# A Convolutional Neural Network for Efficient White Blood Cell Classification

Chandra Prakash[a], Sandeep Madarapu[a] and Samit Ari[a]

[a]*Department of Electronics and Communication, National Institute of Technology Rourkela, Rourkela, Odisha-769008, India*

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ABSTRACT

White blood cells (WBC) are important parts of our immune system and they protect our body against infections by viruses, bacteria, parasites, and fungi. There are five types of WBC Lymphocytes, Monocytes, Eosinophils, Basophils, and Neutrophils. The number of WBC types and total WBCs provide important information about our health status. Diseases such as leukemia, AIDS,immune deficiencies, and blood diseases can be diagnosed based on the number of WBCs. Therefore, it has been the motivation of this study to increase the performance of existing blood test devices with deep learning method. Blood cells have been identified and classified by Regional Based Convolutional Neural Networks. Designed architectures have been trained and tested on PBC data set and Rabbin data set.Convolutional Neural Networks (CNN) has been used as a methodology. In this way, different cell types within the same image have been classified simultaneously with a detector. While training CNN , MobileNet_V2, Xception, DenseNet, ResNet50 architectures have been tested with full learning and transfer learning. At the end of the study, the system has showed 100% success in determining WBC cells. MobileNet_V2, one of the CNN architectures, has showed the best performance with transfer learning. With This Model we got an accuracy of 99.57% for PBC Dataset and 98.54% for Rabbin Dataset.

## 1. Introduction

White blood cells (WBCs) are critical components of the immune system, defending the body against infections caused by viruses, bacteria, parasites, and fungi. Monitoring WBC counts and classifying different types of WBCs is essential for diagnosing a range of diseases, including leukemia, immune deficiencies, and various blood disorders. However, traditional diagnostic methods can be limited in both accuracy and efficiency, driving the need for more advanced solutions. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized image classification, offering significant improvements in medical image analysis. This study applies CNNs to automatically identify and classify WBC types, aiming to enhance the performance of existing blood test systems. By evaluating multiple CNN architectures, such as MobileNet_V2, Xception, DenseNet, and ResNet50, and employing both full learning and transfer learning, this research aims to achieve high accuracy in WBC classification and improve the reliability of diagnostic tools.

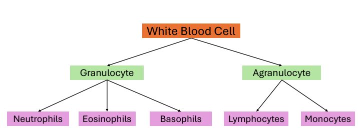


**Figure 1:** Different type of White Blood Cells.

ORCID(s):

## 2. Related Works

The many approaches that are currently being used for the segmentation, classification, and counting of white blood cells will be illustrated in this chapter. These approaches use diverse image processing techniques.

Rosyadi et al. conducted a research that is able to classify WBC from blood cell images taken from blood smear samples using digital microscope. The researchers utilized Otsu threshold method for segmentation and K-Means clustering method for classification. Based on their research it was concluded that upon execution of k-means clustering to classify and count WBC, the most significant geometry feature is its circularity generating an accuracy of 67%.

Gautam et al. proposed a method which utilizes Naive Bayes classifier and morphological features to classify WBC. The features which the researchers used to train their system were; area, eccentricity, perimeter and circularity. The proposed method was able to generate 80.88% accuracy.

Yu et al. proposed a method which uses CNN to automatically classify WBCs. The researchers utilized the network architectures; ResNet50, Inception V3, VGG 16, VGG 19, and Xception. The proposed method was able to generate an accuracy of 88.5

Recently, the study on the field of CNN showed to be increasingly significant in the advancement of image classification. However, recent models proved to be more efficient on the improvement of image classification accuracy specifically on tasks such as object detection and segmentation.

# 3. Methodology

## 3.1. Dataset

Two public WBC datasets Rabbin dataset and PBC dataset are utilized to validate the performance of the proposed CNN model,Both datasets consist of more than 5000 images.

## 3.2. Pre-processing

For the WBC classification task, the dataset, including neutrophils, lymphocytes, monocytes, eosinophils, and basophils, was meticulously prepared. Data cleaning removed duplicates and corrected labeling errors, while preprocessing involved resizing, normalization, Data augmentation techniques like rotations, flips, and zooms were applied to prevent overfitting. The dataset was split into balanced training, validation, and test sets, with labels numerically encoded for machine learning.

