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Blood Cell Classification using Deep Learning

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ABSTRACT: Accurate classification and quantification of White Blood Cells (WBCs) are essential for diagnosing various hematological disorders and immune-related conditions. Traditional microscopic examination methods are time-intensive, prone to human error, and require skilled expertise. This paper proposes an automated approach utilizing image processing and deep learning techniques for WBC classification. A Convolutional Neural Network (CNN) is employed to differentiate between key WBC subtypes: Neutrophils, Lymphocytes, Monocyte, Eosinophils, and Basophils. The proposed method enhances accuracy, minimizes manual intervention, and accelerates the diagnostic process. The experimental results demonstrate that the system achieves high precision, making it a promising tool for clinical applications.

KEYWORDS: White Blood Cells, Image Processing, Convolutional Neural Network, Blood Cell Classification, Automated WBC Counting.

I. INTRODUCTION

White Blood Cells (WBCs) play a crucial role in the human immune system, defending against infections and diseases. Accurate classification of WBCs is critical for diagnosing infections, leukemia, and other hematological disorders.

Conventional methods rely on manual microscopic examination, which is labor-intensive and subject to observer variability. Automated WBC classification using image processing and machine learning provides a reliable and efficient alternative. This study introduces a deep learning-based approach using CNNs for WBC classification. The proposed system follows a structured methodology where WBC images are collected from publicly available datasets and clinical samples. These images undergo preprocessing steps, including noise removal, contrast enhancement, and segmentation, to isolate WBCs. CNN-based feature learning extracts essential characteristics, which are then used for multi-class classification of WBCs. By automating WBC classification, this system improves accuracy and efficiency, reducing reliance on human expertise.

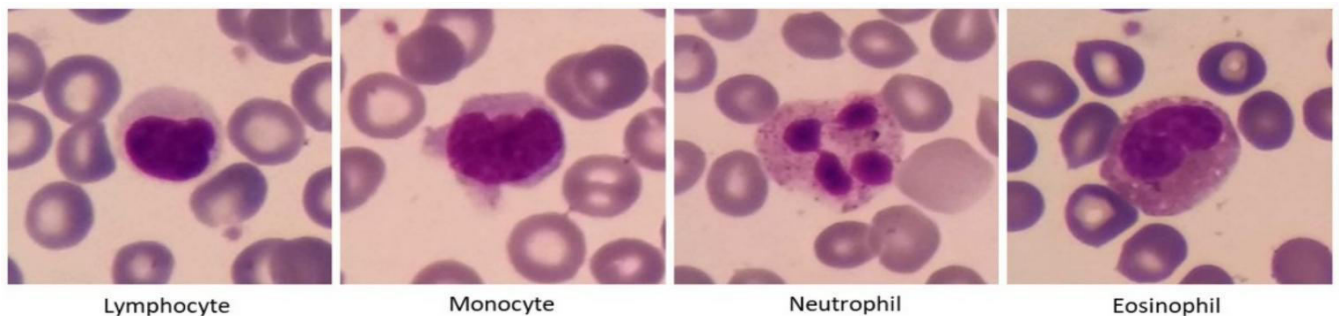


Figure 1: Sample WBC Image Used in Classification



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II. RELATED WORK

The Several researchers have explored automated WBC classification using different techniques. Traditional methods involve morphological feature extraction and statistical classifiers. However, deep learning-based approaches, particularly CNNs, have demonstrated superior performance in feature learning and classification. Prior studies show that CNN models can effectively distinguish WBC subtypes by learning hierarchical features directly from image data, reducing the need for handcrafted features.

III.METHODOLOGY

Image Acquisition and Preprocessing:

The dataset used in this study is the Blood Cell Count and Classification (BCCD) dataset, which consists of labeled images of WBCs. Preprocessing steps involve converting images to grayscale to simplify analysis, followed by noise reduction using Gaussian filtering to enhance clarity. Contrast enhancement techniques are applied to improve visibility, and segmentation is performed using adaptive thresholding to isolate individual WBCs effectively.

Feature Extraction and Classification:

A CNN architecture is designed for feature extraction and classification. The model consists of multiple convolutional layers for automatic feature extraction, max-pooling layers to reduce spatial dimensions, and ReLU activation functions to introduce non-linearity. Fully connected layers at the end of the network perform final classification. The model is trained using labeled WBC images and optimized using the Adam optimizer to ensure high classification accuracy.

Classification of WBC Types:

The trained CNN model classifies WBCs into five main types. Neutrophils are identified by their multi-lobed nucleus and granular cytoplasm, whereas Lymphocytes are characterized by a small, round nucleus with minimal cytoplasm. Monocytes display a kidney-shaped nucleus with abundant cytoplasm, while Eosinophils exhibit bi-lobed nuclei with distinct granules. Basophils, on the other hand, are distinguished by dark-stained granules with a bilobed nucleus. The classification accuracy of the CNN model is evaluated using various performance metrics.

IV. EXPERIMENTAL RESULTS

Dataset and Model Training:

The dataset consists of 12,500 labeled images, which are divided into training (80%), validation (10%), and testing (10%) subsets. The CNN model is trained using Python and TensorFlow for 200 epochs with a batch size of 64, ensuring the model learns effectively from the data.

Performance Evaluation

Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's performance. The CNN model achieved high accuracy in classifying WBCs, demonstrating its effectiveness in distinguishing between different cell types. The results are summarized below:

WBC Type	Accuracy
Neutrophils	92.3%
Lymphocytes	90.1%
Monocytes	93.4%
Eosinophils	91.7%



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V. CONCLUSION

This study presents an automated WBC classification system using image processing and deep learning techniques. The CNN-based approach eliminates manual errors, enhances diagnostic efficiency, and provides a scalable solution for medical applications. Future work includes expanding the dataset, optimizing model performance, and integrating real-time clinical deployment to improve practical usability in healthcare environments.

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