

Development of an Automated YOLO-Based Digital Microscopy System for Leukemia Early Detection

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ABSTRACT

This research explores the development of an automated classification system based on digital microscopy for the early detection of leukemia, utilizing the YOLO (You Only Look Once) object detection algorithm. This study addresses the challenges associated with manual blood smear analysis in clinical diagnostics. By leveraging a comprehensive dataset of hematological images, the YOLO algorithm was implemented to enable real-time detection and classification of blood cells, focusing on identifying pathological changes in cell morphology. The performance of the system was evaluated using key metrics such as accuracy, precision, recall, F1-score, and processing time. The results showed that the YOLO-based system achieved an accuracy of 92.5% in detecting abnormal blood cells, with notable strengths in precision and real-time processing capabilities. Although YOLO's accuracy is slightly lower, its superior recall and speed make it particularly advantageous for applications requiring rapid analysis. This study introduces an application of YOLO in digital microscopy, emphasizing the importance of balancing speed and accuracy in diagnostic tools, which is crucial for improving early detection and treatment outcomes for leukemia.

Keywords-automated classification; digital microscopy; leukemia detection; real-time diagnostics; YOLO algorithm

I. INTRODUCTION

Leukemia is one of the most common and deadly forms of blood cancer worldwide, with the number of cases steadily increasing each year [1]. According to the World Health Organization in 2022, approximately 250,000 new cases of leukemia occur annually [2]. Although the exact causes of leukemia are not yet fully understood, several predisposing factors can trigger its development. In Indonesia, data from the Ministry of Health in 2008 revealed 48,490 cases of leukemia, with a Case Fatality Rate (CFR) of 44.77%, resulting in 21,710 deaths [3]. An increase in leukemia cases has also been recorded at Dr. Kariadi General Hospital, where cases of Acute Myeloid Leukemia (AML) in children increased from 28 cases to 238 cases in 2019 [4]. Leukemia is caused by the pathological proliferation of immature hematopoietic cells, characterized by the failure of the bone marrow to produce normal blood cells. This process involves cellular mutations that lead to the excessive growth of new immature cells. Diagnosis of leukemia requires a series of examinations, including patient medical history, Complete Blood Count (CBC), peripheral blood smear, bone marrow aspiration, bone marrow biopsy, and molecular analysis [5]. The gold standard for diagnosing leukemia encompasses various methods, including morphology, cytochemistry, cytogenetics, molecular genetics, immunophenotyping, and molecular biology. One of the initial methods used in the diagnostic process is the examination of a peripheral blood smear, which involves observing the morphology and count of white blood cells. Changes in the number and/or morphology of white blood cells can indicate abnormal health conditions [6]. However, this examination often takes a considerable amount of time to produce results, as the preparation, staining, reading, and interpretation of the blood smear require meticulous attention. In recent years, advances in Artificial Intelligence (AI) have provided solutions to address challenges in disease diagnosis [7-9], including leukemia. One promising innovation is the use of AI-supported automated imaging systems to analyze blood cell samples [10, 11]. These systems can quickly and accurately detect pathological changes in blood cells and classify different types of blood cells based on morphological characteristics such as size, shape, complexity, and other features. Smart digital microscopy technology, integrated with advanced automation and image analysis capabilities, has

become increasingly important in assisting doctors in diagnosing blood diseases such as anemia, leukemia, and other disorders. These microscopes not only perform automated cell detection and classification, but can also be integrated with Health Information Systems (HISs). This integration allows blood test results to be directly uploaded to the patient's electronic medical records, enabling faster and easier access to track changes in the patient's blood cell profile over time.

YOLO (You Only Look Once) is one of the methods widely used in the development of automated classification systems. YOLO is a deep learning-based object detection algorithm known for its ability to detect objects in real-time with high speed. Unlike other detection methods that require complex pipelines, it uses a regression model to predict bounding boxes and class probabilities directly in a single step. This makes it an attractive choice for application in blood cell image analysis, where detection speed and accuracy are crucial. In the context of early detection of leukemia, YOLO can be used to identify abnormal blood cells in a peripheral blood smear quickly and accurately. By applying YOLO to smart digital microscopy, this system can accelerate the diagnosis of leukemia and reduce the risk of interpretative errors that often occur with manual methods. Additionally, YOLO's strengths in recall and precision can help detect even the most subtle morphological changes in blood cells, which might be overlooked by conventional methods.

