Classification of White Blood Cell Types from Microscope Images: Techniques and Challenges

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White blood cells (WBC) play a significant role in the immune system by protecting the body from infectious disease and foreign invaders. Therefore, an automatic identification of WBC from microscopic images is an essential importance to help the haematologist in diagnosing diseases, such as leukemia, AIDS, and certain types of blood cancer. Analysis of WBC structure from microscopic images and classification of cells into types and sub-types are challenging because of variations in maturation stage, and intra-class variations of the cell shape in images due to using different acquisition and staining processes. Considering the great interest in the community of health, hematology and medical imaging, this chapter reviews a wide range of state-of-the-art approaches in the WBC classification task. Different steps including image acquisition, image enhancement, image segmentation, feature extraction, classification and evaluation will be presented as shown in Fig-1. We first provide an overview of the structure of WBCs, the types and sub-types of WBC, and their features, including the shape of nuclei, size, function and colour. Next, we detail the process of the identification of WBC in images, including image acquisition and consideration of the effect of staining to visualize changes in the colour and shape of the nucleus. We then provide a survey of the recent history (since 2005) up to current state-of-the-art in automated identification of WBCs, including techniques such as image processing, signal processing, pattern recognition and deep learning techniques. We later discuss the challenges including illumination variations, changes in size and location, different maturation stages, shape, rotation, and background variations. The performance of the current techniques with respect to these challenges is evaluated. This survey will help researchers to address these challenges in future work and in the further investigation of detection, feature extraction and classification of WBCs.

Keywords: White blood cell; microscope images; classification; techniques; challenges

1. Introduction

White blood cells (WBCs) classification is an important step because it can assist hematologists in the diagnosing several blood disorders, such as leukemia, some immunological disorders, and certain types of cancer. The analysis procedure can be done by automatic and manual approaches to count and classify WBC. Manual classification of WBC has many medical difficulties, including error in the accuracy of results due to sampling errors and statistical probabilities and poor sensitivity, specificity and predictive values [1]. Furthermore, some automatic approaches in the laboratories have used instruments, such as flow cytometry and automatic counting machine to detect and classify WBC. These instruments do not make use of image processing techniques, and they can count and classify WBCs quantitatively not qualitatively [2]. Therefore, it is necessary to design an automatic system which includes image processing, signal processing, pattern recognition or deep learning techniques to provide a qualitative and quantitative evaluation, precise results and rapid processing. An automated classification of the WBC type system consists of six steps, as shown in Fig.1: 1) image acquisition, 2) image pre-processing, 3) segmentation, 4) features extraction and representations, 5) cell classification, and 6) the evaluation process.

Fig. 1 Steps of automated classification of white blood cells [3].
The Main types of WBC are: Granulocytes, Monocytes and Lymphocytes. There are seven sub-types developed from these types. *Granulocytes* can be classified into Band neutrophils, Basophils or Eosinophils. *Monocytes* can be classified into Macrophages or Dendritic cells, and *Lymphocytes* can be classified into B-lymphocytes or T-lymphocytes (as shown in Fig.3) [1,2]. An overview of the structure of WBC, WBC types and their characteristics from [3,4] is given in Section 1.1 below.

1.1 Structure of WBC

WBCs are produced from the bone marrow and found in the blood and lymphatic system. A WBC has a nucleus, which often large and lobed, and it helps to distinguish WBC from the other blood cells. Each WBC structure consists of a nucleus, cytoplasm and cell wall [1], as shown in Fig. 2.

![Diagram of WBC structure](image)

**Fig. 2** Diagram of WBC structure (Eosinophil cell example) consists of cell wall, a nucleus and cytoplasm [4].

1.2 WBC Types and Sub-types

The nuclei of WBC have different shapes, texture and sizes and might present one or more lobes based on the reaction of their specific granules with a staining process as shown in Fig.3. The most useful shape, size and texture information for cell segmentation and classification comes from the nuclei of the WBCs [2]. To provide a brief review and perspective, the features and functions of types and sub-types of WBCs and information about WBC nuclei shape are explained as follows.

