# Detection and Sub-classification of Acute lymphoblastic leukemia Cell Types from the Microscopic Images Based on The Object Detection Model YOLOV5

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***Abstract*— Acute lymphoblastic leukemia (ALL), a disease that is quite common, necessitates invasive, costly, and time consuming diagnostic procedures for a final diagnosis. The early classification of cancer cases from noncancerous samples plays a crucial role in ALL detection utilizing peripheral blood smear (PBS) images. Due to the general character of all signs and symptoms, misdiagnosis is a common concern when these PBS images are analyzed by laboratory. This research highlights the successful application of the YOLOv5 object detection model in detecting ALL cells and classify it into four distinct types, achieving 97.8%, 96%, 96.7%, accuracy, precision, and recall respectively using an ALL image dataset after adding the bounding boxes manually. Moreover, a comparison is conducted among three popular convolution neural network (CNN) models, namely GoogleNet, ResNet, and AlexNet, alongside YOLOv5 using the ALL dataset. The results clearly demonstrate that YOLOv5 model outperforms the other CNN models, further confirming its superiority in ALL detection.**

***Keywords*— *Acute lymphoblastic leukemia (ALL), AlexNet, blood cancer, CNN, GoogleNet, Object detection, ResNet, YOLOV5***

## I. INTRODUCTION

Acute lymphoblastic leukemia (ALL) is a malignancy of B or T-lymphoblasts characterized by uncontrolled proliferation of abnormal, immature lymphocytes and their progenitors which ultimately leads to the replacement of bone marrow elements and other lymphoid organs resulting in a characteristic disease pattern [1]. To illustrate, Health issues including leukemia, thalassemia, and anemia can result from an increase or reduction in any of the fundamental blood components.

ALL, chronic lymphocytic leukemia, acute myeloblastic leukemia, and chronic myeloblastic leukemia are the four categories according to their development, pace, and effects. The most prevalent and lethal of them is ALL, which accounts for 70% of all instances of leukemia. The progression of the illness is also significantly influenced by environmental and genetic variables. ALL is brought on by the bone marrow's excessive and unchecked multiplication of lymphocytes [2].

ALL is becoming more common within the healthcare system every year, with 64.2 thousand new cases of ALL diagnosed globally between 1990 and 2017. The most common form of leukemia in kids is ALL, which also has a high prevalence in adults [4].

The difficulty in making an early diagnosis of lymphocytes stems from the similarities between normal and lymphoid cell types. As a result, lymphocytes were divided into three groups: reactive, atypical, and normal. The lymphocyte types are identified by microscopic examination, which requires the collection of blood or bone marrow samples for a pathologist to analyze [5].

Obtaining and analyzing bone marrow samples are crucial for diagnosing leukemia accurately. However, manual analysis is laborious, time-consuming, and reliant on pathologists' expertise, leading to potential human errors. Automated recognition of blood cell images enables quick and accurate diagnoses, facilitating evaluation of multiple cells per individual. [6].

Numerous researches were studied for implementing deep learning models to detect and classify various types of All, as in [7]. Advanced algorithms such as the You Only Look Once (YOLO) algorithm provide real-time and accurate detection of objects, including cancer cells, within images.

Implementing YOLO models for image-level classification can aid in diagnosing ALL. These models integrate object detection and instance segmentation techniques, eliminating the need for separate stages such as WBC segmentation and feature extraction. This streamlines the process, making it quicker and simpler to support expertise in diagnosing ALL [8], [9].

Fatichah et al. [8], used YOLO and Mask R-CNN (Region-based Convolutional Neural Network) models for the detection of ALL subtypes, the results showed that YOLO model outperformed Mask R-CNN model.

Emma Chen et al. [9], used YOLOv5, YOLOv6, and YOLOv7 models for real-time detection of leukemic cells, the results showed that YOLOv5 model outperformed YOLOv6 and YOLOv7 models.

The most suitable object detection technique for cancer cell identification is YOLOv5 framework. The post-

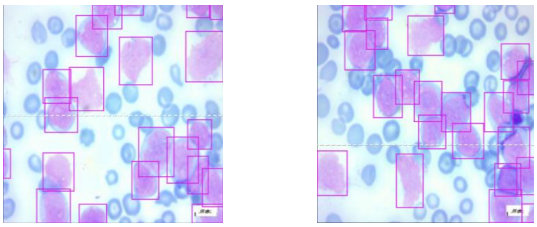


Fig. 1. Samples from ALL images after adding the bounding boxes manually.

processing module in the YOLOv5 framework plays a crucial role in refining the object detection results and improving the overall accuracy of cancer cell identification. So, an accurate and effective YOLOv5 object detection model introduced in this work is used to detect ALL and classify it into four distinct types. It offers advantages in terms of efficiency, accuracy, and streamlining the diagnostic process, ultimately supporting healthcare professionals in diagnosing and treating cancer subtypes more effectively.