## 3.3. Proposed methodology

The proposed architecture consists of a base MobileNet backbone, DKCAB block, CAB block, and multi-scale feature fusion. The MobileNet base extracts features, while the DKCAB block generates attention maps to enhance feature learning by selecting different receptive fields. Multi-scale feature fusion combines features from various stages for rich, hierarchical representations. The CAB block refines features by focusing on important areas, enhancing discriminative learning and reducing noise. Features are upsampled, maxpooled, and passed through DKCAB, MSFF, and CAB blocks, with a final dense layer and softmax activation for classification.

### *3.3.1. backbone*

The proposed architecture incorporates several well-known convolutional neural networks (CNNs) as backbones, including MobileNetV2, Xception, ResNet50, and DenseNet, to evaluate their effectiveness in feature extraction. MobileNetV2, an efficient model designed for mobile and edge devices, employs depthwise separable convolutions and bottleneck residual blocks to reduce computational complexity while maintaining strong feature extraction capabilities. Xception builds upon the idea of separable convolutions by leveraging deep Inception modules, enabling more efficient and accurate feature learning. ResNet50 introduces residual connections to mitigate the vanishing gradient problem, allowing for the training of deeper networks while ensuring robust feature extraction. DenseNet, with its densely connected layers, ensures that each layer receives input from all preceding layers, promoting feature reuse and stronger gradient flow.

### *3.3.2. CAB block*

The CAB Block (Convolutional Attention Block) refines input feature maps by combining convolutional and attention mechanisms. It first applies 1x1 and depthwise convolutions to capture spatial features at different scales. An attention map is generated, highlighting important areas, which is then multiplied with the feature map to focus on significant details. The block includes residual connections, ensuring that key information is preserved while reducing noise. The result is a more discriminative and focused feature map, aiding in better classification performance.

Accuracy Table of proposed network for PBC Dataset

| Model | Accuracy% | QWK |
|---|---|---|
| Mobilenet_v2+DKCAB+CAB | 99.58 | 99.31 |
| Xception+DKCAB+CAB | 99.41 | 99.39 |
| ResNet+DKCAB+CAB | 98.77 | 98.34 |
| DenseNet+DKCAB+CAB | 98.88 | 98.84 |

Accuracy Table of proposed network for Rabbin Dataset

| Model | Accuracy % | QWK |
|---|---|---|
| Mobilenet_v2+DKCAB+CAB | 98.54 | 96.62 |
| Xception+DKCAB+CAB | 97.85 | 95.49 |
| ResNet+DKCAB+CAB | 97.28 | 93.05 |
| DenseNet+DKCAB+CAB | 98.15 | 95.81 |

### *3.3.3. DKCAB block*

The DKCAB Block (Diluted Kernel Convolution Attention Block) leverages multi-scale feature extraction and attention mechanisms to refine feature representations. It uses two branches: one with 3x3 convolutions and another with 5x5 convolutions that include varying dilation rates, allowing the model to capture features at different spatial scales. The outputs from these branches are fused and processed by a global attention mechanism, which adaptively reweights the features. The attention vector is split, with each part influencing the corresponding branches' feature maps. This structure allows the model to focus on important regions while utilizing multi-scale features, enhancing its ability to capture complex patterns.

# 4. Experimental Results

## 4.1. Experimental setup

Our framework is implemented using Keras, with TensorFlow functioning as the backend. During training, the cross-entropy loss function and the Adam optimization technique are employed. The CNN is trained with the following hyperparameters set: a learning rate of 0.001 and a maximum of 50 epochs. To reduce overfitting, real-time data augmentation techniques including random rotation, vertical flipping, and horizontal flipping are applied.

