

Fast and Accurate WBC Classification Through Adaptive Moment Estimation in Deep Learning Models

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ABSTRACT

Blood is composed of key elements including plasma, red blood cells (RBCs), white blood cells (WBCs), platelets, oxygen, carbon dioxide, and essential nutrients required for sustaining life. Imbalances or abnormalities in these components can lead to various blood disorders, such as anemia, abnormal WBC counts, or thrombocytopenia. Accurate identification of WBCs through imaging plays a critical role in diagnosis and treatment, enabling medical professionals to make informed decisions. However, conventional manual methods of WBC classification are time-intensive, prone to misclassification, and often struggle to distinguish between different types of blood cells. These limitations emphasize the need for a faster and more reliable automated approach. The proposed system integrates a Convolutional Neural Network (CNN) with Adaptive Moment Estimation (Adam) optimizer to classify WBCs. CNNs excel in capturing spatial patterns and relationships within blood cell images, which improves classification performance, especially in complex cases involving overlapping or interacting cells. This automated technique accelerates the diagnostic process, minimizes human error, and improves the overall accuracy and efficiency of blood disorder detection.

Keywords: White Blood Cell Classification, Adaptive Moment Estimation (Adam), Hematological Disorders, Microscopic Image Processing.

1. INTRODUCTION

White blood cells, or leukocytes, are vital components of the immune system, defending the body against infections and foreign substances. Produced in the bone marrow, these cells circulate through the bloodstream and lymphatic system, identifying and neutralizing pathogens such as bacteria, viruses, and fungi. Despite comprising only about 1% of total blood volume, their role in maintaining health is crucial [1]. Leukocytes are categorized into five primary types, each with distinct functions: neutrophils, lymphocytes, monocytes, eosinophils, and basophils. Neutrophils, the most abundant, rapidly respond to and ingest invading microbes. Lymphocytes, including B cells, T cells, and natural killer cells, are central to adaptive immunity, targeting specific pathogens and retaining memory for quicker future responses. Monocytes migrate into tissues and differentiate into macrophages and dendritic cells, which engulf pathogens and dead or damaged cells, aiding in immune defense and tissue repair [2].