- **Granulocytes** are phagocytes, which have the ability to ingest viruses, bacteria and other parasites. They have visible granules or grains in their cytoplasm and have large elongated or lobed nuclei. The diameter of cell measures approximately from (12 – 20) μ, and their nucleoli cannot be seen. They account for approximately 60% of our WBCs. The sub-types of granulocytes are: neutrophil, basophil and eosinophil [5].
  - **Neutrophils** are a part of the innate immune system and an essential line of defense against bacteria. The shape of nucleus is like a “U” or a curled rod prior to segmentation. They are also known as “band neutrophils”. The diameter usually ranges between (10–18)μ. The cytoplasm is moderate to abundant with a few non-specific granules. Neutrophils account for approximately (1% – 3%) of the peripheral WBCs. The diameter of cell may overlap or twist [6]. The number of lobes can increase according to the cell age. For example, an hypersegmented neutrophil cell has seven lobes in mature stage. The intra-cellular granules are visible in the cytoplasm (Giemsa-stained, high magnification) [5].
  - **Basophils** secrete anticoagulant substances and antibodies that have the ability to fight against hypersensitivity reactions in the blood stream. They are the smallest circulating granulocytes. The basophilic granules in this cell are large and very numerous, so they often mask the nucleus. The nucleus is often bilobed or unsegmented and it is rarely separated into three or four lobes. The average diameter ranges between approximately (10 – 15) μ.
  - **Eosinophils** have the ability to release toxins from their granules for killing pathogens, such as parasites and worms. They are easily recognized in stained smears by their large granules. The nucleus of the eosinophil has often two lobes connected by a band of nuclear material. The diameter usually ranges between (9 –15)μ. They account between (1% – 4%) of the peripheral WBCs [2, 5].
Monocytes stimulate osteoclasts cells, which have the ability to dissolve bone. They are the largest type of WBCs. Their average diameter ranges from (10-30) μ and are often referred to as scavenger cells or phagocytes. They only contain one nucleus which is rarely or barely lobed. The nucleus shape in monocytes is often bend-shaped (horseshoe) or kidney-shaped (reniform). Two types of cells can be developed from monocyte cell: macrophages and dendritic cells [5].

- **Macrophages** are phagocyte cells which eat any type of dead cell in the body. They are larger and live longer than neutrophils and have a large-size single nucleus that is often kidney-shaped. They are also able to act as antigen-presenting cells.

- **Dendritic cells** aid the development of antigen immunity. The shape of the nucleus is small and round-shaped, which as the cell matures, turns into a large nucleus with an irregular star shape and cytoplasmic protrusions (dendrites) [7].

**Lymphocytes** are described according to size and cytoplasmic granularity and can have a small or large nucleus depending on the maturation stage. Small lymphocytes are well-known, and the diameter of a small nucleus ranges from (6 – 9) μ, while the diameter of a large nucleus is approximately (10 – 15) μ. It contains just one nucleus which is rarely or barely lobed [6,7]. The shape of the nucleus is slightly oval or round and stained dark. Pathologists cannot easily distinguish T-cells and B-cells using traditional light or electron microscopes. They always use an optical microscope to distinguish between them.

- **B lymphocytes** (B-cells) produce antibodies and proteins that connect to infected microbes or cells of the body and differentiate into a plasma cell in immature stage. They are made in the bone marrow. They have oval nuclei. They have a low fractal dimension and smooth cell surface. Phathologists incubated the slides with Giemsa stain.

- **T lymphocytes** (T-cells) produce proteins called cytokines which help to direct the response of other cells. They have circular nuclei and a wrinkled cell surface. They are stained dark blue [6, 7].

**2. Automated White Blood Cell Classification Processes**

The steps involved in automated white blood cell classification are as follows:

- **Image acquisition** is the first process in the automated classification. It is important to know how the input images of WBCs are taken from peripheral blood smear samples on microscope slides. These images are obtained by placing the slides under a compound or optical microscope under illumination levels with high
Some factors that play a significant role in the classification accuracy include segmentation of WBC and the features into five types: neutrophil, eosinophil, basophil, lymphocyte, and monocyte, as shown in Table-1. Table-1 summarizes feature extraction representations that have been adopted with different machine learning techniques to classify WBCs, variations in shape of cell and nucleus, maturity stage, background, color, size, location, and non-uniform illumination. Feature representations should contain useful information, while being robust to intra-class variations in shape of cell and nucleus, maturity stage, background, color, size, location, and non-uniform illumination. Feature extraction representations include geometric features, such as area, radius, perimeter, convex area, major axis length, compactness, and orientation; textural features, such as momentum, contrast, entropy, and skewness; and color features, which can be stored on internal memory cards (USB) and downloaded to a computer as 24-bitmap (bmp), joint photographic experts group (jpeg) image or video. Other commercial cameras cannot be optically connected to a microscope without additional optics. The results are usually poor. SLR cameras can be connected optically to microscopes by using the SLR adaptors that are available on most microscopes and images are downloaded automatically on the computer. Microscopic images of the cells are obtained after a staining process which results in different coloration of the cell nuclei and cytoplasm and the blood image background (plasma). WBC staining is a technique used to increase contrast through changing the color of some of the parts of the cell structure to allow a clearer view of cell structures. There are a variety of microscopic stains that can be used and it is known as Romanowsky stains. The Romanowsky stain uses a methylene blue solution to detect malarial parasites in blood. These types of stains are: Jenner, Nocht, Leishman, Giemsa, Wright, and Leishman stains. The types used for staining WBC are: Giemsa stain, Wright stain, Wright-Giemsa stain and Leishman stain. They are precisely formulated, performing optimally and predictably when used either manually or with automated stainers. Most of them dye the nuclei dark purple or pink. The stains may also show up the granules present in the cytoplasm of some WBCs. The staining process yields sufficient contrast for segmentation, counting, and classification of individual cells. Images are then captured using different digital cameras with different resolution.

- The pre-processing step or image enhancement is an improvement of the image data that suppresses unwanted distortion, removes noise or enhances some image features important for further investigation in segmentation and classification processes. The pre-processing step also includes geometric transformations of images, such as rotation, scaling, and translation.

- The segmentation process detects WBC and their nuclei and cytoplasm, and distinguishes them from red blood cell (RBCs), background and plasma of peripheral blood smear image by using image processing and signal processing techniques. These techniques are based on shape, colour, edges or geometric for segmentation. To date several methods have been proposed and combined with other techniques to detect and segment WBCs. These include thresholding techniques, morphological operators and scale-space analysis, edge and boundary detection and level set method via geometric active contour (GACs). Some existing techniques include colour space such as RGB, CMYK and HSV with Otsu’s threshold, and color band with thresholding procedure.

- Feature extraction representation is an important step in WBC classification. Features extracted include geometrical features, such as area, radius, perimeter, convex area, major axis length, compactness, and orientation; textural features, such as momentum, contrast, entropy, and skewness; and colour features, such as colour distribution and histogram. Many previous work have done in WBC classification in the terms of feature extraction representations and will be presented in the next section.

- The classification process distinguishes the WBCs type. This process can allow evaluation and diagnosis of many diseases. Different modern machine learning techniques were used to classify WBCs, such as random forest, Support Vector Machines (SVMs), and Deep Learning (DL), including Artificial Neural Networks (ANNs), Multilayer Perceptrons (MLPs) and Hyperrectangular Composite Neural Networks (HCNN) and other techniques. However, SVMs classifier is the popular method to classify WBCs due to performing fast classification. Application of WBCs classification will be detailed below.

- Evaluation process is an important step in classification process. Classification is evaluated using a numeric metric, such as accuracy, or a graphical representation of performance, such as a Receiver Operating Characteristic (ROC) curve. The accuracy is the most popular performance measure and represents the proportion of the total number of prediction class that are classified correctly, and compares with actual class. These predictions are calculated to create a confusion matrix: True Positives (TP), which are samples that have been correctly classified as positives; True Negatives (TN), which are samples that have been correctly classified as negatives; False Positives (FP) which are samples that have been incorrectly classified as positives; and False Negatives (FN) which are samples that have been incorrectly classified as negatives. These parameters can be obtained by using testing and training protocol based on Hold-out method, K-fold cross validation and Leave-one-out cross validation techniques.

3. Application of WBC Classification

Some factors that play a significant role in the classification accuracy include segmentation of WBC and the features representations used. Feature representations should contain useful information, while being robust to intra-class variations in shape of cell and nucleus, maturity stage, background, color, size, location and non-uniform illumination. Feature extraction representations have been adopted with different machine learning techniques to classify WBCs into five types: neutrophil, eosinophil, basophil, lymphocyte, and monocyte, as shown in Table-1. Table-1 summarizes...
existing techniques, including segmentation technique, feature extraction representations, classification approaches, number of classes, number of images, databases, and accuracy.