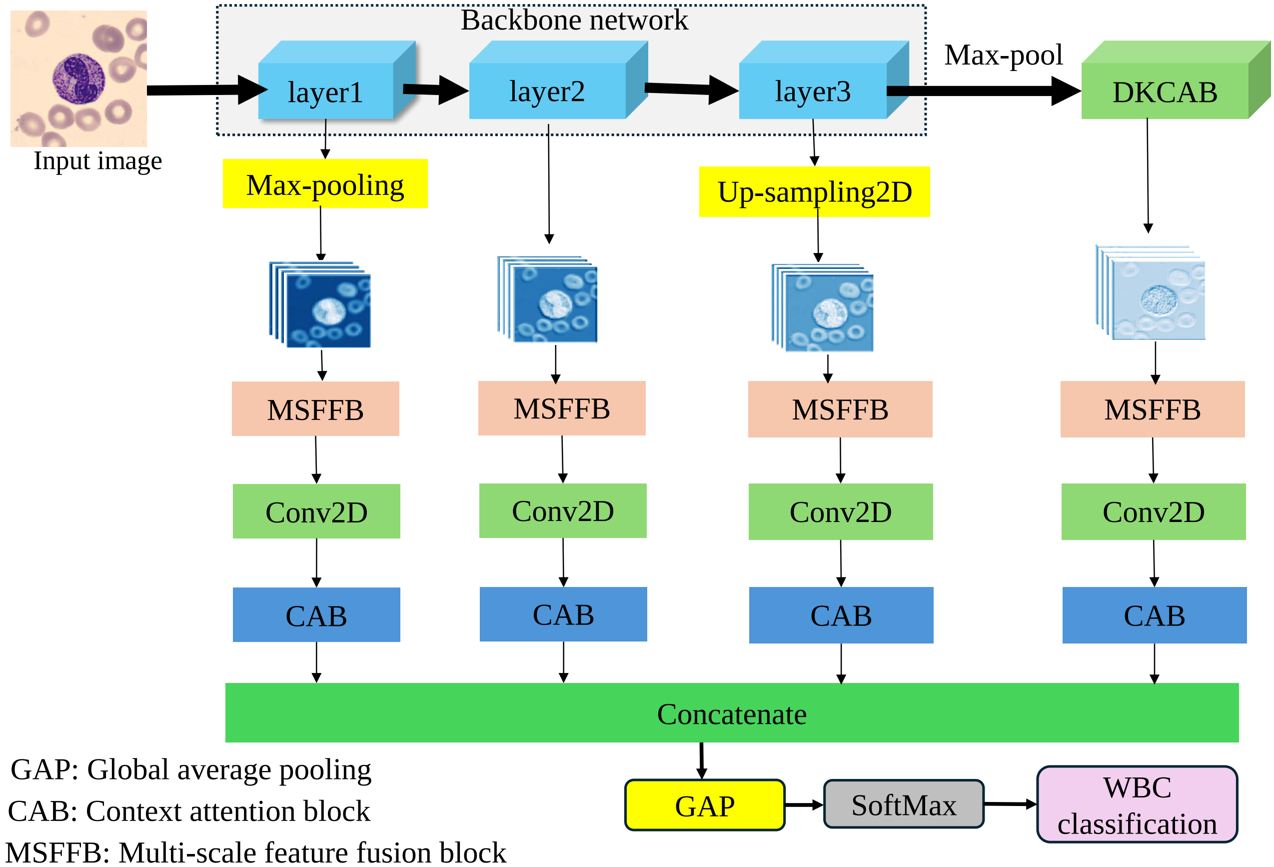


**Figure 2:** Main block of classification of while blood cells.

### 4.2. Results for multiclass classification on the PBC and Rabbin dataset.

The proposed architecture with the DKCAB Block achieved significant results, with MobileNetV2 attaining 99.58% accuracy on the PBC dataset and 98.54 % on the Rabbin dataset. Transfer learning improved performance across all models,in white blood cell classification.

## 5. Conclusion

This study demonstrated the effectiveness of using the CAB and DKCAB blocks in conjunction with various CNN architectures for classifying white blood cells. The results indicate that MobileNetV2, especially when combined with these attention mechanisms, achieved superior accuracy, showcasing the potential of deep learning techniques to enhance diagnostic processes in medical imaging. [1][2] [3] [4] [5] [6] [7] [8] [9] [10][11]

