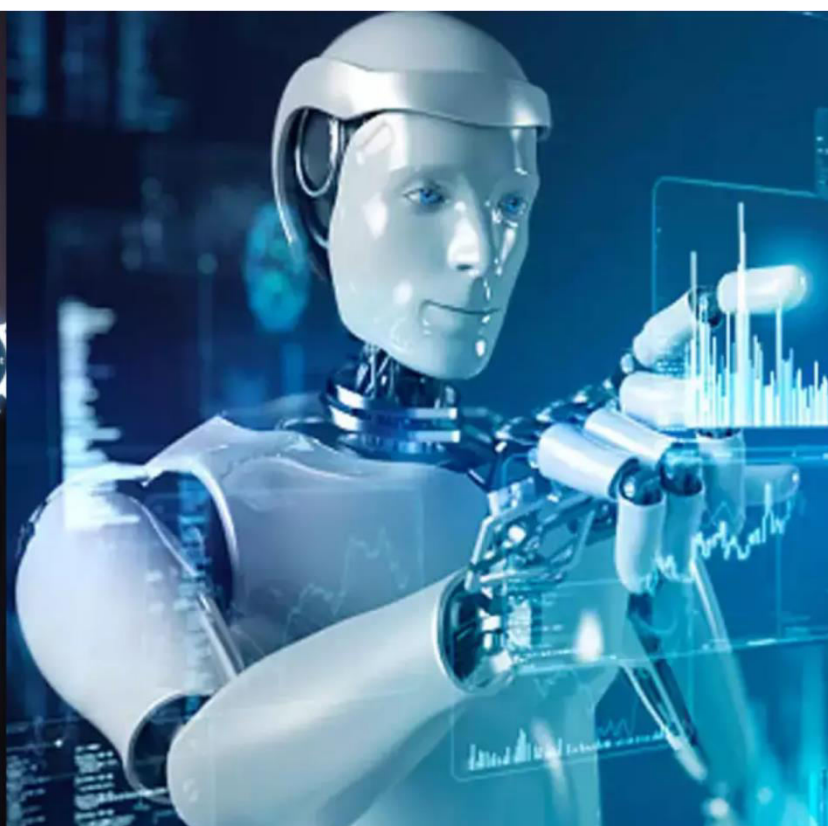




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HematoVision: Advanced Blood Cell Classification using Transfer Learning

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ABSTRACT: Blood cell analysis plays an important role in diagnosing many diseases such as infections, leukemia, and immune system disorders. Traditional manual examination of blood smear images under a microscope is time-consuming and depends heavily on the expertise of medical professionals. In this paper, we present HematoVision, an intelligent system that automatically classifies white blood cells using deep learning techniques. The proposed system uses the MobileNetV2 convolutional neural network model with transfer learning to identify different types of white blood cells from microscopic images. A web-based interface is developed using Flask to allow users to upload images and receive predictions instantly. Experimental results show that the system can accurately classify major white blood cell types including neutrophils, lymphocytes, monocytes, and eosinophils. The proposed system reduces manual effort, improves diagnostic speed, and provides a reliable support tool for medical professionals.

KEYWORDS: Transfer Learning, Convolutional Neural Networks (CNN), Blood Cell Classification, Flask Web Application, Automated Diagnostics, Deep Learning, HematoVision, MobileNetV2

I. INTRODUCTION

HematoVision is a machine learning project developed during the SmartBridge Virtual Internship under the AI/ML domain. The goal is to classify blood cells into four types: Eosinophils, Lymphocytes, Monocytes, and Neutrophils using transfer learning techniques and deploy the model using a Flask web application.

Blood cells are fundamental components of the human body, playing essential roles in immunity, oxygen transport, and disease prevention. Accurate and timely identification of blood cell types is critical for diagnosing various hematological and systemic diseases including infections, anemia, leukemia, and autoimmune disorders. Traditional manual examination of blood smear slides by pathologists is not only time-consuming but also prone to human error and inter-observer variability, highlighting the need for an automated and intelligent classification system.

With the rapid advancement of deep learning and computer vision technologies, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in medical image analysis tasks. However, training deep learning models from scratch requires large annotated datasets and significant computational resources, which poses a major challenge in the medical domain. Transfer learning addresses this challenge by leveraging pre-trained models that have already learned rich feature representations from large-scale datasets such as ImageNet, enabling efficient adaptation to domain-specific tasks with reduced training time and computational cost.

