HemeAI: Final Presentation

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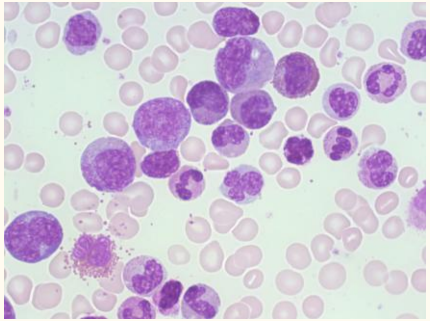
Introduction

- Complete blood counts (CBCs) are one of the most commonly ordered lab test
- Abnormal CBC results in a peripheral blood smear
    - Manual count of white blood cells and abnormalities
- Takes several days, critical in diagnostic process
- Limited in rural & developing areas

Abnormal CBC shows high WBC count

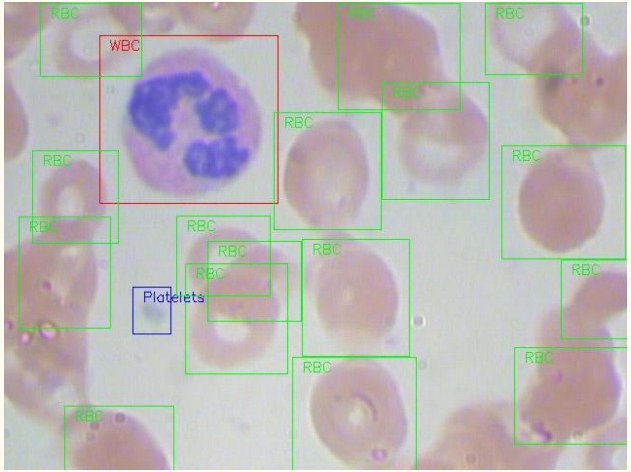


Peripheral Blood Smear Conducted

Diagnosis: Myelogenous Leukemia

Dataset #1

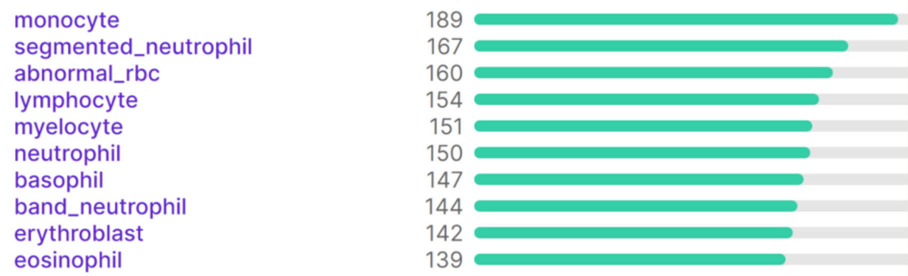
- Annotated dataset obtained from researchers from the Bangladesh University of Engineering and Technology (Alam et al.)
- Cell categories: white blood cells (WBCs), red blood cells (RBCs), and platelets
- The annotations were stored in XML format which were converted to YOLO-friendly plain text annotations