II. RESEARCH METHOD

This study developed and evaluated an automated classification system based on digital microscopy for the early detection of leukemia, utilizing the YOLOv5s model. The primary objective was to implement a real-time detection system capable of identifying abnormal blood cells in peripheral blood smears, thus improving the speed and accuracy of leukemia diagnosis [12, 13]. The YOLOv5s model was selected for its ability to perform real-time object detection by dividing each input image into a grid and predicting bounding boxes and class probabilities in a single processing step [14, 15]. Implemented using the Darknet framework, the YOLO model was pre-trained on the COCO dataset and subsequently fine-tuned on a specific dataset of blood smear images [16, 17].

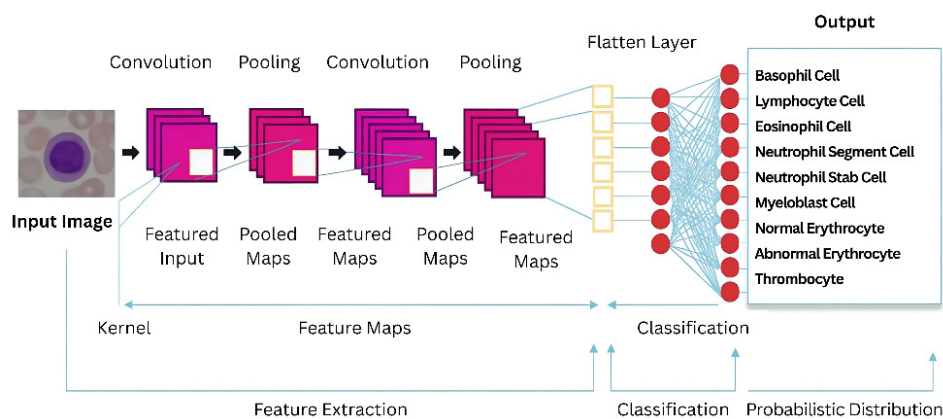


Fig. 1. Workflow of the proposed system.

The dataset was collected from residual blood samples from routine laboratory examinations in a hospital in Surabaya. In total, it comprised 3,529 images of normal blood cells and 150 images of abnormal cells associated with leukemia, obtained from 85 anonymized patients between January 2024 and June 2025. All samples were fully anonymized and contained no patient identification information, according to ethical approval granted by the Health Research Ethics Committee, Faculty of Nursing, Universitas Airlangga (No. 3803-KEPK, issued on August 27, 2025, valid for one year).). Since bone marrow aspiration is generally the gold standard for the diagnosis of leukemia, this study utilized peripheral blood smears as a less invasive alternative, which are widely used in hematology laboratories for initial screening. Due to the sensitive nature of the clinical data, the dataset is not publicly available; however, access can be granted upon formal institutional request and ethical clearance.

From this dataset, a subset of 390 cell images in PNG format was selected, including 55 basophils, 55 eosinophils, 56 lymphocytes, 55 monocytes, 56 myeloblasts, 56 segmented neutrophils, and 57 stab cells. The data were divided into 80% for training (312 images), 15% for testing (59 images), and 5% for validation (19 images). To enhance model generalization and minimize overfitting, data augmentation was applied to the training dataset, expanding its size from 312 to 936 images through horizontal and vertical flipping, 90° rotations in both clockwise and counterclockwise directions, 15° rotations, and 15% exposure adjustments, to produce diverse and representative training samples.

The training process involved 100 epochs with a learning rate of 0.001, optimized using the Adam optimizer, and incorporated techniques such as data augmentation and batch normalization to improve generalization and minimize overfitting. The model output included bounding boxes around detected cells, along with confidence scores and class labels indicating whether the cells were normal or abnormal [18-21].