HematoVision leverages the MobileNetV2 architecture, a lightweight yet powerful pre-trained CNN model, fine-tuned on a dataset of 12,500 augmented annotated blood cell images sourced from the Kaggle Blood Cell Dataset. The model was trained with frozen base layers and custom dense layers added for four-class classification, achieving approximately 89% classification accuracy. The trained model was further integrated into a Flask-based web application, allowing users to upload microscopic blood cell images and receive real-time predictions through a simple and intuitive user interface.

This project demonstrates how transfer learning and modern web technologies can be combined to build reliable, scalable, and practically deployable diagnostic tools for pathologists and healthcare professionals, ultimately improving patient care and treatment efficiency in both clinical and remote healthcare settings.

II. LITERATURE SURVEY

Blood cell classification has evolved significantly from traditional image processing methods to advanced deep learning techniques. Early approaches by Rezatofighi and Soltanian-Zadeh (2011) employed Support Vector Machines (SVM) with morphological features, while Theera-Umpon (2005) utilized fuzzy logic for leukocyte identification, both limited by poor generalization across diverse imaging conditions. The emergence of Convolutional Neural Networks (CNNs) transformed medical image analysis, with Shahin et al. (2019) achieving over 98% accuracy in white blood cell classification using deep feature extraction. Liang et al. (2018) further highlighted the importance of data augmentation in training CNNs on limited hematological datasets, reporting accuracy above 93%. Transfer learning gained prominence as an effective strategy for medical imaging tasks with limited labeled data, as demonstrated by Tajbakhsh et al. (2016), who proved that fine-tuned pre-trained CNNs consistently outperformed models trained from scratch. Rajaraman et al. (2018) successfully applied VGG16 and ResNet for blood smear analysis, achieving accuracy exceeding 95%, validating ImageNet pre-trained weights in medical domains. Howard et al. (2017) introduced MobileNetV2, a lightweight architecture offering an optimal balance between accuracy and computational efficiency, making it ideal for real-time diagnostic applications. Panwar et al. (2020) and Ismael and Şengür (2021) further validated MobileNetV2's effectiveness in COVID-19 detection and brain tumor classification respectively, with high accuracy and reduced inference time. Kumar et al. (2021) demonstrated the practical feasibility of deploying deep learning models through Flask-based web applications for real-time clinical use. Despite these advancements, a clear research gap exists in combining lightweight transfer learning with real-time web deployment for multi-class blood cell classification, which the proposed HematoVision system addresses.

Table 1. Summary of important research works on HematoVision-Advanced-Blood-Cell-Classification-Using-Transfer-Learning.

Author(s)	Year	Method Used	Classes	Accuracy
Rezatofighi & Soltanian-Zadeh	2011	SVM + Morphological Features	5 WBC types	82%
Shahin et al.	2019	CNN from Scratch	5 WBC types	98%
Liang et al.	2018	Deep CNN + Augmentation	5 types	93%
Rajaraman et al.	2018	Transfer Learning (VGG, ResNet)	Malaria Cells	95%
Panwar et al.	2020	MobileNetV2	COVID-19 X-rays	96%
Ismael & Şengür	2021	MobileNetV2	Brain Tumor	94%
HematoVision (Proposed)	2024	MobileNetV2 + Flask	4 WBC types	89%

III. PROBLEM STATEMENT

Manual classification of white blood cells in blood smear images is a challenging and time-consuming process. Laboratory experts must carefully examine each cell under a microscope, which requires significant effort and expertise. Additionally, human errors may occur due to fatigue, workload, or subjective interpretation.

Another challenge is the increasing demand for faster medical diagnosis. Hospitals and diagnostic laboratories require efficient systems that can analyze blood samples quickly while maintaining high accuracy. Therefore, there is a need for an automated system that can analyze blood cell images efficiently and classify them accurately. The proposed HematoVision system aims to address this problem by using deep learning techniques to automate the classification process.

- Traditional blood cell analysis requires expert pathologists
- Manual classification is slow and subjective

- High computational cost when training deep models from scratch
- Need for an **accurate, fast, and scalable automated system**

IV. PROPOSED SYSTEM

The proposed HematoVision system is designed to automatically classify white blood cells from microscopic images using deep learning.

