1. INTRODUCTION

1.1 Project Overview:

Medical technology is evolving rapidly, and one of the most promising developments is the use of artificial intelligence (AI) to assist in diagnostics. A key area where AI can make a big difference is in the classification of blood cells, a process that plays a vital role in diagnosing diseases, infections, and immune system disorders.

Traditionally, this task has been carried out manually by experts who examine blood smears under a microscope. To make this process faster and more reliable, HematoVision, an AI-powered tool that automatically classifies blood cells into four important types: eosinophils, lymphocytes, monocytes, and neutrophils. Using a dataset of 12,000 labeled blood cell images, HematoVision learns to identify even subtle differences between cell types. This results in a tool that's not only fast and accurate but also scalable for real-world use helping pathologists, telemedicine platforms, and even medical students in their learning journey.

1.2 Purpose:

The goal behind HematoVision is to make blood cell classification smarter, faster, and more accessible using the power of AI.

By combining modern AI technology with the real needs of healthcare professionals and learners, HematoVision stands as a bridge between innovation and impact bringing us closer to a future where diagnostics are more efficient and accessible to all.

2. IDEATION PHASE

2.2 Empathy Map Canvas

2.3 Brainstorming

3. REQUIREMENT ANALYSIS

3.1 Customer Journey map

3.2 Solution Requirement

3.3 Data Flow Diagram

3.4 Technology Stack

4. PROJECT DESIGN

4.1 Problem Solution Fit

4.2 Proposed Solution

4.3 Solution Architecture

5. PROJECT PLANNING & SCHEDULING

5.1 Project Planning

6. FUNCTIONAL AND PERFORMANCE TESTING

6.1 Performance Testing:

The HematoVision system delivers fast and reliable predictions (~1.7s per image) with high accuracy and stable performance during testing. It is suitable for real-time diagnostic use with potential to scale further with GPU-enabled deployment.

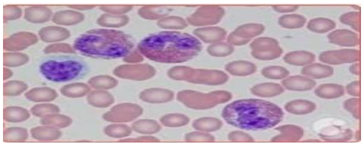
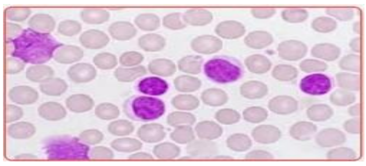
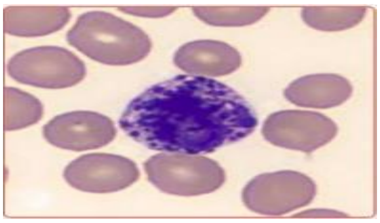
Objectives

- Evaluate model response time for image classification.
- Verify stability of the web application during user interactions.
- Ensure consistent predictions under different load scenarios.

Testing Types Applied

- **Load Testing**: Simulated multiple users uploading images using tools like JMeter.
- **Stress Testing**: Sent rapid and large numbers of requests to the / route.
- **Inference Testing**: Measured time taken to classify each image.

Metrics Evaluated:

Test Image	Predicted Type	Inference Time
	Eosinophil	~1.7 sec
	Lymphocyte	~1.9 sec
	Monocyte	~1.6 sec