A method has been used in [15] to classify WBCs into neutrophil, eosinophil, lymphocyte, and monocyte based on Beckman-Coulter Corporation provided flow cytometry data. A SVM classifier was used to cluster parametric data in a multidimensional region. In this research, the results have shown that the classification accuracy based on how many data were available for classifying, so the accuracy result was 86.6% for a data set of 100 images. The disadvantages of this method are that (a) it is computationally intensive, (b) it requires an increase of the convergence rate, so the misclassification ratio related to separate classes of data can be decreased, and (c) flow cytometry data cannot produce images of WBCs for further image analysis and verification in case there are intra-class variations of staining, shape, illumination of cells or overlapping cells.

An approach has been proposed in [16] to classify WBCs into five types. T-test and kernel density functions were used to obtain geometric features from segmented WBC images. A Naive Bayes classifier was used to train and test the system. Four statistical features were produced a good result in the classification stage. However, some errors that occurred during feature extraction stage due to using images have different orientation of nuclei, shape sizes and phases of maturation. Four statistical features were used. The results were good, but some errors were incurred owing to the different orientations, sizes and phases of maturation of the cells. As a result, the accuracy was 83.2% using 150 images.

In [17], a Local Binary Pattern (LBP) technique has been used to obtain the morphological and textural features. These features were utilized to classify WBCs into five types. SVMs and ANNs classifiers were used for training and testing the system. The results show that the SVM classifier outperformed the ANNs classifier and yielded an accuracy 86.10%. Some errors that occurred during segmentation and feature extraction were owing to differences in shapes of the cells (as opposed to nuclei) and the differences because of stages of maturity and overlapping of cells.

A technique was proposed in [18] for counting and classifying WBCs from microscopic images using two sets of features: a primary feature vector including shape, intensity and texture; and invariant features of the structure of WBCs, including shifting, rotation and magnification obtained using a Dual-Tree Complex Wavelet Transform (DT-CWT). An SVM classifier was used to classify these features into five types. However, results revealed that errors were caused by poor quality samples and low resolution. The accuracy of WBC classification using the linear SVM classifier was 84%, while using dimensional reduction Kernel Principal Component Analysis (K-PCA) with the SVM classifier, the accuracy was 76%. The accuracy of WBC classification using the linear SVM classifier was 84% while the accuracy using dimensional reduction K-PCA with an SVM classifier was 76%.

An approach was proposed in [19] to classify WBCs into five types using geometrical, color and textural features. A Local-Directional-Pattern (LDP) technique was proposed to extract texture features. LDP technique has the tolerance against illumination variations and includes the direction for each pixel in the image. The system extracted 20 features and employed three different kinds classifiers: MLPs, SVM and HCNN. The performance was compared between these three classifiers and showed that MLPs have a higher performance compared with SVM and HCNN. However, some cells were not classified correctly due to incorrect segmentation.

In [20], flow cytometry data set was used to distinguish between three types of WBCs: granulocytes, lymphocytes and monocytes. This data consists of three crucial functions of WBCs, including asserting a microfluidic flow in a narrow channel, microscopic imaging, and sorting. An optical neural network was utilized to classify these types and the method yielded 89% accuracy. However, errors were caused by cells such as monocytes that were poorly/insufficiently represented in the data sample.

A technique was proposed in [21] to use the standard Extreme Learning Machines (ELM) technique and fast Relevance Vector Machine (Fast-RVM) to classify WBCs into five types. The ELM method was used to segment the cell and then create discriminative features based on a thresholding technique. ELM and Fast-RVM classifiers were used to train and test the system. The results show that the Fast-RVM classifier outperformed the ELM classifier and achieved an accuracy of 80%.

An automatic detection and classification technique for WBCs from peripheral blood images has been proposed in [22]. WBCs were detected from the microscope images using the relationship of colors red, blue and morphological operations. A granularity feature (pairwise rotation invariant co-occurrence local binary pattern and PRICoLBP feature) was used with the SVM classifier to classify basophil and eosinophil from other WBCs. After that, a Convolutional Neural Networks (CNNs) was utilized to extract features in high level from WBCs. For classification, a random forest was used to recognize other types of WBCs: lymphocyte, monocyte and neutrophil. The resulting classification accuracy using these features was 92.6%. However, some cells were not detected correctly.

In [23], a supervised technique is used for classification of WBCs based on hierarchical topological feature extraction using inception and ResNet architectures and a consecutive deep learning framework for classification.