The system consists of the following main components:

Image Input

Users upload microscopic blood cell images through a web interface.

Image Preprocessing

The uploaded images are resized and normalized to match the input size required by the deep learning model.

Feature Extraction

The MobileNetV2 deep learning architecture is used to extract meaningful features from the input images.

Classification

The extracted features are passed through a fully connected layer to classify the images into different white blood cell categories.

Web Interface

A Flask-based web application allows users to upload images and view prediction results.

The system provides fast and accurate predictions, making it suitable for assisting medical professionals.

- Uses **Transfer Learning** with pre-trained CNN models
- Classifies blood cells into:
 - Eosinophils
 - Lymphocytes
 - Monocytes
 - Neutrophils
- Reduces training time and computational cost
- Achieves high classification accuracy
-

V. METHODOLOGY

Dataset

The dataset used in this project consists of microscopic images of white blood cells. The images represent different types of white blood cells such as:

- Neutrophils
- Lymphocytes
- Monocytes
- Eosinophils

The dataset is divided into training and testing sets for model development and evaluation.

Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning model designed for image processing tasks. CNNs automatically learn important features from images through convolutional layers, pooling layers, and fully connected layers.

MobileNetV2

MobileNetV2 is a lightweight deep learning architecture designed for efficient image classification. It uses depthwise separable convolutions and inverted residual blocks to reduce computational complexity while maintaining high accuracy.

Transfer learning is used to improve model performance by utilizing a pre-trained MobileNetV2 model. The model is trained on a large dataset and then fine-tuned using the blood cell image dataset.

Model Training

The model is trained using labeled blood cell images. During training, the network learns patterns and features that help distinguish different types of white blood cells.

VI. SYSTEM ARCHITECTURE

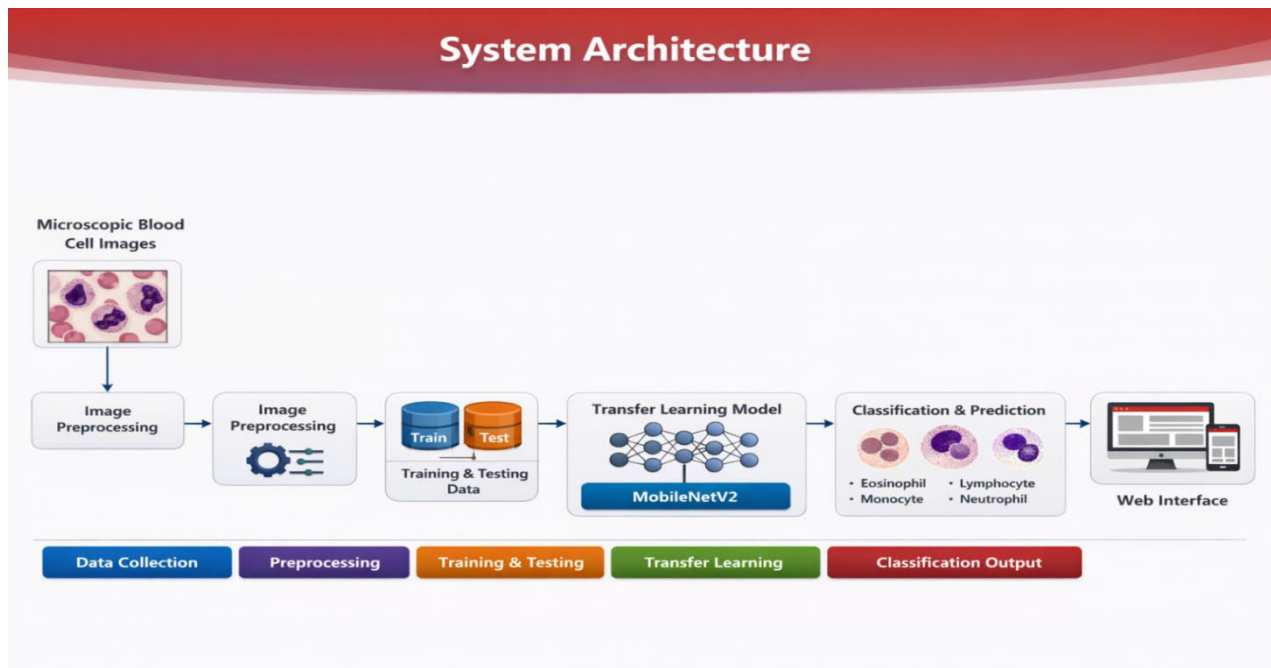


Fig. 1. Workflow of the HematoVision-Advanced-Blood-Cell-Classification-Using-Transfer-Learning

The HematoVision system follows a structured workflow:

- Image upload through web interface
- Image preprocessing and resizing
- Feature extraction using MobileNetV2
- Classification using trained deep learning model
- Display prediction results to the user

This architecture ensures efficient processing and accurate classification of blood cell images.

