

Comparative Evaluation of YOLOv5, YOLOv8, and YOLOv11 for Real-Time Leukemia Cell Detection in Blood Smear Images

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Abstract - This study compares and implements three deep learning-based object detection models, YOLOv5, YOLOv8, and YOLOv11, for the purpose of detecting leukemia cells in blood smear samples using image analysis via light microscopy. The primary aim of the study was to investigate the performance of the three models to assess their worth in targeting abnormal leukemia cells in peripheral blood, with the metrics of precision, recall, mean Average Precision (mAP) and inference time considered using the ALL-IDB1 dataset. YOLOv5 was selected to deploy the model for real-time use, primarily because it is lightweight, and has a high recall—theoretically at 1.0 recall, which is ideal in order to limit false negatives in medical diagnosis; despite YOLOv11 yielded higher accuracy and recall. A Flask-based web application was developed for ease of use that utilized supported standard upload of images, displayed the prediction on the input image, and monitored real-time detection while integrating YOLOv5 for the detection of leukemia cells in microscopic blood smear images. Through careful testing and system integration, a conclusion was outlined that considered the potential of YOLO-based models in improving early and accurate diagnosis of leukemia, while providing a novel and exciting platform for diagnosis/image analysis via real time methods.

Key Words: Leukemia Detection, YOLO, Object Detection, Deep Learning, Flask Application, Blood Smear Analysis, Medical Imaging

1.INTRODUCTION

The identification and classification of blood cells remain the primary determining factors for diagnosing leukemia alongside various other hematological diseases. The continuous rapid development of deep learning and computer vision technology makes automated medical image analysis diagnostics more practical by the day. The R-CNN family of algorithms together with its multiple versions ruled the object detection field since they delegated the classification process to one stage while

performing region suggestions in another stage. Medical applications operate with limited real-time functionality because these techniques possess long processing times along with complex designs although they deliver exceptional accuracy according to [9].

Detectors from the You Only Look Once (YOLO) family earned recognition for single-step detection and classification procedures at high accuracy speeds. The YOLO architecture demonstrates significant advancements from YOLOv5 through YOLOv11 because each version introduces improved feature extraction together with new attention mechanisms and loss functions [1] [7].

YOLOv5 has become the standard baseline approach for real-time object detection because it achieves high performance through its superior speed and operational precision [6]. Multiple research works show how this technology effectively detects blood cells and bearing defects [4] [8]. Scientists have introduced YOLOv8 and YOLOv10 and YOLOv11 variants with enhanced precision capabilities and improved speed of convergence in addition to better performance when detecting small or overlapping objects [1, 3, 7].

Medical researchers developed SDE-YOLO specifically for blood cell detection to handle dense and overlapping cells effectively in clinical environments [2]. A modified YOLOv5 approach boosted blood cell image detection outcomes showing YOLO-based architectures work well in medical image processing applications [8]. Real-time detection stands as essential according to [5] for Acute Lymphoblastic Leukemia (ALL) cell identification because it demonstrates the practical requirement for swift and accurate detection tools.

[1] conducted a broad comparative study which analyzed how structural design changes in YOLOv8 transformed into YOLOv11 and affected performance assessment. A study by

[3] dedicated its focus to analyzing YOLOv5n, YOLOv8n, and YOLOv11n with regards to their performance in blood cell classification tasks which shows their importance for medical applications. The three

leading models for real-time vision applications according to [7] include YOLOv5 and YOLOv8 and YOLOv10.

A performance evaluation uniting YOLOv5, YOLOv8, and YOLOv11 is presented in this paper regarding their application to medical diagnostics for leukemia cell detection despite ongoing model development and rising use scenarios. The project compares multiple essential metrics of these models before deploying them through a minimal web platform for providing real-time diagnostic tools.

2. LITERATURE SURVEY

The architectural evolution from YOLOv8 to YOLOv11 has been explored through extensive analysis of academic journals, official documentation, and source code. YOLOv8 is renowned for its anchor-free detection technology, which excels at small object recognition and multitasking. YOLOv9 introduced a flexible gradient data structure that eliminates information bottlenecks, while YOLOv10 brought NMS-free training, enhancing deployment efficiency, and incorporated a spatial-channel decoupled reduction technique to reduce computational overhead. YOLOv11, which introduced the C3k2 block, has managed to lower the number of parameters while retaining robust feature extraction capabilities [1].

A modified YOLOv5s-based detection algorithm was proposed in SDE-YOLO: A Novel Method for Blood Cell Detection to enhance blood cell detection accuracy. The approach integrates the Swin Transformer for improved feature extraction, optimizes the Path Aggregation Network (PANet) by reducing parameters, and replaces Euclidean Intersection over Union (EIOU) loss with Complete Intersection over Union (CIOU) to enhance convergence. This combination led to significant performance improvements, achieving a mean Average Precision (mAP) of 99.5% for white blood cells, 95.3% for red blood cells, and 93.3% for platelets, surpassing models like SSD, YOLOv4, and YOLOv5s [2].

