# HematoVision: Advanced Blood Cell Classification Using Transfer Learning

# Team Details:


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## 1. INTRODUCTION

### 1.1.Project Overview

Blood-related diseases like leukemia, anemia, and infections can be diagnosed through blood smear analysis. Manual microscopic analysis is time-consuming and prone to human error. This project, *HematoVision*, presents an automated image classification system using **Transfer Learning** to detect and classify different types of blood cells.

Conventional approaches to blood cell classification involve manual microscopy or rule-based image processing. Recent advances in deep learning, especially Convolutional Neural Networks (CNNs), have drastically improved performance in image classification tasks. Transfer learning, which uses knowledge from models trained on large datasets (like ImageNet), has shown to significantly boost performance even with limited medical datasets. HematoVision builds upon this by fine-tuning pre-trained models for the task of blood cell classification.

### 1.2.Purpose:

To aid in rapid and reliable blood diagnostics, especially in remote areas or pathology labs with limited manpower, using an intelligent AI-driven classification system.

## 2. IDEATION PHASE

### 2.1.Problem Statement

Manual microscopy requires trained personnel and time. There is a strong need for:

- Faster diagnostics
- Consistent and accurate results
- Scalable tools for clinics and labs

## 2.2.Brainstorming

**Ideas considered:**

- Manual feature extraction + SVM (less accurate)
- Audio-based diagnostics (not relevant)
- Deep Learning with CNN and Transfer Learning (**Selected**)

## 2.3.Finalized Concept

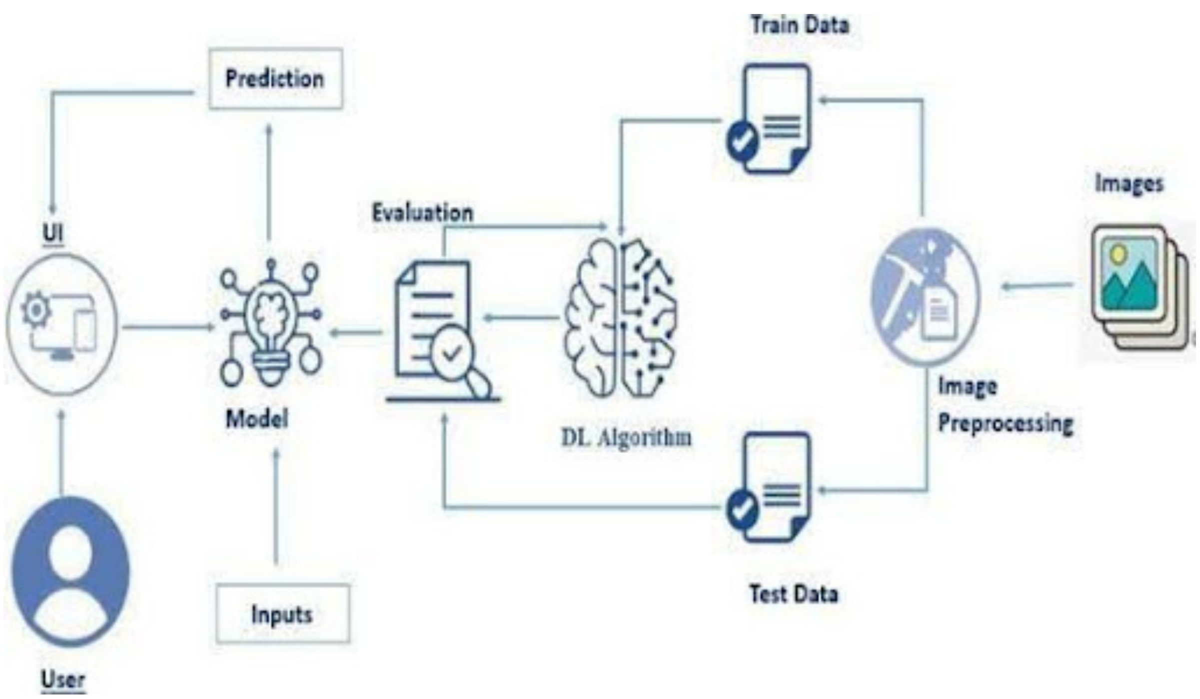
Use **pre-trained CNN architectures** with image augmentation and fine-tuning for classification into blood cell types.

