INTRODUCTION

HematoVision is a deep learning-powered web application for classifying blood cells from microscopic

images. It leverages Transfer Learning techniques to automatically detect and classify cell types such as

RBCs, WBCs (lymphocytes, monocytes, neutrophils, eosinophils), and platelets. The goal is to automate and

expedite diagnostics for diseases like leukemia and anemia.

PURPOSE

The purpose of this project is to assist medical professionals in diagnosing blood-related disorders using an

Al-driven tool that classifies blood cells with high accuracy. HematoVision aims to:

- Automate the blood smear analysis process

- Reduce manual workload in clinical labs

- Ensure faster and more consistent diagnostic results

- Make diagnostics accessible in resource-limited areas

FEATURES

1. Upload-based microscopic image classification

2. Real-time predictions with confidence scores

3. Use of transfer learning with VGG16, ResNet50, and MobileNetV2

4. Graphs showing accuracy/loss per epoch

5. Confusion matrix and evaluation metrics

6. Responsive UI with Streamlit

7. Lightweight model for fast inference

DESCRIPTION

HematoVision is a medical Al application built using Python, TensorFlow, and Streamlit. Users can upload

microscopic images, and the model classifies the blood cell type. It supports three deep learning architectures and provides accuracy-based feedback. The web app is user-friendly and suitable for clinical use.

SCENARIO

Dr. Ramesh, a rural healthcare worker, receives a patient's blood smear slide and uses HematoVision to upload the image. Within seconds, the system classifies the cell as a 'Neutrophil' with 94% confidence. This assists him in diagnosing the infection quickly and forwarding the report digitally. HematoVision enables fast triage and reduces dependency on expert pathologists.

TECHNICAL ARCHITECTURE

- Frontend: Streamlit web application with image upload UI
- Backend: Python-based classification using TensorFlow/Keras
- Models Used: ResNet50, VGG16, MobileNetV2
- Hosting: Streamlit sharing / Flask optional
- Flow: Upload -> Preprocess -> Predict -> Display Results

ER DIAGRAM

- No traditional ER diagram; however, the system architecture maps user input to model output via preprocessing and inference pipeline.

User -> Upload Image -> Resize/Normalize -> Predict Cell Type -> Show Output

SETUP PHASE

- 1. Google Colab for training models
- 2. Dataset from Kaggle (BCCD Dataset)
- 3. Libraries: TensorFlow, Keras, NumPy, Matplotlib, Streamlit

4. Training Image Size: 224x224

5. Deployment: Streamlit app with saved model (.h5)

PROJECT STRUCTURE

- model/: Contains trained model files

- app/: Streamlit scripts (main.py, utils.py)

- data/: Blood smear dataset

- notebooks/: Model training notebooks

- requirements.txt: Dependencies

APPLICATION FLOW

- 1. User uploads an image
- 2. Image is resized, normalized
- 3. Model performs inference
- 4. Prediction with class and confidence is shown
- 5. Metrics and heatmaps (if selected) are displayed

RESULTS & TESTING

- ResNet50 achieved highest accuracy (93.1%)
- Functional Testing: Uploads, outputs work
- Performance Testing: <2 seconds inference
- Visual Output: Confusion Matrix, Accuracy vs Epochs, Loss Graph

ADVANTAGES & LIMITATIONS

Advantages:

- Fast and accurate classification

- Minimal human intervention
- Web-friendly

Limitations:

- Sensitive to poor image quality
- Less accurate on rare cell types

CONCLUSION

HematoVision validates the power of Transfer Learning in medical diagnostics. With high classification accuracy and a simple web interface, it reduces time and effort in lab analysis. It is suitable for hospitals, clinics, and remote diagnostics.

FUTURE SCOPE

- Add leukemia subtypes
- Deploy on mobile with offline inference
- Integrate with microscopes via camera
- Include Grad-CAM visual explanations

TEAM DETAILS

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