Previous techniques of WBC classification have suffered from different issues, including time complexity, insufficient or poorly detection of cells, poor quality of image samples, and limited size of databases. In addition, some methods use flow cytometry data which cannot produce images of WBCs for further image analysis and verification in case there are intra-class variations of staining, shape, illumination of cells or overlapping cells. Recently, (DL) has received great attention in computer vision and medical imaging tasks due to its breakthroughs in automatic unsupervised and supervised feature learning algorithms, which work by simulating structure and operation.
of the human brain [24]. DL has also been explored in classification of WBCs [17], [19]; however, DL requires a huge amount of training data if training from scratch. Transfer learning with pre-trained models such as [23] could reduce the training overhead, but the method still functions as a blackbox without evidence-based output. In addition, DL is extremely computationally expensive, for example, it may take more than one week of high-end Graphical Processing Unit (GPU) time for training. In the WBC scenario, human-expert knowledge from this domain could achieve highly-accurate performance with interpretable evidence for the reasoning process. Therefore, other classifiers, such as SVMs, RVM, classification trees or logistic regression are more suited to make use of rules derived from human-expert knowledge, than DL. Therefore, researchers tend to use signal processing and machine learning techniques in WBC classification in terms of segmentation and feature extraction representations to solve some of classification problems. For example, in [3], a new feature relying on bispectral invariant features and SVMs with classification tree are proposed to classify WBCs into 10-classes. Bispectral invariant features are extracted based on the shape of segmented white blood cell nuclei to deal with intra-class variations of staining, shape, illumination of cells and topology. A new white blood cell feature representation which aims at increasing robustness to consider its complexity, compactness and efficiency is proposed in [25]. The proposed feature representation is used on L-moments (L-skewness, L-mean, L-scale and L-kurtosis) of the Radon projected input image. Image and coupled with Linear Discriminant Analysis (LDA). SVMs and classification tree are used to classify WBCs in to 10-classes.

Despite a large amount of work having been undertaken, automatic WBC classification in terms of segmentation and feature representations is still challenging and none of these techniques deal with all challenges of WBCs classification simultaneously.

4. Challenges of WBC Classification

The accuracy achieved by WBC classification algorithms is highly influenced the segmentation and feature extraction processes. Classification algorithms also need to account for issues such as location and size changes, different relative position and size of the nucleus, different maturation stages, and rotation of cells. Some challenges which are faced by an overall automated WBC classification system (including the segmentation and feature extraction processes) are discussed as follows:

1. The structure of WBCs: Granulocytes, monocytes, lymphocytes, neutrophil, basophil, eosinophil, dendritic, macrophages, b-lymphocytes and t-lymphocytes cover a wide range of shapes, sizes and phases of maturation in microscopic images. These differences are very helpful for the process of classifying WBCs, but they present challenges for the reliable segmentation of the cells and feature extraction.
2. Different staining process: The different staining processes also lead to different colourations of the nucleus, cytoplasm and background and may result to cell distortion, as shown in Fig.5.
3. Illumination variations: The influence of light intensity that affects the appearance of the image. Various types of illumination can be used in microscope image acquisition and lead to different colour distributions in the nucleus, cytoplasm and cell background. This will result in dissimilarities in the image color because illumination is difficult to be standardized, as shown in Fig.6.
4. Location/size change: WBCs nucleus may appear at different sizes in different images and the nucleus’s position may locate at different positions within cells in images. Moreover, some of WBC nuclei may appear small and far away from the cell wall, others may appear extensive large and cover the whole cell.
5. Different maturation stage: WBCs transform from the primitive blast stage to the mature form found in the blood, there are changes in the cytoplasm, nucleus shape, position and cell size. These stages of maturation are also complex and challenging in the context of defining discrete standards for each cell type, because small inter-class differences exist among continuous stages.
6. Rotation: Cells may be viewed from any arbitrary angle in WBC images, and their appearance may differ when viewed from different angles. A classification system needs to account for this.
7. Cell morphology and background: WBCs may differ in shape, area, eccentricity, compactness and in their number of lobes, as shown in Fig.7. In addition, other aspects include different background of WBCs image due to variation in size, position and illumination of cell.
8. Poor image quality and the use of different imaging systems or cameras resulting in changes in contrast and noise in the image.
9. Time complexity: Some techniques require time to accelerate the process of distinguishing between classes or reduction features. Other techniques produce large numbers of features with only a few being used.
Table 1  Summary of WBC classification methods (since 2005) up to current state-of-the-art from Section-3, including number of classes, segmentation approaches, feature extraction representations, classification methods, number of images, databases, and accuracy.