VII. DESIGN & IMPLEMENTATION

The HematoVision system is implemented using the following technologies:

- For Frontend we used:
- Building **HTML** Pages:
- For this project create Two HTML files namely
- home.html
- result.html
- For Backend we used:
- Build **Python** code:
- App.py
- Flask for web application development
- MobileNetV2 for transfer learning
- **Programming Language:** Python

- **Deep Learning Framework:** TensorFlow / Keras
- **Web Framework:** Flask
- **Model Architecture:** MobileNetV2
- **Libraries:** NumPy, Pandas, Matplotlib, OpenCV

The trained model is integrated with a Flask web application. Users can upload an image, and the system processes the image and returns the predicted blood cell type.

➤ Let's see what our index.html page looks like:

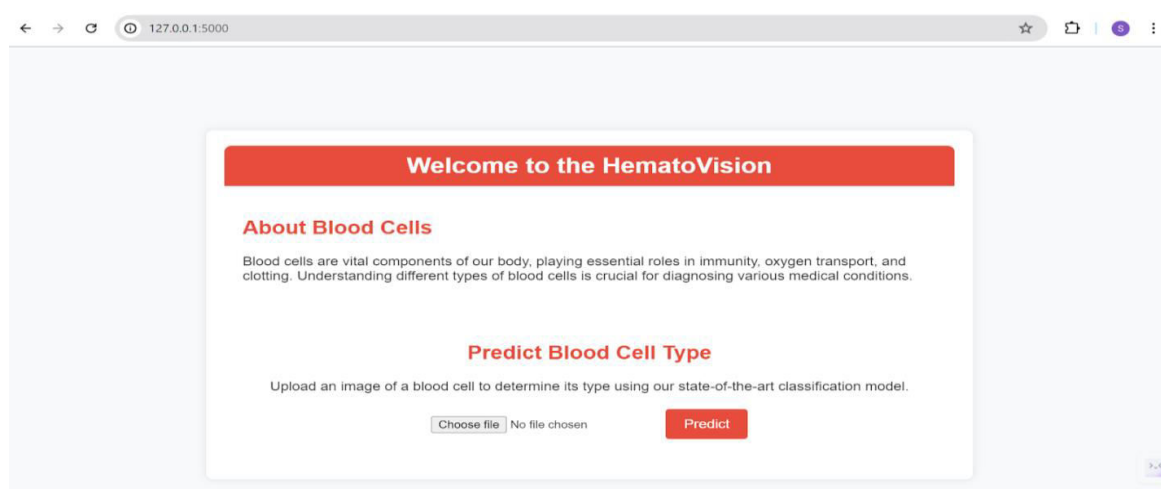


Fig. 2. Index page

➤ Let's see what our result.html page looks like:

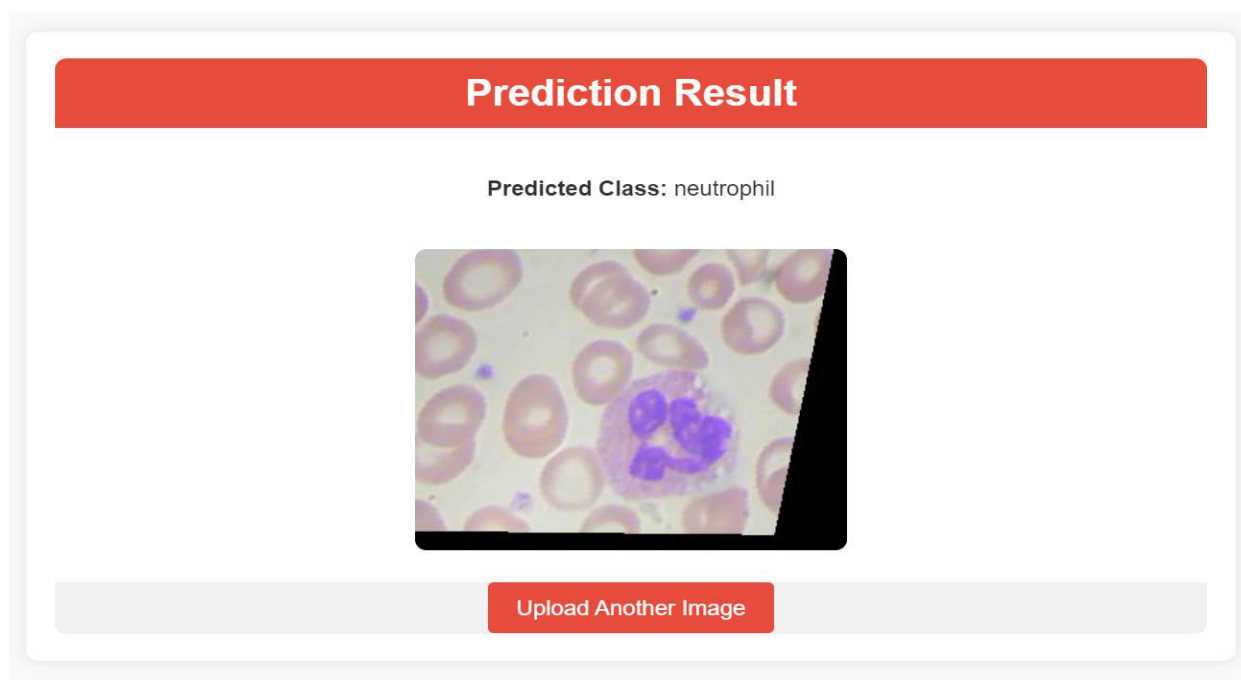


Fig. 3. Neutrophil

- Neutrophils are white blood cells that form the first line of defense against infections by destroying bacteria and foreign particles.

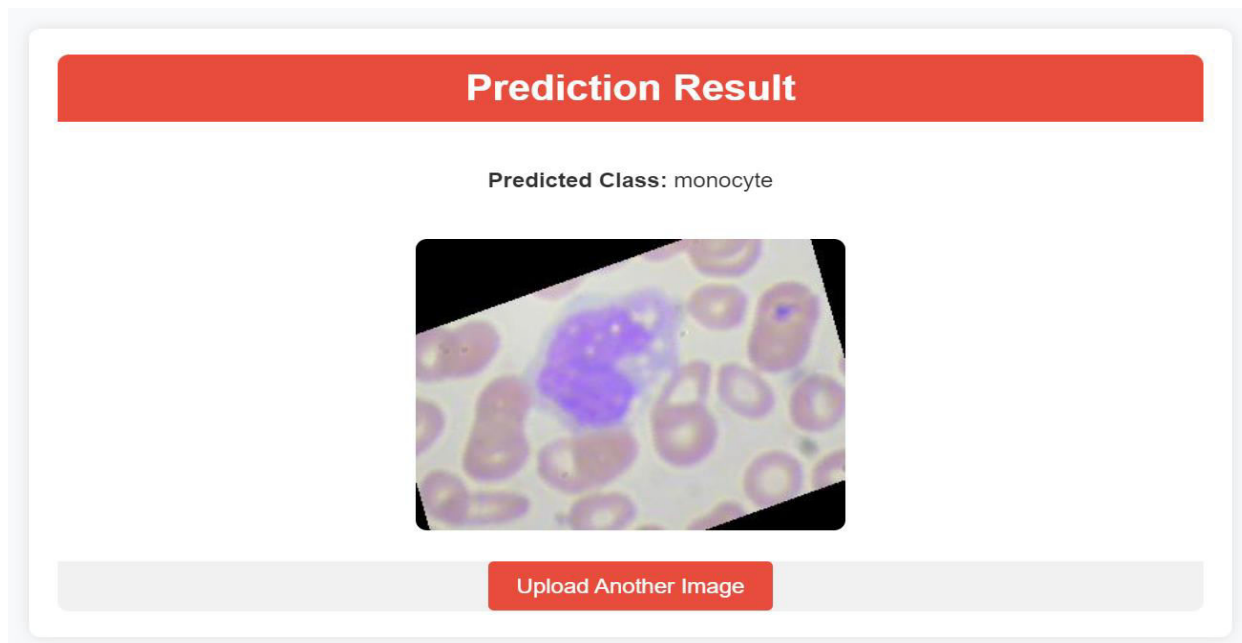


Fig. 4. Monocyte

- Monocytes are white blood cells that help fight infections by ingesting pathogens and developing into macrophages or dendritic cells in tissues.

