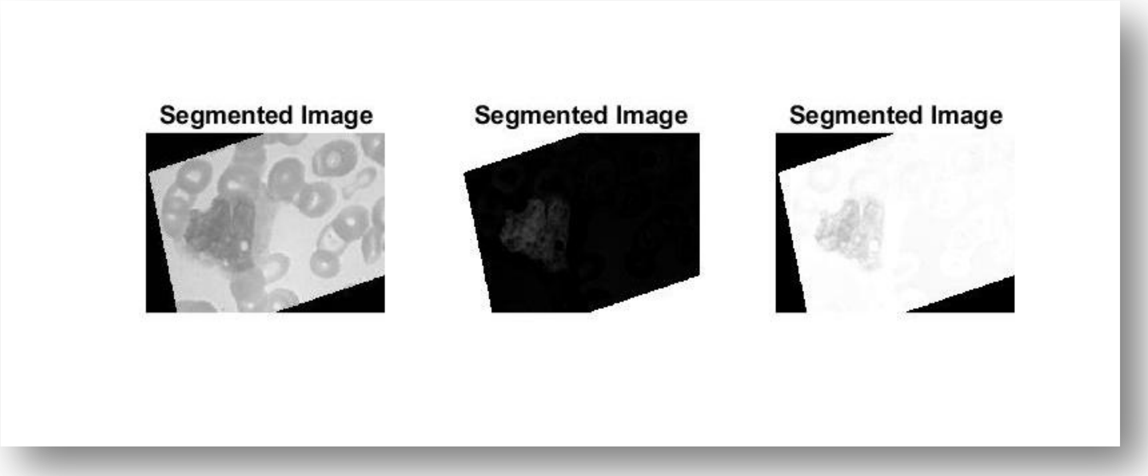

Figure 5.3Segmentation in Blood Cells Classification Using CNN

5.3Classfication of Blood Cells using CNN:

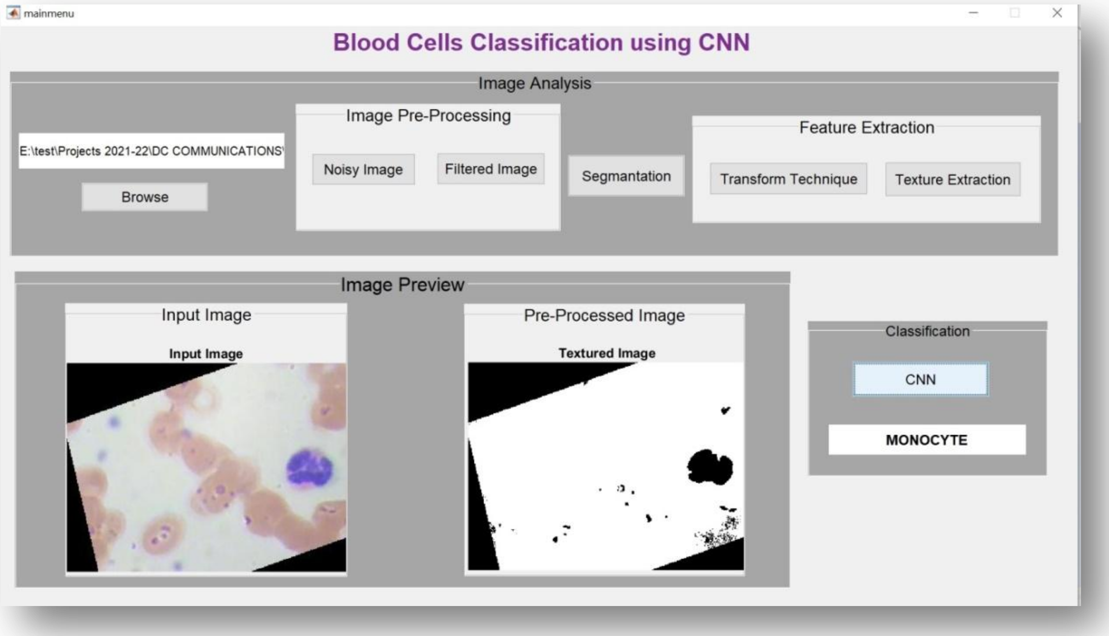

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Figure 5.6Classification of Blood Cells Using CNN

VI. CONCLUSION

In this work, a fast, accurate and robust blood group judgment method is proposed for the rapid and accurate identification of blood types in the case of emergency transfusion. A large number of experiments show that this method can quickly and accurately identify whether the serum and antibody agglutination reaction, and then get blood type determination, to meet the needs of automated rapid blood type analyzer.

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