The YOLO (You Only Look Once) object detection algorithm treats object detection as a regression problem, predicting bounding boxes and class probabilities directly from input images in a single pass. Unlike other approaches, it uses a sophisticated architecture with a backbone network for feature extraction and multiple detection heads for processing different scales and resolutions of feature maps, enabling accurate detection of objects of varying sizes. While YOLOv5 isn't pre-trained on the ALL Image Dataset, bounding boxes can be manually set, and the model can be trained using platforms like Roboflow.

The rest of this paper is organized as follows: in section two, materials and methods are introduced, whereas results and discussion in section three. Finally, the conclusion is given in section four.

## II. MATERIALS AND METHODS

This section displays the methods used to analyze ALL image dataset for early detection of lymphoblastic leukemia.

### A. Dataset description

This study evaluates an object detection model specifically on the ALL image dataset [10] provided by Taleqani Hospital's bone marrow laboratory in Tehran, Iran. The dataset consists of 3256 PBS pictures from 89 individuals suspected of having ALL, with blood samples processed and stained by professional laboratory personnel. It is divided into benign and malignant classes, with the latter including Early Pre-B, Pre-B, and Pro-B ALL subtypes. Images were captured using a Zeiss camera at 100x magnification and saved as JPG files. Cell types and subtypes were identified by a professional

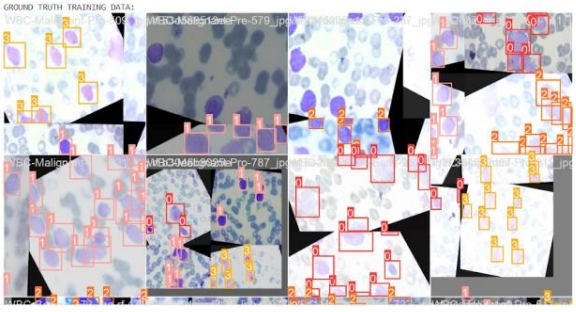


Fig. 2. Ground truth training data.

using flow cytometry instrumentation. Figure 1 illustrates samples from the dataset. [10].

### B. Image Enhancement

Image preprocessing and augmentation are two of the most powerful tools that if used correctly it can enhance the image quality hence the results to great extent [11]. Therefore, for original dataset some preprocessing techniques were applied for better accuracy. Zoom 10%, rotation 10, brightness was set randomly from 0.8 to 1.5, and vertical flip and horizontal flip were applied. Moreover, images width and height were set to 224 and rescaled to 1/255.0.

### C. Object detection and YOLOv5

Object detection is a computer vision task that involves identifying and localizing specific objects within an image or a video. The goal of object detection is to not only determine the presence of objects in an image but also to accurately delineate their boundaries or regions of interest [12]. There are various approaches to object detection, including region-based methods, sliding window methods, and single-shot methods. Single-shot methods, such as YOLO and Single Shot MultiBox Detector (SSD), directly predict object bounding boxes and class labels in a single pass over the image.

### D. Training

We trained the network using segmented cells to enhance its ability to identify lymphoblast cells, but found that this approach led to a loss of important information compared to using original images alone. To address this, we employed both original images and segmented cells as inputs. Each input sample comprised an image pair containing both versions of the same image. These were divided into training, testing, and validation sets (64%, 20%, and 16% respectively), with 2083, 652, and 521 paired samples in each set, totaling 3256 across all sets. This allocation aimed to create a balanced dataset for training and evaluating the model's accuracy and generalization capabilities.

TABLE I. LIST OF STUDIES TO CLASSIFY AND DETECT ALL AND ALL SUBTYPES.

| Priowork | The used model | mAP |
|---|---|---|
| **[9]** | YOLOv7 | 73.7% |
| **[9]** | YOLOv6 | 64.4% |
| **[9]** | YOLOv5 | 85.3% |
| **[9]** | YOLOv5s | 97.2% |
| **[8]** | YOLOv4 | 93.2% |
| **Proposed** | YOLOv5 | 97.8 % |

Figure 2 displays training images with true labels before inference.

## III. RESULTS AND DISCUSSION

The effectiveness of the suggested method is assessed through different techniques and the findings are presented in this section.