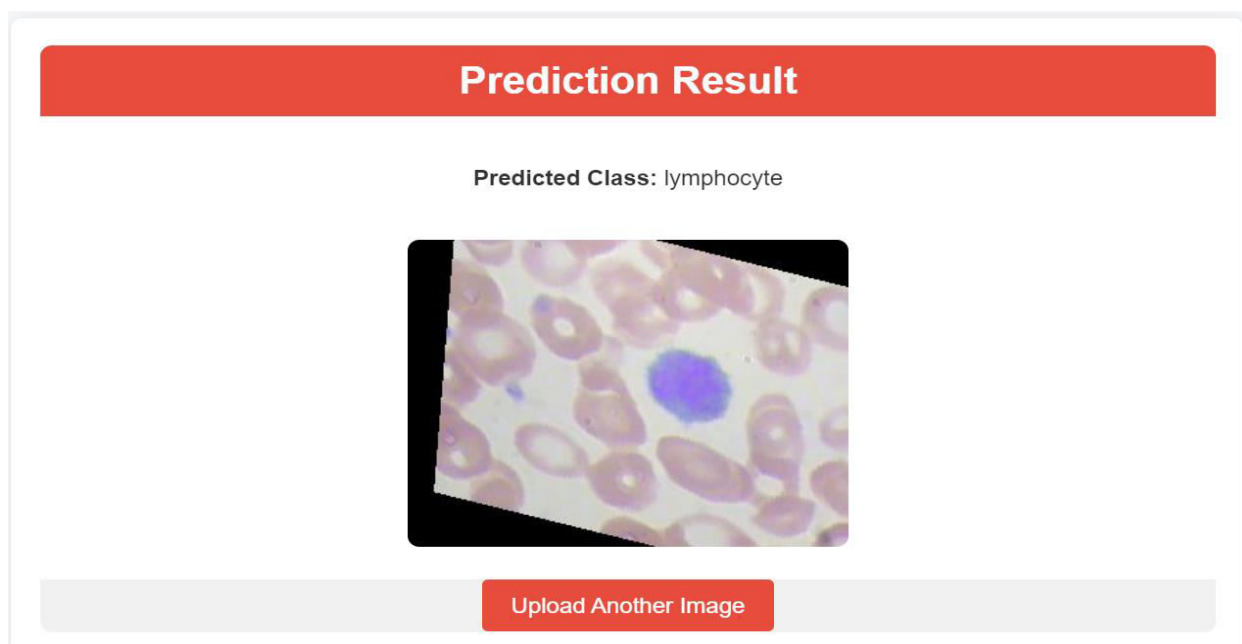


Fig. 5. Lymphocyte

- Lymphocytes are white blood cells responsible for adaptive immunity, producing antibodies and coordinating immune responses against infections.