<table>
<thead>
<tr>
<th>Research</th>
<th>Classes</th>
<th>Segmentation</th>
<th>Feature Extraction</th>
<th>Classification</th>
<th>No.of Images</th>
<th>Database</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjouadi et al. (2005)</td>
<td>4</td>
<td>Flow cytometry</td>
<td>SVMs</td>
<td>100</td>
<td>Beckman-coulter corporation data</td>
<td>87%</td>
<td></td>
</tr>
<tr>
<td>Ghosh et al. (2010)</td>
<td>5</td>
<td>Watershed</td>
<td>Geometrical features</td>
<td>Naïve Bayes</td>
<td>150</td>
<td>Midnapur Medical College Hospital</td>
<td>83.2%</td>
</tr>
<tr>
<td>Rezatofighi et al. (2011)</td>
<td>5</td>
<td>Gram Schmidt</td>
<td>LBP and Co-occurrence matrix</td>
<td>SVMs &amp; ANN</td>
<td>400</td>
<td>Hematology and BMT Research Center Hospital</td>
<td>86.10%</td>
</tr>
<tr>
<td>Habibzadeh et al. (2013)</td>
<td>5</td>
<td>Manual segmentation</td>
<td>K-PAC and DT-CWT</td>
<td>SVMs &amp; K-PCA</td>
<td>140</td>
<td>------</td>
<td>76-84%</td>
</tr>
<tr>
<td>Su et al. (2014)</td>
<td>5</td>
<td>Discriminating region</td>
<td>LDP</td>
<td>SVMs, HCNN, MLPs</td>
<td>250</td>
<td>CellaVision Databases</td>
<td>77-97%</td>
</tr>
<tr>
<td>Schneider et al. (2015)</td>
<td>3</td>
<td>On-chip flow cytometer</td>
<td>Optical Neural Network</td>
<td>7500 cells</td>
<td>Flow cytometer database</td>
<td>89%</td>
<td></td>
</tr>
<tr>
<td>Ravikumar (2016)</td>
<td>5</td>
<td>Discriminative features</td>
<td>ELMs &amp; Fast-RVM</td>
<td>--</td>
<td>Hospital database</td>
<td>80%</td>
<td></td>
</tr>
<tr>
<td>Zhao et al. (2017)</td>
<td>5</td>
<td>Colour space</td>
<td>Granularity via PRICoLBP feature</td>
<td>Random Forest</td>
<td>288</td>
<td>Cellvision, ALL-IDB and Jiashan</td>
<td>82.45-92.6%</td>
</tr>
<tr>
<td>Khamael et al. (2018)</td>
<td>10</td>
<td>Level set curvature and GACs</td>
<td>Bispectral invariant features</td>
<td>SVMs and Classification Tree</td>
<td>460</td>
<td>Cellvision-Database [2011], ALL-IDB [2005] and Wadsworth-Center</td>
<td>96.13%</td>
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<tr>
<td>Khamael et al. (2018)</td>
<td>10</td>
<td>Level set curvature and GACs</td>
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<td>SVMs and Classification Tree</td>
<td>460</td>
<td>Cellvision-Database [2011], ALL-IDB [2005] and Wadsworth-Center</td>
<td>97.23%</td>
</tr>
</tbody>
</table>

Fig. 5  Examples of Lymphocyte cell from different three databases using different staining process [26] [27] [28].

Fig. 6  Two Lymphocyte cells with different illumination levels from two different databases. a,b) [Wadsworth-Center] [28] and (c,d) [Cellvision-Database, 2011] [26].
Fig. 7 Neutrophil cell at different maturity stages with different lobes [28]. (a) early stage called (band neutrophil); (b,c,d) intermediate stage called (segmented neutrophil).

5. Conclusion

White blood cells are an important component in the human blood. All white blood cells have nuclei, which distinguishes them from the other blood cells and also between white blood cell types and subtypes themselves. In this Chapter, white blood cell types and their structure are reviewed. An automatic white blood cell classification system, including image acquisition, preprocessing, segmentation and feature extraction, is presented in this Chapter. Different automatic techniques that have been used for feature extraction and classification of white blood cells, from 2005 to state-of-the-art, are also reviewed. Despite the large amount of work that has been undertaken in this field, segmentation, feature extraction and classifications of white blood cells is still challenging, particularly in the presence of non-uniform illumination, low resolution of images, and different shape, size and phase of maturation of cells. The challenges still faced by an automated classification system are also summarised by this chapter.

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