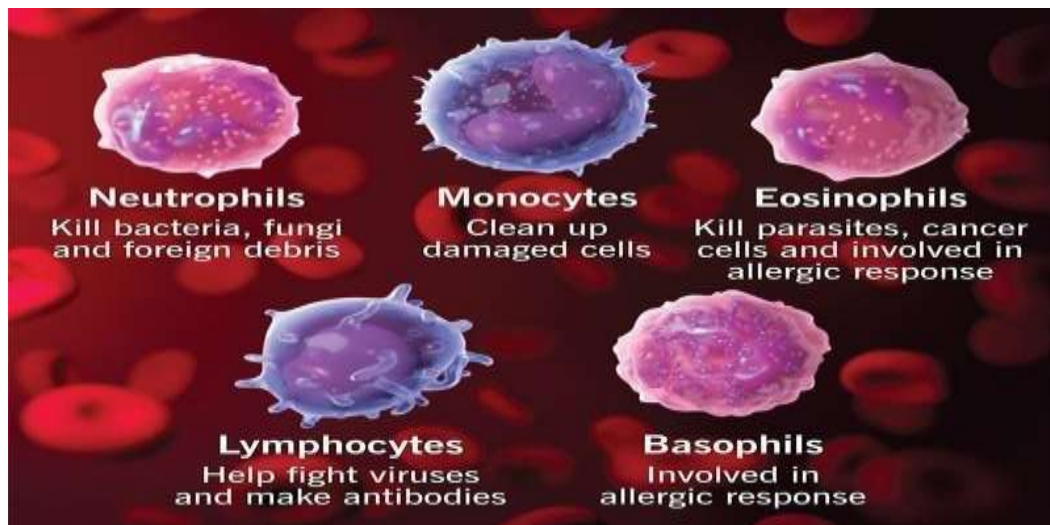


Fig 1: Types of White Blood Cells

The image is an illustration of different types of white blood cells, labeled as Monocyte, Eosinophil, Basophil, Lymphocytes, and Neutrophil. Each cell is uniquely colored and textured, representing their distinct appearances under a microscope. Monocytes have an irregular, large nucleus with a surrounding cytoplasm, while Eosinophils and Basophils have granulated cytoplasm with bilobed nuclei [3]. Lymphocytes appear more spherical with a large nucleus occupying most of the cell, and Neutrophils exhibit a multi-lobed nucleus with fine granules in their cytoplasm. The image visually represents the diversity and functionality of white blood cells in the immune system.

2. LITERATURE SURVEY

Yujie, Lianghong Wu, et al [4] (2025) White blood cells play a crucial role in the human immune system. various diseases for patients. To enhance the classification accuracy of white blood cells micro- vision images, an efficient lightweight deep learning network called ICAFF- MobileNetv2 is proposed.

Kandasamy, et al [5] (2025) Diagnosing hematological illnesses relies on correct labeling and categorizing nucleated cells in the bone marrow. However, timely diagnosis and treatment are hampered by pathologists' need to identify specimens, which can be sensitive and time- consuming manually. Humanity's ability to evaluate and identify these more complicated illnesses has significantly been bolstered by the development of artificial intelligence, particularly machine, and deep learning.

Dhibar, Sibasish, et al [6] (2025) proposed a novel ensemble approach that integrates three CNN architectures, each uniquely configured with different dropout and max-pooling layer settings to enhance feature learning. This ensemble model, named DCENWCNet, effectively balances the bias-variance trade-off. When evaluated on the widely recognized Rabbin-WBC dataset, our model outperforms existing state-of-the-art networks, achieving highest mean accuracy.

KT, Navya, et al [7] (2025) proposed blood cells were then counted and classified as normal and abnormal along with the type of abnormalities using the SqueezeNet Deep Learning (DL) model which offered an average classification accuracy of 97.9%.

Lagana, Alessandro, et al [8] (2025) recognized as a marker of clinical and subclinical systemic inflammation, and its elevation has also been associated with poor outcome in a wide spectrum of benign disorders and in different types of neoplasms.

Yataco, Angel O, et al [9] (2025) proposed a restrictive strategy was preferable to a permissive approach because it does not increase the risk of death or complications, but does decrease RBC use significantly.

3. PROPOSED SYSTEM

Deep learning has significantly advanced the automatic classification of white blood cells (WBCs), enhancing diagnostic accuracy and efficiency in hematology. Traditional manual examination of blood smears is labor-intensive and subject to observer variability, whereas deep learning offers a more standardized and rapid approach.