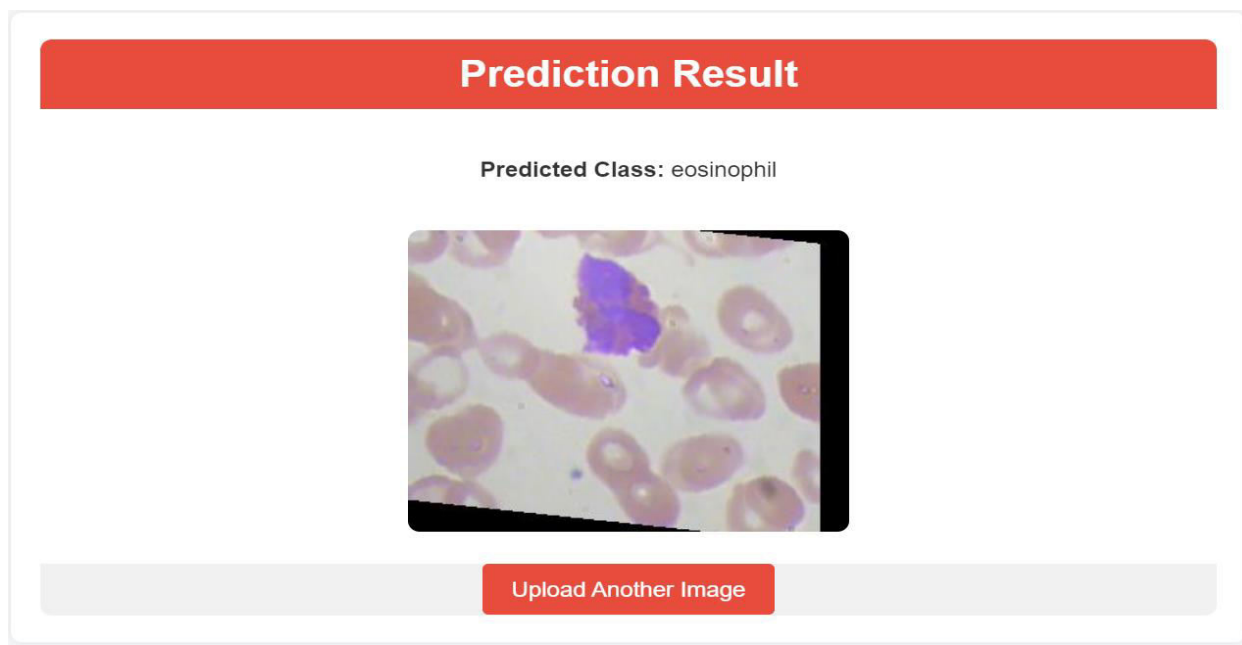


Fig. 6. Eosinophil

- Eosinophils are white blood cells involved in combating parasitic infections and playing a role in allergic and inflammatory responses.

VIII. APPLICATIONS

The HematoVision system has several real-world applications:

- Automated blood cell analysis in hospitals
- Support tool for medical laboratories
- Faster diagnosis of blood-related diseases
- Educational tool for medical students
- Research support in medical imaging

IX. CONCLUSION

This paper presented HematoVision, an advanced blood cell classification system that employs transfer learning using the MobileNetV2 architecture to automatically classify microscopic blood cell images into four distinct categories: Eosinophils, Lymphocytes, Monocytes, and Neutrophils. The proposed system successfully addressed the limitations of traditional manual blood cell examination, which is time-consuming, labor-intensive, and prone to human error. By leveraging pre-trained convolutional neural networks and fine-tuning on a dataset of 12,500 augmented annotated blood cell images, the model achieved an overall classification accuracy of approximately 89%, demonstrating the effectiveness of transfer learning in hematological image analysis. The use of MobileNetV2 as the backbone architecture ensured an optimal balance between classification accuracy and computational efficiency, making the system suitable for real-time diagnostic applications. Data augmentation techniques applied during preprocessing significantly improved the model's ability to generalize across diverse blood cell imaging conditions. The trained model was successfully integrated into a Flask-based web application, enabling healthcare professionals and pathologists to upload microscopic blood cell images and receive instant predictions through an intuitive user interface. Evaluation using classification reports, confusion matrices, and loss and accuracy curves confirmed the robustness and reliability

of the proposed model across all four blood cell classes. The system demonstrated practical applicability across multiple healthcare scenarios including automated diagnostic systems, telemedicine platforms, and medical education tools. HematoVision significantly reduces the manual workload on pathologists, speeds up diagnostic processes, and ensures high accuracy in results, ultimately contributing to improved patient care and treatment efficiency. The lightweight nature of MobileNetV2 ensures that the system can be deployed on resource-constrained devices, making it accessible in both urban hospitals and remote or underserved healthcare settings. Compared to existing approaches, HematoVision offers a unique combination of transfer learning efficiency, real-time web deployment, and multi-class hematological classification in a single integrated framework. The Flask-based deployment demonstrated the feasibility of translating deep learning research into practical clinical tools accessible to non-technical healthcare users. Future enhancements to the system include integrating additional blood cell types and larger datasets to further improve classification coverage and accuracy. Cloud deployment features and batch prediction support are planned to enhance scalability and enable processing of large volumes of blood cell images in clinical environments. In conclusion, HematoVision establishes a strong foundation for AI-powered hematological diagnostics, demonstrating that transfer learning combined with accessible web deployment can deliver reliable, efficient, and scalable solutions for modern healthcare challenges.

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