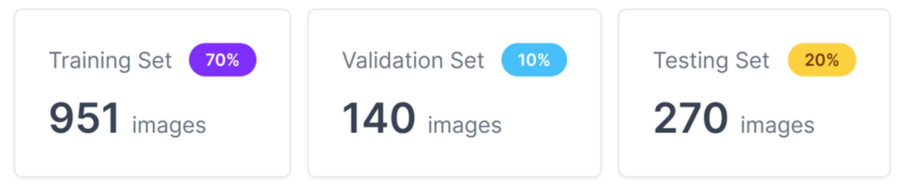


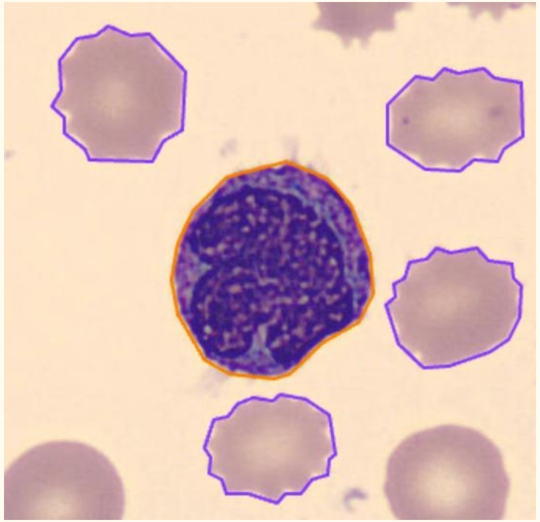
Training: 300 images
Testing: 64 images

Dataset #2

- Dataset obtained from researchers at the Hospital Clínic de Barcelona
- Cell categories: neutrophils, eosinophils, basophils, lymphocytes, monocytes, myelocytes, erythroblasts, and abnormal RBCs
- Annotated using Roboflow







Methods: AutoCBC

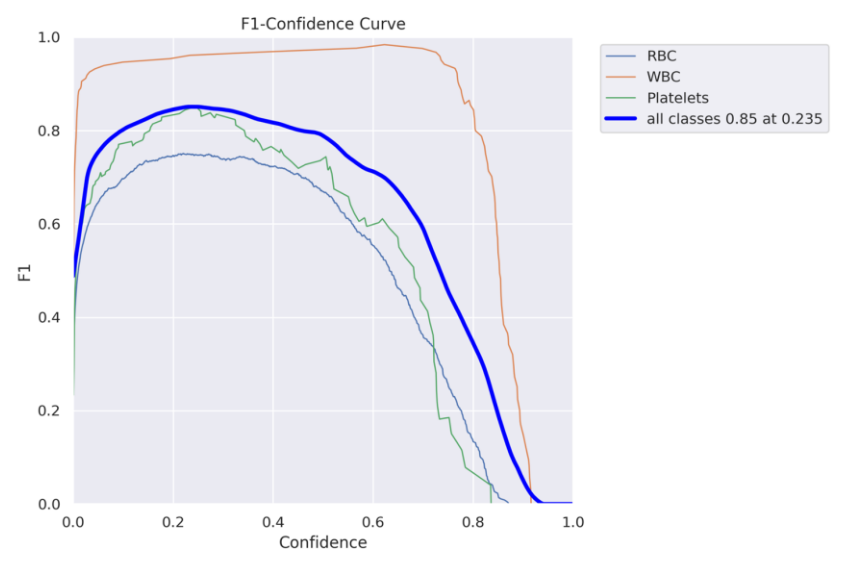
- **Object Detection**
  - Annotated dataset obtained from researchers from the Bangladesh University of Engineering and Technology (Alam et al.)
  - Retrained the pretrained YoloV8m model using our dataset using 50 epochs and Adam Optimizer.
  - Evaluated the evaluation metrics emitted by the model and overrode model parameters such as Confidence Threshold, NMS IoU Threshold, NMS class agnostic and Maximum detections on an image.
- **Ratio Calculation**
  - YOLOv8 does not have a built in function to obtain the count of the objects
  - Developed code to view the model predictions and count the frequency of each class

YOLO: You Only Look Once (Version 8)

- State-of-the-art object detection model
- Uses a single-stage detector with a fully convolutional network.
- Network consists of a backbone network and a detection head.
    - Backbone network used for feature extraction using a pretrained CNN called Darknet-53
    - Detection head predicts the object class and location using Feature Pyramids
- Significantly faster and more accurate than previous versions of YOLO
    - 540 FPS on RTX 4070 TI GPU
    - Faster because of larger feature map and more efficient CNN
- User-friendly API, allowing users to implement their applications easily