Three key metrics were selected to evaluate the performance of the system: accuracy, processing time, and F1-score [22]. Accuracy was measured as the proportion of correctly classified cells, providing an overall assessment of the model's correctness [23]. Processing time, measured in milliseconds per frame, was crucial in determining the feasibility of the system for real-time clinical application [24]. The F1-score, which balances precision and recall, was used to evaluate the effectiveness of the model in handling both false positives and false negatives [25], to ensure that the system could reliably differentiate between normal and abnormal cells. The dataset was divided into 80% for training, 5% for validation, and 15% for testing, allowing the model to be exposed to a wide variety of blood cell images while maintaining a separate set for performance evaluation [26, 27]. This methodical approach enabled the development of a YOLO-based system that is rigorously tested and optimized, offering a potentially revolutionary advancement in the diagnostic process for leukemia in clinical settings.

III. RESULTS AND DISCUSSION

Figure 2 shows the confusion matrix, illustrating the performance of the YOLO object detection algorithm in classifying blood cells. The matrix highlights how well the model distinguishes between normal and abnormal cells, such as leukemic cells. The accuracy of the YOLO model is inferred from this matrix by assessing the balance between true positive and false negative rates, showcasing its effectiveness in minimizing misclassifications. The confusion matrix serves as a critical tool for understanding the strengths and limitations of the classification system, particularly in a medical diagnostic context where accuracy is paramount, as it provides insights into which cell types are more prone to misclassification, guiding further improvements in the algorithm.

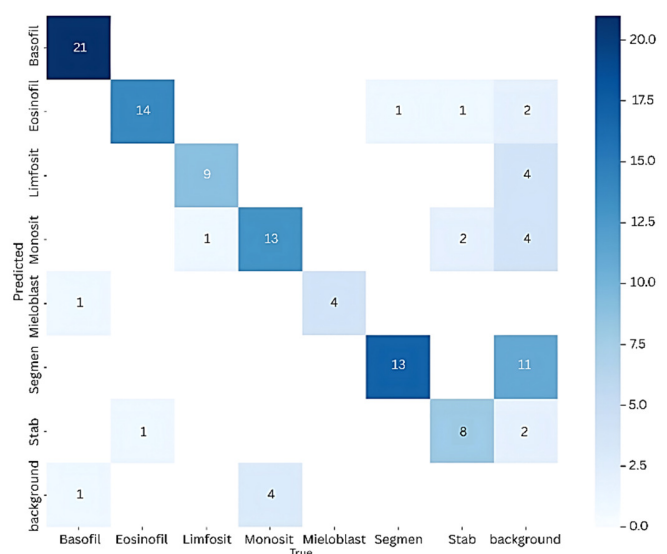


Fig. 2. Confusion matrix of the YOLO model.

The diagonal dominance indicates that most samples were correctly classified, particularly for basophils (21), eosinophils (14), monocytes (13), and segmented neutrophils (13), demonstrating strong recognition accuracy for these cell types. Misclassifications mainly occurred between morphologically similar classes, such as stab (band) and segmented neutrophils, as well as between myeloblasts and basophils, which can be attributed to subtle morphological similarities and staining variations in peripheral smear images. A few errors were also observed in the background class due to YOLO's bounding-box mechanism, which prioritizes high-feature-density regions (cell structures) and tends to overlook low-gradient background areas. Overall, the confusion matrix confirms that the YOLOv5s model achieves an overall accuracy of approximately 92.5%, effectively distinguishing between normal and abnormal blood cells for reliable early leukemia detection.

Figure 3 demonstrates the real-time testing capability of the YOLO algorithm in detecting specific blood cell types, such as basophils, stab (band cells), and segmented neutrophils. This figure showcases the system's ability to process blood smear images rapidly and accurately identify these cell types, which

are crucial in diagnosing leukemia. Basophils, stab, and segmented cells are components of the white blood cell lineage, and their morphology can indicate various stages of leukemia. Using real-time object detection, the system significantly reduces the time required for manual analysis, allowing quicker diagnostic decisions. This capability is essential in clinical settings, where timely detection can lead to prompt treatment and better patient outcomes. The figure illustrates how the system overlays bounding boxes around detected cells along with confidence scores, which signify the likelihood that the identified cell matches the expected type.