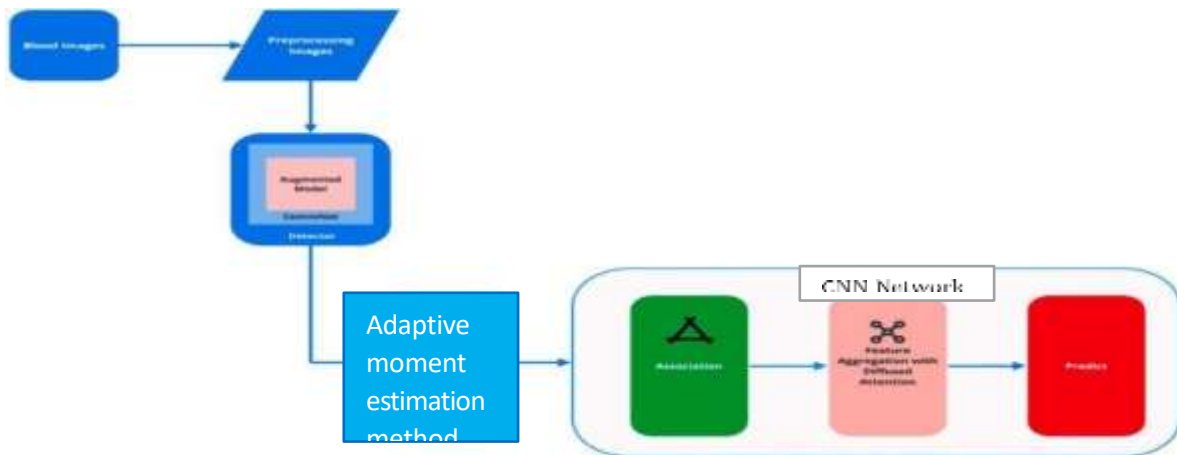


Fig. 2: Block Diagram of Proposed Model.

Diagram represents a pipeline for analyzing blood images using deep learning techniques. The process begins with the collection of blood images, which are subjected to a preprocessing stage to enhance image clarity and normalize input data. These preprocessed images are then passed into an augmented detection model based on CentreNet, a keypoint-based object detection framework that identifies and localizes important regions within the images. These regions may highlight abnormal cells or patterns crucial for disease identification.

Convolutional Neural Network

Convolutional Neural Network (CNN) is an advanced version of artificial neural networks (ANNs), primarily designed to extract features from grid-like matrix datasets. This is particularly useful for visual datasets such as images or videos, where data patterns play a crucial role. CNNs are widely used in Computer vision applications due to their effectiveness in processing visual data.

CNNs consist of multiple layers like the input layer, Convolutional layer, pooling layer, and fully connected layers

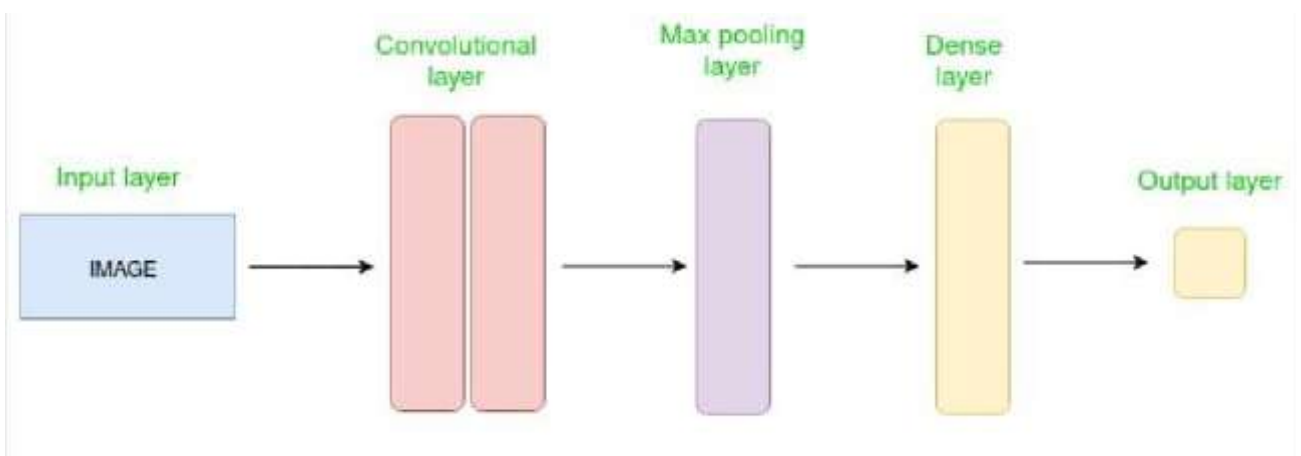


Fig. 3: Simple CNN Architecture

Convolution Neural Networks are neural networks that share their parameters. Imagine you have an image. It can be represented as a cuboid having its length, width (dimension of the image), and height (i.e the channel as images generally have red, green, and blue channels). Imagine taking a small patch of this image and running a small neural network, called a filter or kernel on it, with say, K outputs and representing them vertically. The neural network across the whole image, as a result, we will get another image with different widths, heights, and depths. Instead of just R, G, and B channels now we have more channels but lesser width and height. This operation is called Convolution. If the patch size is the same as that of the image it will be a regular neural network. Because of this small patch, we have fewer weights.