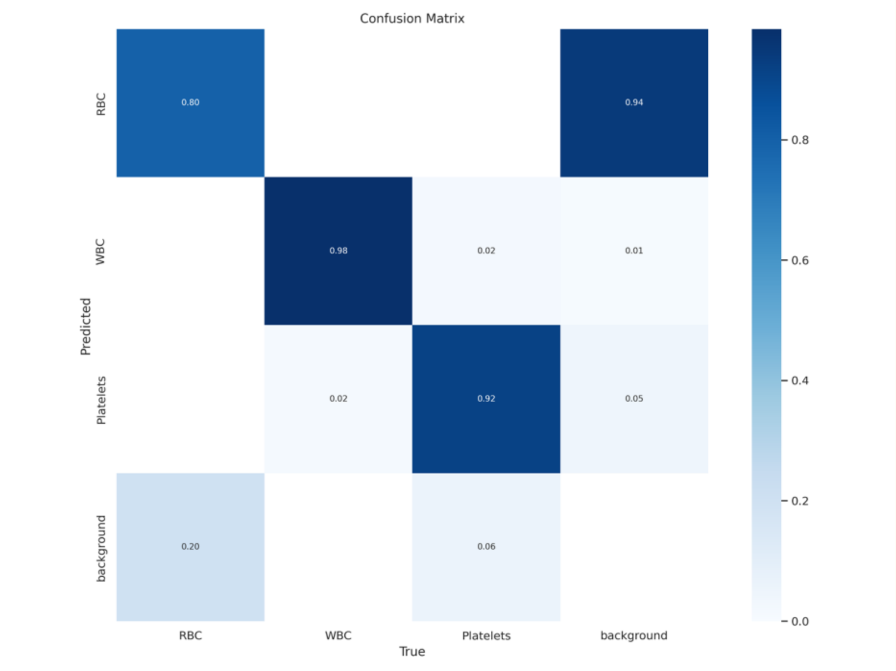
Results - F1 Score

- F1 scores can be used in determining the confidence that balances the precision and recall values for the given model, hence is a good indicator of the overall model performance.
- F1 score is a combination of Precision and Recall Values
- Optimal Confidence is 0.25



Results - Confusion Matrix

- Confusion Matrix used to identify the ratio of true positive, true negative, false positive, and false negative cases emitted by the model.
- can conclude that the model performs well. The ratio of true positives for RBC, WBC, and platelets is 0.80, 0.98, and 0.92
- Cause for concern: False Positive Ratio for Background