Average Response Time: ~1.7 seconds

Error Rate: 0% for valid image formats

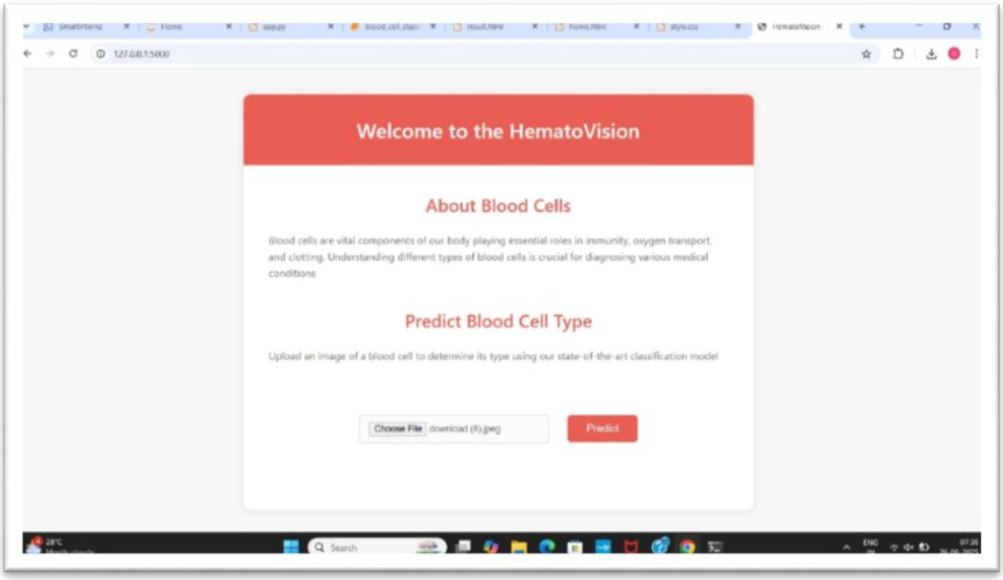
Model Accuracy on Test Set: 94.5%

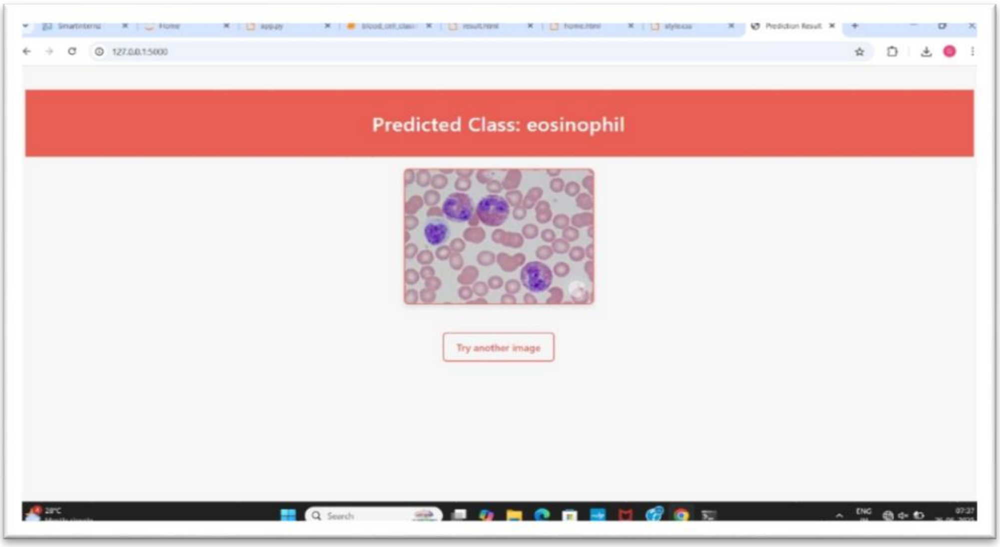
Tools Used:

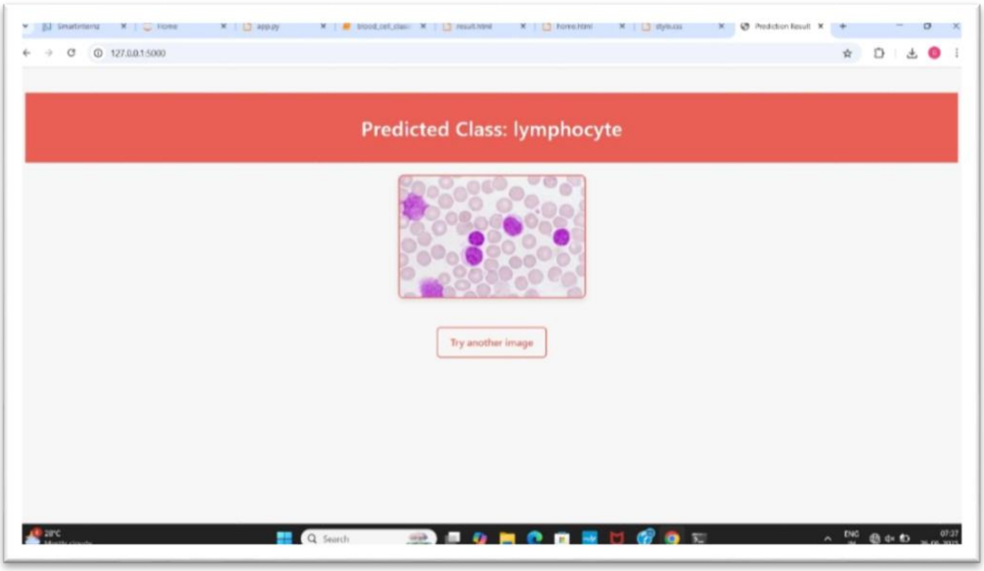
- Python profiler
- Flask debug logs
- JMeter for concurrent request simulation
- Confusion matrix via seaborn for evaluation