The comparative performance of YOLOv5nu, YOLOv8n, and YOLOv11n in identifying and classifying red blood cells (RBCs), white blood cells (WBCs), and platelets was evaluated in A Comparative Analysis of YOLOv5nu, YOLOv8n, and YOLOv11n Models for Blood Cell Detection and Classification. YOLOv5nu achieved 96.8% precision and 94.5% recall, while YOLOv8n performed better with 97.3% precision and 95.1% recall. YOLOv11n showed the highest accuracy, with 98.5%

precision and 96.7% recall, indicating its potential for precise blood cell analysis in medical applications [3].

In the study of GRP-YOLOv5, improvements were made to the regular YOLOv5 model by adding the Gamma transformation and the ResC2Net module. These modifications enhanced the model's ability to capture small features, boosting precision without significantly lowering recall. Additionally, an adaptive anchor box selection method was introduced to minimize misclassification errors. Experimental results demonstrated that GRP-YOLOv5 outperformed the standard YOLOv5 model in terms of F1-score and mAP, making it more suitable for practical flaw detection [4].

In Real-time Detection of Acute Lymphoblastic Leukemia Cells Using Deep Learning, YOLOv5s was implemented for leukemia cell detection. The model achieved an impressive 97.2% accuracy and an inference speed of 80 frames per second (FPS), making it effective for real-time medical diagnostics. The model's high recall ensured minimal false negatives, which is crucial for accurate diagnosis [5].

YOLOv5 is known for its efficiency, accuracy, and speed in real-time object detection. It provides a scalable and adaptable architecture with various model variations (YOLOv5s, m, l, x), making it suitable for a wide range of applications. It has shown superior performance on benchmark datasets like COCO and PASCAL VOC, outperforming older models like YOLOv4, SSD, and Faster R-CNN. Its applications in real-time systems like autonomous driving, healthcare, and surveillance showcase its versatility [6].

The improvements in YOLOv5, YOLOv8, and YOLOv10 have significantly impacted the architecture and performance of real-time object detection models. YOLOv5 introduced CSPDarknet and mosaic augmentation to balance speed and accuracy, while YOLOv8 added an anchor-free design for better small object detection. YOLOv10 improved on this with large-kernel convolutions, spatial-channel decoupling, and NMS-free inference, enhancing both efficiency and accuracy [7].

The performance of three YOLO-based models—YOLOv5, YOLOv8, and YOLOv11—for the task of identifying leukaemia cells in microscopic blood smear images was assessed and contrasted in this study. YOLOv5 was chosen for real-time deployment because of

its lightweight design, ease of integration, and superior recall—all of which are critical in reducing false negatives in medical diagnostics—even though YOLOv11 demonstrated the highest overall accuracy and recall. The viability of using deep learning models for real-time leukemia detection is demonstrated by the successful integration of YOLOv5 into a Flask-based web application. With room for improvement and clinical adaptation, the results validate the efficacy of YOLO-based detectors in facilitating automated, early, and efficient leukemia diagnosis. [8].

3. METHODOLOGY

This section outlines the complete pipeline for developing the leukemia cell detection system, from data acquisition and preprocessing to model training and deployment in a web-based interface.

A. Dataset Collection and Annotation

The **ALL-IDB1** dataset was selected for its high-resolution microscopic blood smear images. The dataset contains images labeled with either Acute Lymphoblastic Leukemia (ALL) or healthy hematogones (HEM). Each image with leukemic cells includes centroid coordinates in the .xyc format. These centroids were converted into bounding boxes using *Roboflow*, enabling the dataset to be used for object detection tasks.

B. Data Preprocessing and Augmentation

To ensure the dataset was model-ready, the following preprocessing and augmentation techniques were applied:

- All images were resized to **640 × 640** pixels.
- Pixel normalization scaled all values to the range **[0, 1]**.
- Data augmentation techniques included HSV color shifts, random rotations ($\pm 15^\circ$), brightness and contrast variation, as well as horizontal and vertical flips.
- The dataset was split into **70% training**, **20% validation**, and **10% testing** subsets to ensure fair model evaluation.