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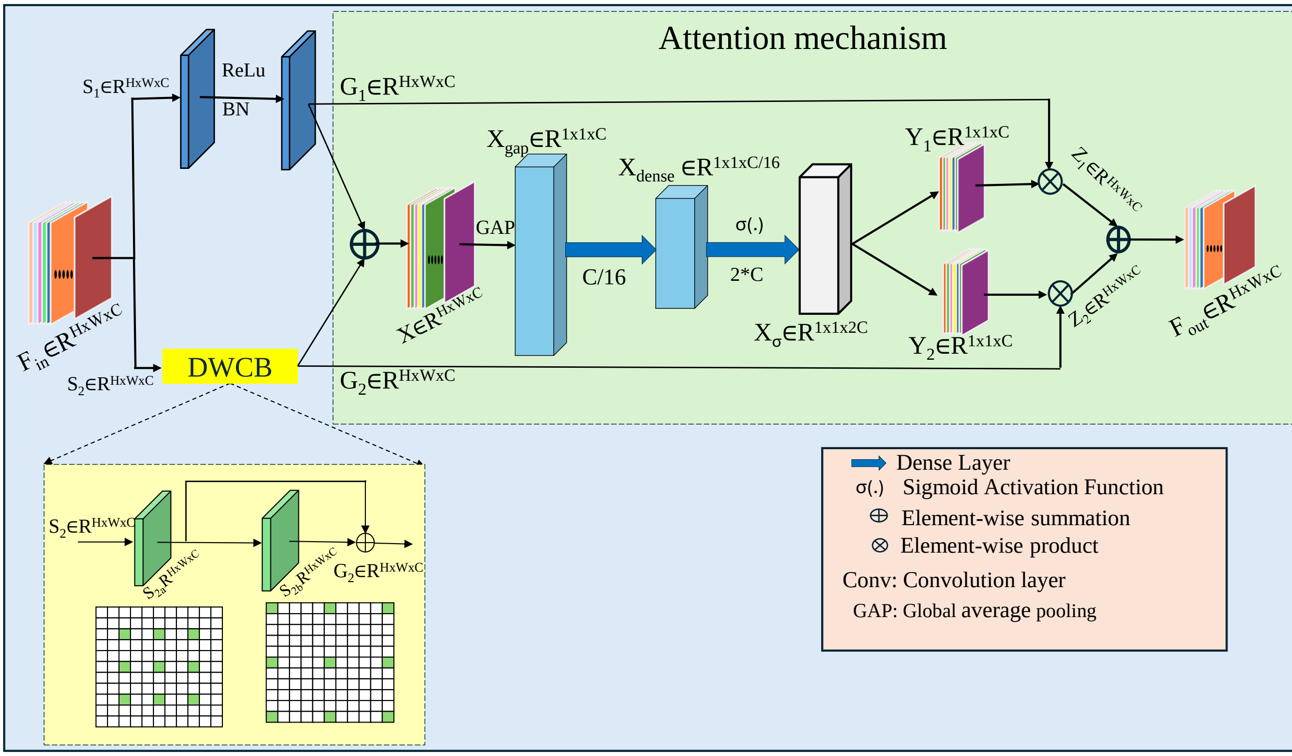


**Figure 3:** DKCAB block (Dilated kernel convolution attention block.


**Figure 4:** accuracy for multi-class classification of the proposed model on PBC dataset.

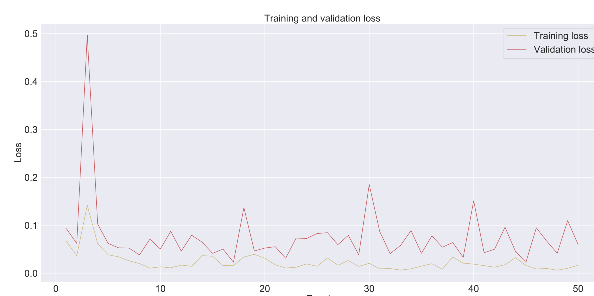


**Figure 5:** Loss for multi-class classification of the proposed model on PBC dataset.

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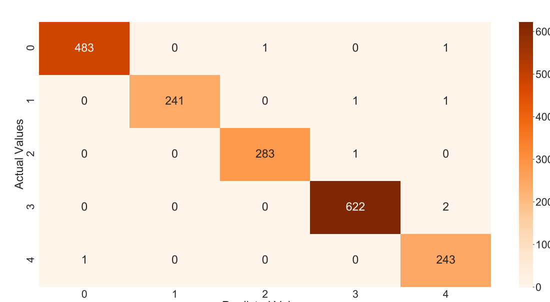


**Figure 6:** confusion matrix for multi-class classification of the proposed model on PBC dataset.