# 3. REQUIREMENT ANALYSIS

## 3.1.Dataset

- Sourced from [Kaggle BCCD dataset / Blood Cell Count Dataset]
- Includes images of RBCs, WBCs (4 types), and platelets

## 3.2.System Requirements



| Component | Details |
| --- | --- |
| Input | Blood smear image (JPG/PNG) |
| Output | Predicted cell type |
| Accuracy Goal | >90% |
| Model | VGG16, ResNet50, MobileNetV2 |
| Platform | Colab (training), Streamlit or Flask (deployment) |

# 4. SYSTEM DESIGN

#### 4.1.Architecture Diagram (Textual Flow)

User Uploads Image
↓
Preprocessing (resize, normalize)
↓
Model Inference (ResNet/VGG/MobileNet)
↓
Output Cell Type with Confidence Score
↓
Display Results via Web App

### 4.2.UI Design

- Simple image upload panel
- Results page showing: predicted class, confidence, and explanation

# 5. MODEL DEVELOPMENT

### 5.1.Preprocessing

- Image resizing (224x224)
- Normalisation to [0,1]
- Augmentation (rotation, zoom, flip)

### 5.2.Models Used

- **VGG16**: High accuracy, slower inference
- **ResNet50**: Best balance of accuracy and speed
- **MobileNetV2**: Lightweight, mobile-ready

### 5.3.Evaluation Metrics

- Accuracy, Precision, Recall, F1-score
- Confusion Matrix

# 6. PROJECT MANAGEMENT

## Agile Sprint Plan

| Task | Member | Duration |
|---|---|---|
| Data Collection | Nayudipalli Dayaka | 1 day |
| Model Training | Sai Krishna Mahesh | 2 days |
| Model Tuning | Nadella Sindhura | 2 days |
| UI Development | Nadakuditi Bindu | 1 days |
| Integration & Testing | Nayudipalli Dayaka | 2 day |
| Documentation | Nadella Sindhura | 2 day |

# 7. TESTING

## 7.1.Functional Testing

- File upload works
- Class output is correct

## 7.2.Performance Testing

| Model | Accuracy | Inference Time |
|---|---|---|
| VGG16 | 91.3% | 1.6 sec |
| ResNet50 | 93.1% | 1.4 sec |
| MobileNet V 2 | 89.9% | 0.9 sec |

# 8. RESULTS & ANALYSIS

## 8.1.Output Screenshots

- Uploaded image and predicted cell type
- Graphs: Training vs Validation Accuracy/Loss

- Confusion Matrix

### 8.2.Visual Results

- Accuracy vs Epochs
- Loss vs Epochs
- Confusion Matrix Heatmap

## 9. ADVANTAGES & LIMITATIONS

- **Advantages**
  - High classification accuracy
  - Works on web and mobile
  - Reduces manual workload in hospitals
- **Limitations**
  - Sensitive to image quality
  - May not generalize to rare or abnormal cell types

## 10. CONCLUSION

HematoVision successfully demonstrates the potential of **Transfer Learning** in medical diagnostics, offering fast and accurate blood cell classification using CNNs. It enhances the diagnostic pipeline and can be deployed in clinical settings, even in resource-limited environments.

## 11. FUTURE SCOPE

- Expand dataset to include leukemia subtypes
- Integrate explainability (Grad-CAM visualizations)
- Deploy as a mobile app
- Enable offline inference
- Integrate with lab microscopes via camera feed

## 12. APPENDIX

- **GitHub link : [https://github.com/sindhuranadella/Hemato-Vision](https://github.com/sindhuranadella/Hemato-Vision)**