ADVANTAGES OF CNN

Good at detecting patterns and features in images, videos, and audio signals. Robust to translation, rotation, and scaling invariance. End-to-end training, no need for manual feature extraction. Can handle large amounts of data and achieve high accuracy.

4. RESULTS AND DISCUSSION

Figure 4 illustrates the dataset uploading process, where users select and upload the dataset into the system for further processing.

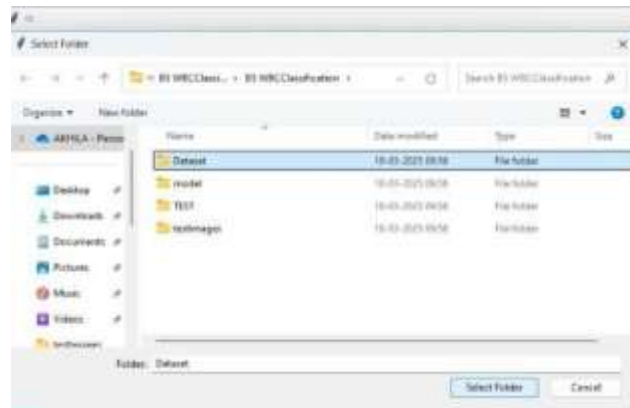


Fig. 4: Dataset Uploading.

Figure 5 presents the performance of the proposed Deep Learning CNN with AME, achieving a perfect accuracy, precision, recall, F-score, sensitivity, and specificity of 100%, indicating flawless classification across all categories.



Fig. 5: Proposed DLCNN with AME.

Figure 6 displays the selection of a blood cell image for testing, where an image is input into the trained model for classification.

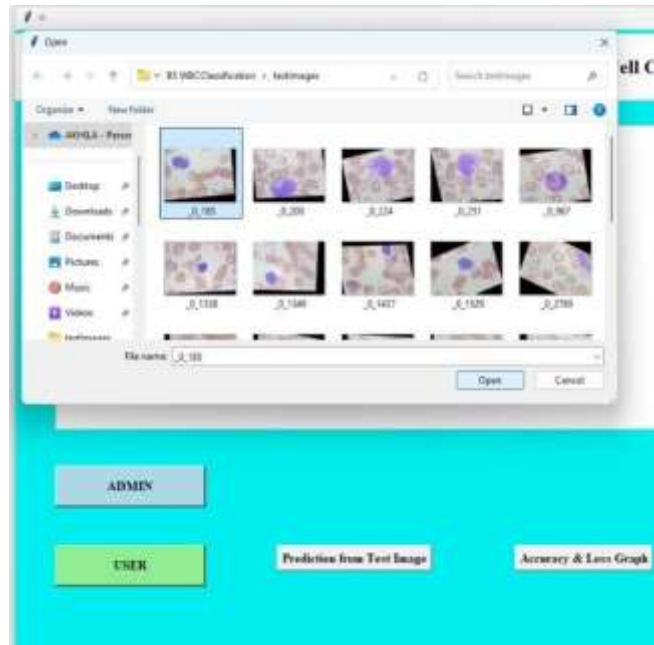


Fig. 6: Selecting image for testing.

Figure 7 shows the model successfully classifying a blood sample as a Monocyte, demonstrating its high accuracy in cell recognition.



Fig. 7: Classified blood sample of Monocyte.