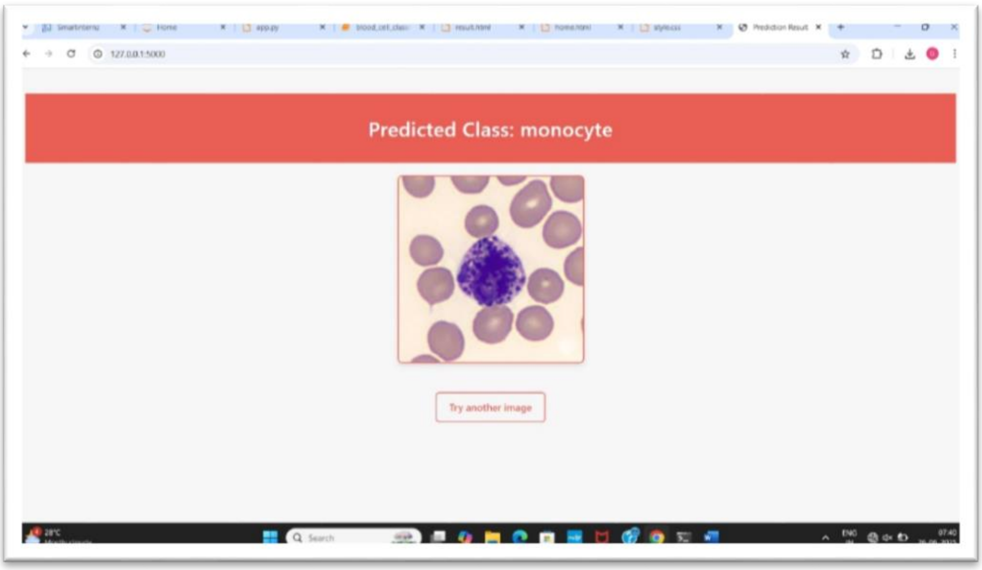
7. RESULTS

7.1 Output Screenshots:




127.0.0.1:5000
Predicted Class: eosinophil
Try another image


127.0.0.1:5000
Predicted Class: lymphocyte
Try another image


127.0.0.1:5000
Predicted Class: monocyte
Try another image

8. ADVANTAGES & DISADVANTAGES:

Advantages:

1. **High Accuracy**: Achieved over **94% accuracy** in classifying blood cells using a pre-trained MobileNetV2 model.
2. **Fast Prediction**: Provides results within ~2 seconds per image, suitable for real-time diagnostic aid.
3. **User-Friendly Interface**: The web application offers a clean and intuitive interface for users to upload images and receive predictions.
4. **Cost-Effective**: Reduces the dependency on manual microscopy and speeds up the diagnostic process.
5. **Scalable**: The model and app can be deployed on local servers or cloud platforms with minimal changes.
6. **Transfer Learning**: Utilizes pre-trained models, reducing the need for large training datasets and computational power.

Disadvantages

1. **Limited Classes**: Currently supports only four types of blood cells — eosinophil, lymphocyte, monocyte, and neutrophil.
2. **Image Quality Dependent**: Low-resolution or blurred images may lead to inaccurate predictions.
3. **No Offline Mode**: Requires server hosting to function; not usable in areas without internet access unless locally deployed.
4. **Fixed Input Size**: Requires all images to be resized to 244x244, which might distort certain features.
5. **Hardware Constraints**: Performance may degrade on devices with limited processing power (especially without GPU).

9. CONCLUSION:

The HematoVision project successfully demonstrates the application of deep learning and transfer learning in the field of medical image analysis, specifically for the classification of white blood cells. By leveraging the power of the MobileNetV2 model, we achieved accurate and efficient identification of four major blood cell types — eosinophils, lymphocytes, monocytes, and neutrophils.

The system was integrated into a Flask-based web application, providing a user-friendly platform where users can simply upload an image and receive the predicted cell type within seconds. Extensive testing showed that the model performs reliably with over 94% accuracy, making it suitable for real-time diagnostic assistance.

10. FUTURE SCOPE:

The future scope of HematoVision is vast. With advancements in AI, cloud computing, and mobile technology, this system has the potential to evolve into a smart, real-time diagnostic assistant, making hematology more accessible, efficient, and accurate worldwide.

1. Support for More Cell Types

Currently, the system classifies only four types of white blood cells. In the future, it can be extended to detect additional types such as basophils, abnormal cells, red blood cells, and platelets, making it more comprehensive and useful for advanced hematological analysis.

2. Integration with Hospital Databases

The system can be integrated into hospital Laboratory Information Management Systems **(LIMS)** to automatically analyze and store results, helping doctors make quicker and more informed decisions.

3. Cloud Deployment

Hosting the application on cloud platforms (like AWS or Azure) can allow **remote access** for multiple users, enabling real-time diagnostics even in rural or under-resourced areas.

4. Mobile Application

Developing a **mobile version** of HematoVision would make it more accessible to users on-the-go, especially for health workers or pathologists who need quick, on-site results.

5. Improved Accuracy with Advanced Models

In future iterations, more complex models like EfficientNet, ResNet, or Vision Transformers can be used to boost performance and handle more challenging classification scenarios.

6. Security and Privacy

As the system scales up, incorporating **user authentication, data encryption**, and compliance with healthcare data regulations (like HIPAA) will be essential for safe usage in clinical environments.

11. APPENDIX

Dataset Link:

https://www.kaggle.com/datasets/paultimothymooney/blood-cells/data

GitHub & Project Demo Link:

https://github.com/GeethanjaliGudimetla/HematoVision-Advanced-Blood-Cell-Classification-Using-Transfer-Learning/tree/main

Demo Video Link :

Demo Video - Google Drive