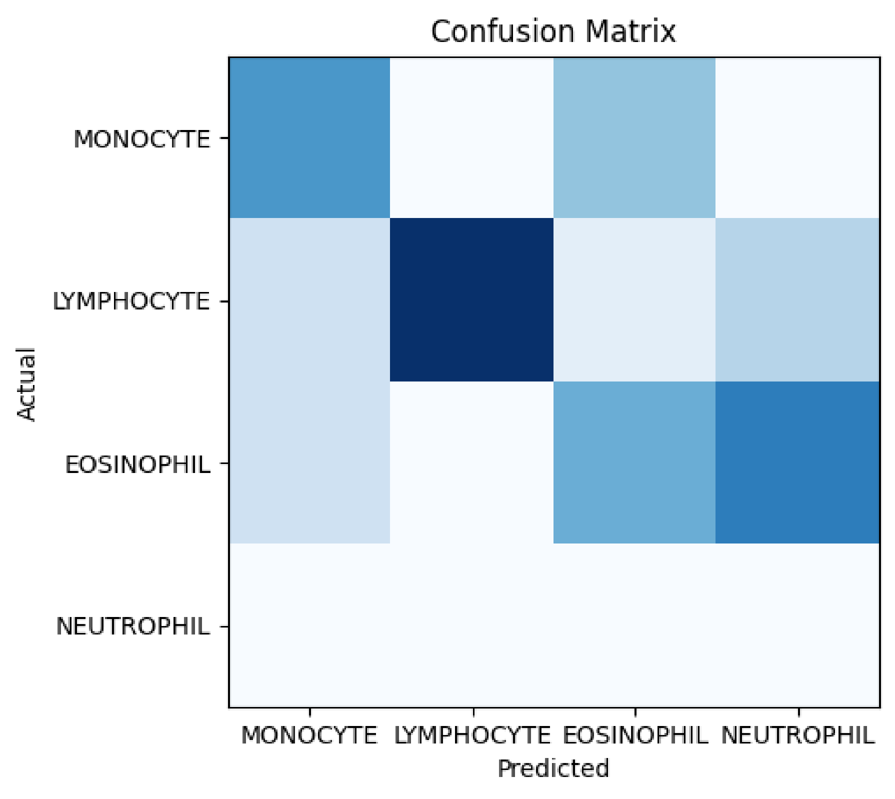


Methods: Disease Detection

- **Object Detection**
  - An Object Detection algorithm had to be used to identify certain characteristics of diseases.
  - Three models were considered for this task:
    - Resnet-50
    - RetinaNet
    - **YOLOv8 ← shows the best results**
- **Disease Diagnosis**
  - Using the classes obtained from Dataset #2, we diagnose from the following diseases:
    - Anemia
    - Thrombocytopenia
    - Allergic Reaction (Basophilia)
    - Fungal/Parasitic Infection (Eosinophilia)
    - Leukemia (lymphocytic and myelogenous)

ResNet

- Image classification algorithm
- 50-layer neural network
- Residual Neural Network
    - Variant of a CNN
    - 48 convolutional layers, 1 MaxPool layer & 1 average pooling layer
- Trained for 100 epochs
- Produced worse results than YOLO
- Accuracy: 0.53
    - Monocyte: 0.67
    - Lymphocyte: 1.00
    - Eosinophil: 0.50
    - Neutrophil: 0.00



RetinaNet

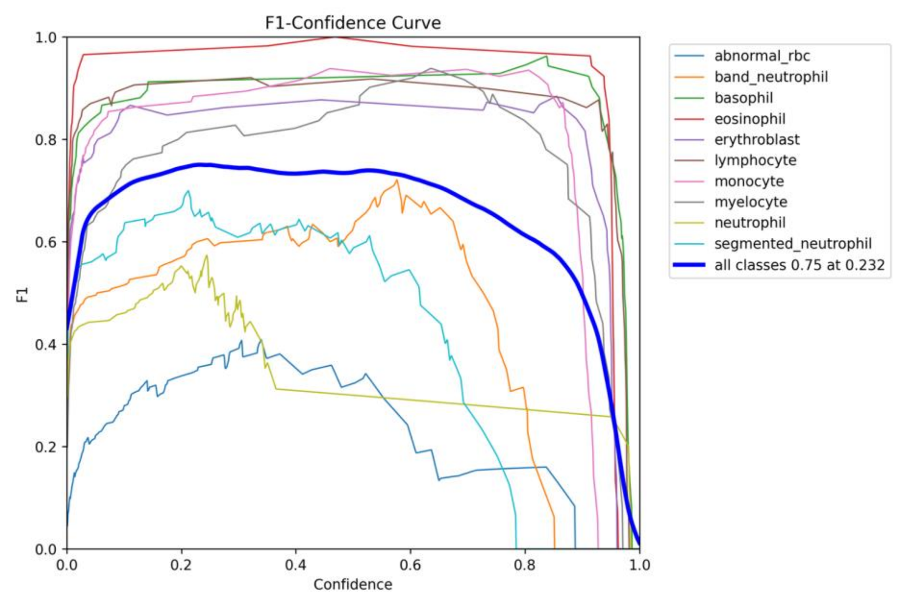
- An object detection algorithm that uses deep neural networks and feature pyramids
  - Feature pyramid is a representation of an image at different scales that allows detection of objects of different sizes, hence making the model more accurate that other object detection algorithms.
- Consists of a backbone network, a feature pyramid network, and two task-specific subnetworks - a classification subnet and a regression subnet.
- Focal Loss function is used to address class imbalance in object detection.
- Trained by optimizing the classification and regression subnetworks simultaneously
- Computationally Expensive

Results: RetinaNet

- No results were obtained using this model
  - Training time was too long
  - We were limited by the amount of GPU accelerators available
  - Model fails at epoch 53
- The following were the mAP for each class at the last epoch:
  - Monocyte: 0.99
  - Segmented Neutrophil: 0.67
  - Abnormal RBC: 0.36
  - Lymphocyte: 1.00
  - Neutrophil: 0.46
  - Band Neutrophil: 0.54
  - Myelocyte, Basophil, Eosinophil, Erythroblast: 0.00