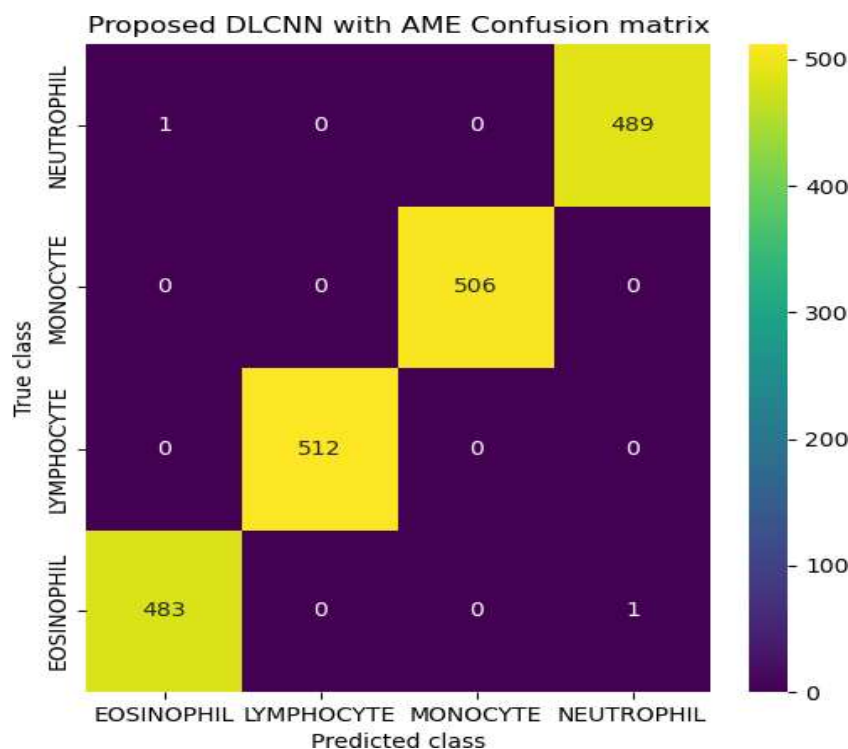


Fig. 8: Proposed DLCNN with AME Confusion Matrix.

The figure 8 represents the confusion matrix for the "Proposed DLCNN with AME" model, assessing its classification performance for four different cell types: Neutrophil, Monocyte, Lymphocyte, and Eosinophil. The vertical axis indicates the true class labels, while the horizontal axis shows the predicted class labels. The diagonal elements, highlighted in bright yellow, signify correctly classified instances, while the off-diagonal elements, represented in darker shades, indicate misclassified cases. The matrix demonstrates exceptional classification accuracy, with nearly all samples correctly classified. Notably, Monocytes and Lymphocytes are perfectly classified with no misclassifications, and only minimal errors are observed for Eosinophils and Neutrophils. The high values along the diagonal and the near-zero values in the off-diagonal positions indicate a significant improvement in classification performance compared to previous models. The accompanying color bar provides a reference for the numerical values, where brighter shades denote higher counts. The title "Proposed DLCNN with AME Confusion Matrix" confirms that this matrix evaluates the performance of a Deep Learning Convolutional Neural Network (DLCNN) enhanced with an AME mechanism.

5. CONCLUSION

In the study, a deep learning-based approach for White Blood Cell (WBC) classification using a Convolutional Neural Network (CNN) integrated with Adaptive Moment Estimation (Adam) is proposed. The model effectively addresses the limitations of manual WBC classification, such as time complexity, high error rates, and difficulty in identifying multiple blood cell types. By leveraging CNN's ability to process complex relationships between cells, the system enhances classification accuracy and efficiency. The automated classification of WBCs from microscopic blood images significantly improves diagnostic speed, reduces human errors, and supports early disease detection. This approach not only aids in accurate medical diagnoses but also lays the foundation for future advancements in AI-driven healthcare solutions. Further improvements in model architecture, dataset diversity, and real-time deployment can enhance the system's reliability and clinical adoption, ultimately contributing to more efficient and precise medical diagnostics.

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