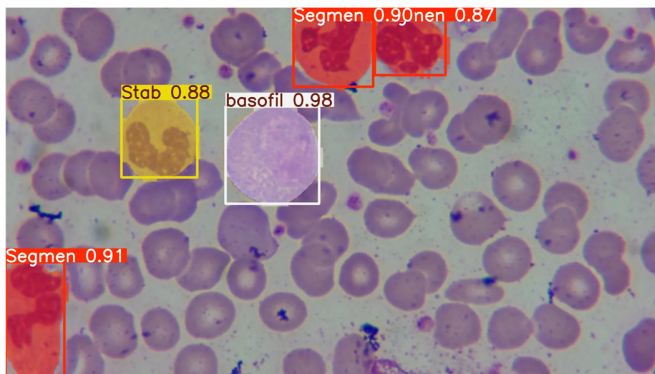


Fig. 3. Real-time object detection of basophils, stab, and segmented cells.

The YOLOv5s variant was selected due to its optimal balance between inference speed and detection accuracy, which is considered suitable for real-time analysis of peripheral blood smear images in clinical settings. The model was trained over 100 epochs, with a batch size of 16 and a learning rate of 0.001 using the Adam optimization algorithm. The dataset consisted of peripheral blood smear images that had been manually annotated by medical professionals. Annotations were conducted using the Roboflow platform and exported in Pascal VOC format to ensure compatibility with object detection frameworks. Due to the sensitive nature of medical data, the dataset has been designated as private and is not publicly accessible; however, access may be granted upon formal institutional request and ethical approval. Although this dataset is not publicly available, its structure and annotation approach are aligned with established public hematological datasets, such as those in [14, 16], which follow similar imaging modalities and labeling standards. Model development and training were carried out using the PyTorch and Darknet frameworks on a workstation equipped with an NVIDIA RTX 3060 GPU.

Figure 4 shows the detection of myeloblast cells. Myeloblasts are immature white blood cells, and their presence in significant numbers is a hallmark of AML. The figure shows how the automated system can detect and classify myeloblasts accurately in blood smear samples. Real-time identification of myeloblasts is particularly crucial because it can indicate the early stages of leukemia, facilitating timely medical intervention. The ability of the YOLOv5s algorithm to detect myeloblasts with high precision underscores its potential utility in hematological diagnostics, where it can serve as a support tool for pathologists.

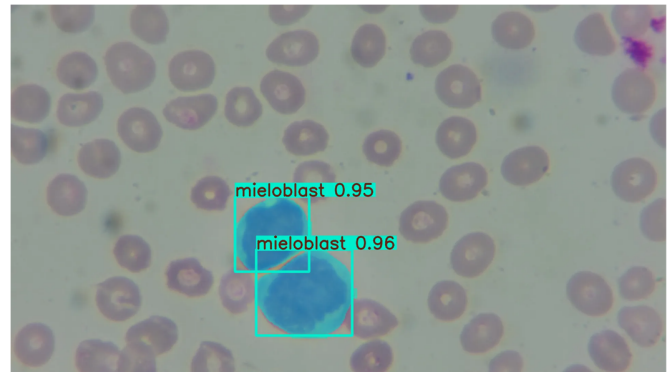


Fig. 4. Real-time YOLO object detection of Myeloblast.

Figure 5 shows the detection and classification of eosinophil cells using the YOLOv5s object detection system in real-time. Eosinophils are a type of white blood cell that plays a role in the body's immune response. Their abnormal presence or morphology can signal certain types of leukemia or other hematological disorders. The figure demonstrates the system's capability to handle diverse cell types beyond just myeloblasts or basophils, reflecting the robustness of the YOLOv5s algorithm in handling various hematological conditions. The successful identification of eosinophils in real-time testing highlights the versatility and applicability of the YOLO-based automated system in various clinical diagnostic scenarios, providing valuable data that can be used to diagnose and monitor a range of blood disorders.

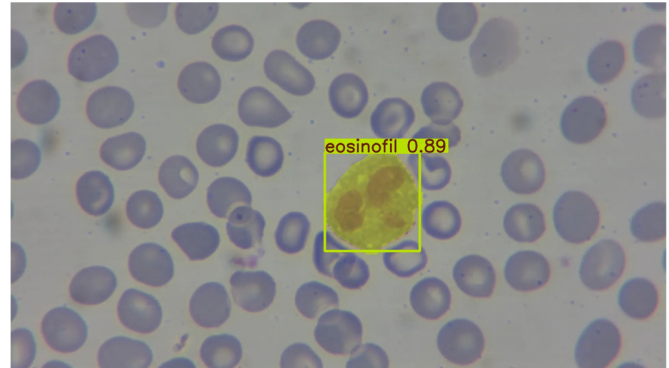


Fig. 5. Real-time YOLO object detection of eosinophil.