C. Model Configuration and Training

Three YOLO variants—YOLOv5, YOLOv8, and YOLOv11—were trained for comparative analysis of detection performance. Each model was trained using PyTorch in a GPU-accelerated environment with the following configuration:

- Epochs: 100

- Batch Size: 16
- Image Size: 640×640
- Learning Rate: 0.01 (YOLOv5), 0.001 (YOLOv8/YOLOv11)
- Optimizer: SGD (YOLOv5), AdamW (YOLOv8/YOLOv11)

Performance was measured using the following metrics:

- a) Precision and Recall
- b) Mean Average Precision at IoU thresholds 0.5
- c) (mAP@50) and 0.5:0.95 (mAP@50:95)
- d) Inference Time per image

D. Backend Development

The YOLOv5 model was deployed using a Flask-based Python server. The backend was designed to:

- a. Accept image uploads through a RESTful API.
- b. Perform inference using the trained YOLOv5 model.
- c. Render results with bounding boxes and class labels on the image.
- d. Return detection results including the output image path
- e. and structured JSON data containing class-wise counts,
- f. confidence scores, and bounding box coordinates.

E. Frontend Interface

A simple, lightweight, and user-friendly web interface was developed using HTML, CSS, and JavaScript. Key features include:

- Image upload functionality for users.
- Side-by-side display of original and annotated output images.
- Display of statistics such as detected cell count, confidence scores, and class distribution.
- Interactive UI elements for improved usability and user experience.

F. System Workflow Summary

The end-to-end workflow of the system is summarized as follows:

- 1) User uploads a blood smear image via the web interface.
- 2) The Flask backend receives the image and processes it using the YOLOv5 model.
- 3) Detection results are rendered with bounding boxes and saved.

- 4) The processed image and detection statistics are returned to the frontend for display.

G. Experimental Results

The comparative evaluation of the three YOLO models is summarized in Table I. The metrics used include precision, recall, mean Average Precision at IoU thresholds 0.5 and 0.5:0.95, and inference time per image.

Table -1: Experimental Results of YOLO Models

Model	Precision	Recall	mAP@50	mAP@50:95	Time
YOLOv5	0.680	0.853	0.836	0.630	14.2 ms
YOLOv8	0.796	0.830	0.846	0.637	14.2 ms
YOLOv11	0.754	0.896	0.878	0.674	13.1 ms

With the highest overall accuracy and recall, YOLOv11 is perfect for clinical settings where reducing false negatives is crucial. YOLOv8 had a lower recall but a marginally better precision than YOLOv5. In spite of this, YOLOv5 was selected for deployment because of its high recall score, ease of use, and speed of integration—all of which are critical for lowering the number of missed leukemia detections. Additionally, YOLOv5 had established support for deployment on edge devices and integration with Flask.

4. RESULT SCREENSHOTS

To validate the performance of the system and visualize how detections appear in practice, we captured the output of the web application during real-time analysis of sample blood smear images.



A. Upload Interface

Screenshot 1 shows the web interface where users can upload blood smear images. It includes a drag-and-drop upload box, an interactive button to trigger cell detection, and placeholders for image preview.



Fig. 1: Screenshot 1

B. Detection Results

Screenshot 2 displays the results page where the original image and the annotated result image are shown side-by-side. Detected cells are highlighted with bounding boxes labeled as ALL or HEM, depending on classification. Below the image, a panel summarizes the number of cells detected, class distribution, average confidence, and highest confidence scores.

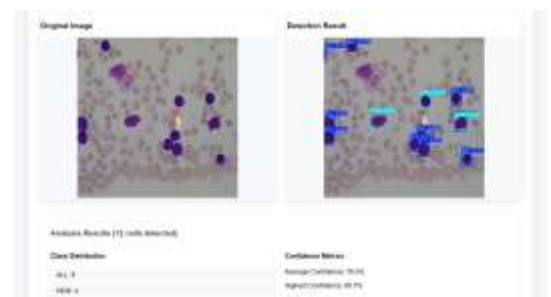


Fig. 2: Screenshot 2

C. Detection Insights

Screenshot 3 shows a detailed breakdown of individual detections, including:

- Cell type (ALL or HEM)
- Confidence level in percentage
- BBox (bounding box) coordinates



Fig. 3: Screenshot 3

3. CONCLUSIONS

Three YOLO-based models—YOLOv5, YOLOv8, and YOLOv11—that are used to identify leukemia cells in microscopic blood smear images are described and their architectures compared in this study. The latest development in the YOLO series, YOLOv11, achieves the highest overall accuracy by introducing enhanced feature extraction and attention mechanisms. With its modular design, YOLOv8 provides a fair compromise between speed and accuracy. But YOLOv5, which is renowned for its lightweight design and simplicity of use, beat the others in terms of recall for identifying ALL (acute lymphoblastic leukemia) cells. This makes it particularly useful in reducing false negatives, which are a critical component of medical diagnosis. It was chosen for real-time deployment via a Flask-based web application due to its exceptional recall and dependable performance. The integration's success validates that using deep learning-based object detection systems for early, automated, and efficient leukemia detection, with scope for future clinical adaptation and enhancement

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