### A. Parameter tuning

All the parameters started operating with random weights for network training. The batch size, number of epochs, and learning rate in the suggested technique were set to 32, 100, and 1e-3, respectively. The classes were weighted

proportionately to the number of samples in order to address the issue of unbalanced data. The use of the Adam optimizer with a 1e-3 starting learning rate helped the gradient descent process perform better.

### *B. Evaluation metrics*

Many experiments were conducted to evaluate the effectiveness of the proposed detection and classification model in detecting ALL cells.

In this study, clinically significant statistical parameters like precision, recall, and mean average precision (mAP) are used to assess the performance of the proposed detection and classification model.

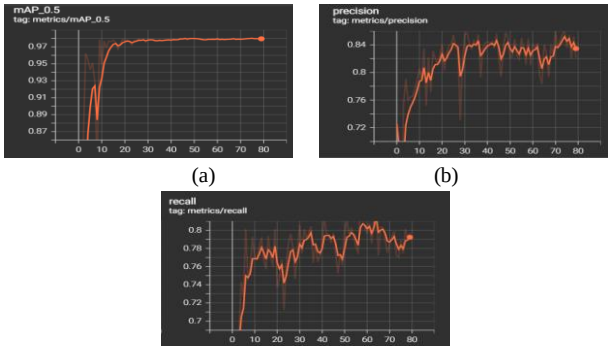
The proposed model achieves remarkable classification accuracy with mAP of 97.8%, recall of 96.7%, and precision of 96%. Fig. 3 illustrates the training graph of proposed YOLOv5 object detection model. Fig. 4 shows the visual representations for the results. Our results show that, the high mAP score reflects the consistent and accurate localization and classification of ALL cells into the four subtypes within the microscopic images. The recall score demonstrates the model's ability to identify the majority of positive cases. Additionally, the precision score highlights the model's capability to minimize false positives, resulting in a high degree of accuracy in classifying the different types of ALL cells.

To examine the ability and performance of the YOLOv5 model in detecting ALL cells and classify it, the three popular convolution neural network (CNN) models, GoogleNet, ResNet, and AlexNet, are implemented using the same benchmark ALL dataset. The results clearly demonstrate that YOLOv5 model outperforms the other CNN models, as listed in Table II.

## IV. CONCLUSION

This study has successfully demonstrated the effectiveness of YOLOv5, an object detection model, in accurately detecting Acute lymphoblastic leukemia (ALL) and classifying it into four distinct types. The model achieved remarkable classification accuracy with mAP of 97.8%, recall of 96.7%, and precision of 96%. The three popular convolution neural network (CNN) models, GoogleNet, AlexNet and ResNet were implemented using the same benchmark ALL dataset. The GoogleNet, AlexNet and ResNet exhibited 95.3%, 95.7%, 96.3% mPA, 95.5%, 95.1%, 95.9% recall, 95.3%, 95.7%, 96.3% mPA, 95.7%, 94.9%, 95.8% precision, respectively. The results clearly demonstrate that YOLOv5 model outperformed the other CNN models, further confirming its superiority in ALL detection.

The core module of the YOLOv5 model lies in its object detection algorithm, which is responsible for accurately localizing and classifying cancer cells within biopsy images. These outstanding results underline the potential of YOLOv5 as a valuable tool for precise and efficient ALL detection, classification, and subsequent treatment planning. The model's high accuracy provides confidence in its ability to assist medical professionals in accurate diagnosis and appropriate patient management. The remarkable precision and recall scores underscore the model's ability to precisely identify and classify the four types of ALL cells, reducing the risk of misclassification and supporting effective treatment decisions.




(a) (b) (c)

Fig. 3. Training graph of YOLOv5 object detection model: (a) mAP, (b) Precision, (c) Recall.

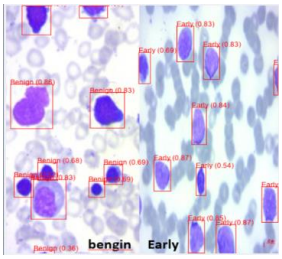



Fig. 4. Resulting image from our YOLOv5 object detection model.

TABLE II. MAP, RECALL, AND PRECISION RESULTS FOR GOOGLENET, ALEXNET, RESNET, AND YOLOV5

| | **GoogleNet** | **AlexNet** | **ResNet** | **YOLOv5** |
|---|---|---|---|---|
| **mAP** | 95.3% | 95.7% | 96.3% | 97.8% |
| **recall** | 95.5% | 95.1% | 95.9% | 96.7% |
| **precision** | 95.7% | 94.9% | 95.8% | 96% |

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