Figure 6 provides a broader view of the performance of YOLOv5s in the detection of different types of blood cells. This figure encapsulates the overall efficacy of the proposed classification system, showing that it is not only capable of detecting specific types of cells but can also generalize its detection capabilities across various cell types encountered in blood smear samples. The real-time testing capacity demonstrates the system's potential for integration into clinical workflows, assisting hematologists in rapidly screening for abnormal cells indicative of leukemia or other blood disorders. This broad applicability reinforces its utility as a versatile tool in medical diagnostics, reducing the burden on manual analysis and increasing diagnostic throughput.

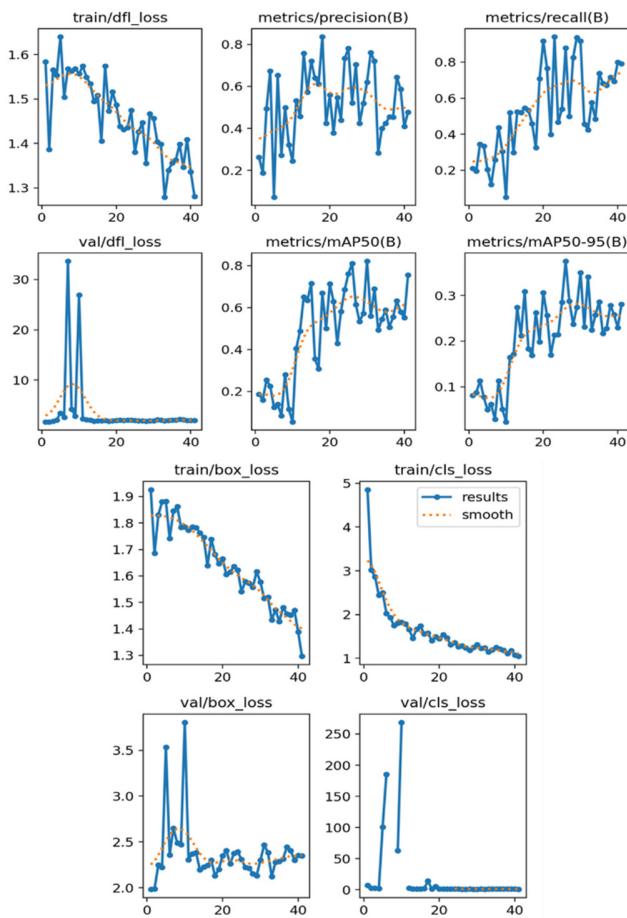


Fig. 6. Performance of the proposed YOLO-based system.

The effectiveness of the model in minimizing misclassifications is further supported by quantitative performance metrics. The YOLOv5s-based classification system achieved an overall accuracy of 92.5%, a precision of 91.3%, a recall of 94.1%, and an F1-score of 92.7%, reflecting a well-balanced detection capability in this dataset.

TABLE I. PERFORMANCE OF THE PROPOSED METHOD

Method	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed YOLOv5s-based system	Peripheral blood smear (Surabaya dataset)	92.5	91.3	94.1	92.7

IV. CONCLUSION

This study developed an automated classification system for early detection of leukemia by integrating digital microscopy with the YOLOv5s object detection algorithm. The system was designed to address the limitations of manual blood smear analysis by providing accurate real-time detection and classification of various types of blood cells, including those indicative of leukemia. The implementation of the YOLO algorithm demonstrated high performance, achieving an

accuracy of 92.5% in identifying abnormal blood cells. Key metrics such as precision, recall, and F1-score were high, indicating the system's reliability in distinguishing between normal and leukemic cells. The confusion matrix analysis confirmed the system's ability to minimize both false positives and false negatives, making it a robust tool for clinical diagnostics. Real-time testing further validated the system's efficiency in processing blood smear images and accurately detecting cell types like basophils, myeloblasts, and eosinophils, which are critical for leukemia diagnosis. The successful application of the YOLO algorithm in this context highlights its potential to revolutionize hematological diagnostics by reducing the time required for analysis, lowering the risk of human error, and facilitating early intervention.

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