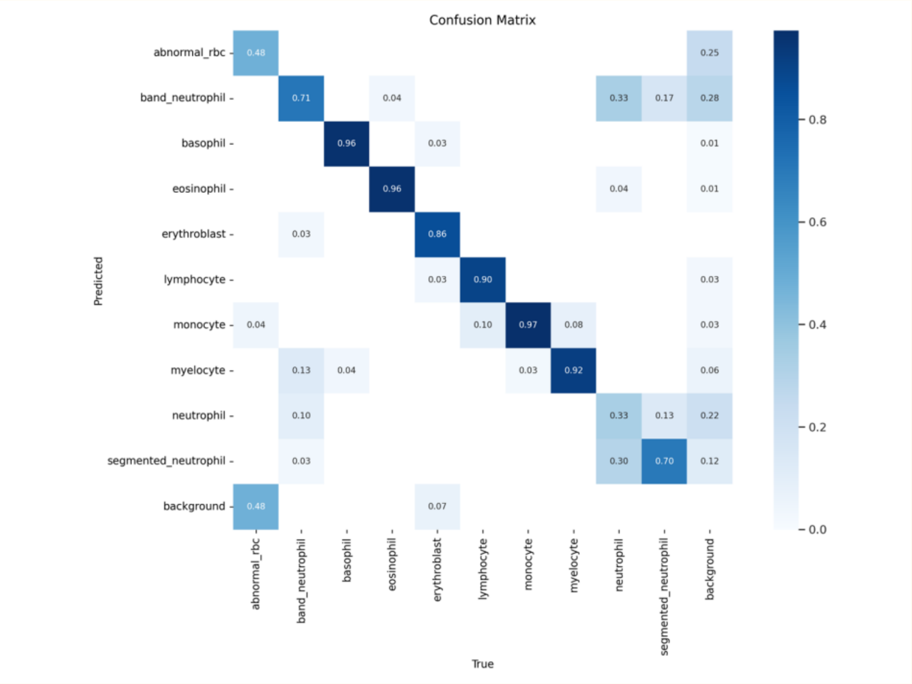
Results: YOLO (F1 Scores)

- The F1 - Curve shows that the neutrophil, segmented neutrophil, and the band neutrophil having a lesser confidence as well as abnormal RBCs.
- F1 Scores are a combination of precision and recall values making it a good indicator of model performance.
- Optimal confidence shows 0.25



Results: YOLO (Confusion Matrix)

- The Confusion Matrix shows ratio of true positives, true negatives, false positives, and false negatives.
- This confusion matrix performs well generally. This excludes the confusion between the three different neutrophils and it not being good at predicting abnormal rbcs.



Methods: Webpage

- Frontend: Javascript, CSS, HTML
  - React & Next.js
- Backend: Python (Flask)
- Application was containerized using Docker
- Developed k8 pods for the docker application
  - Kubernetes pods are hosted on https://cloud.cs.vt.edu

Demo

Novelty of Methods

- “Machine learning approach of automatic identification and counting of blood cells” is state of the art, able to automate a CBC using YOLO
- HemeAI takes it a step further
- Uses YOLO to perform a peripheral blood smear
- Also makes an initial diagnosis

Team Member Contributions: Ritvik Prabhu

- Project and technology research
- Data Cleaning and Feature Engineering
- Model training, fine tuning, model evaluation for AutoCBC
- Researched and developed code for alternatives to YOLO for milestone 2 .i.e RetinaNet
- Website Development - developed boiler plate code for the back end and front end
- Containerized the application using Docker
- Created k8 pods to deploy the application on https://cloud.cs.vt.edu

Team Member Contributions: Bhargav Iyer

- Dataset annotations for Milestone 2 disease detection using Roboflow
- Contributed in creating the docker file for the application
- Created a model using YOLO which includes model training, model fine tuning, and model evaluation.
- Contributed to the disease detection backend to find the different ratio of specific WBCs and abnormal RBCs as well as connected it to the frontend.

Team Member Contributions: Amrita Ballurkar

- Project and technology research
- Dataset research, acquisition and cleaning
- Image annotations using Roboflow
- Researched and developed code for alternatives to YOLO for milestone 2 .i.e ResNet
- Built frontend, worked on backend
- Built diagnostic capability of the website

References

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